Three Essays on Hedge Fund Trading and Stock Market

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Declaration

I, Xinyu Cui, declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright Statement

Abstract

This thesis aims to understanding the hedge fund trading behaviors, including stock picking, stock price manipulation, and their impact on stock market. It consists of three chapters, which are independent research papers.

In the first chapter, we investigate who the counterparties of hedge fund equity trading are and what the economic reasons behind their trading decisions might be. We find that hedge funds earn positive ex-post abnormal returns and avoid negative abnormal returns on their equity portfolios when trading in the opposite direction of highly-diversified low-turnover institutional investors (quasi-indexers). This pattern is pronounced for short- and long-term holding periods, as well as if trading is conditional on return predictability associated with well-known market anomalies. It seems to be driven by the preferences of quasi-indexers for liquid, high-market-beta stocks, which tend to exhibit low future abnormal returns. Trading against other institutional investors or non-institutions does not result in abnormal performance for hedge funds.

In the second chapter, we analyze the equity trading of hedge funds facing substantial outflows. We find that hedge funds that trade against the flow display significant stock-picking skills. Stocks purchased by hedge funds facing large outflows deliver positive ex-post abnormal returns. Such "revealed under pressure" stock-picking skills are higher after 2007-2008 financial crisis and for hedge funds with larger size, more illiquid assets, or stronger incentives to perform to build up a track record. We also find that hedge funds that engage in the trading against the flow have higher chances of survival over the consequent quarter.

In the third chapter, we investigate the stock manipulation of hedge funds. We follow a research paper published in The Journal of Finance (Ben-David et al., 2013) presenting empirical evidence of stock price manipulation by hedge funds between 2000 and 2010. They show that stocks held by hedge funds exhibited positive daily abnormal returns and then reversals ("blips") at quarter end. These results are cross-sectionally robust: we replicate them using a different sample of hedge funds during the same time period. In the post-publications period from 2011 to 2018, however, we find no significant relation between hedge fund ownership and end-of-quarter stock returns, suggesting reduction in stock price manipulation by hedge funds post-publication.

We is for first person and he/she is for third person throughout the thesis to indicate that three chapters are co-authored with my supervisor Olga Kolokolova (and with George Wang for the first chapter). The empirical analysis in all chapters is my own work, while we equally contributed with the co-authors to the development of the idea, discussion of methodology, and structuring of the papers.

Table of Contents

This thesis contains 29,218 words, including title page, tables, and footnotes.

List of Figures

List of Tables

Chapter 1

On the Other Side of Hedge Fund Equity Trades

Keywords: Institutional Trading, Alpha, Market Beta, Market Anomalies, Quasi-Indexers, Hedge Funds.

1.1. Introduction

> *If you are making money more often than not, what is motivating others to trade the other way, and will they continue to do so in the future? Remember that for every buyer, there is a seller, so someone is always taking the other side of your trades, and if you do not understand the economics of the trade, they may.*

Lasse Pedersen, "Efficiently Inefficient", 2015

As professional arbitrageurs and sophisticated investors, hedge funds (HFs) play an essential role in stock price formation and improving market efficiency (see Stulz, 2007; Agarwal et al., 2015). Using equity holdings of HFs disclosed in 13F filings to Security and Exchange Commission (SEC), recent studies find comprehensive evidence on the link between HF trading, future stock returns, and mispricing.[1] For example, Cao et al. (2018) show that HFs tend to hold undervalued stocks and their trading predicts future stock returns and delivers a positive alpha. Cao et al. (2018) find that HF equity holdings improve efficiency of stock prices. Calluzzo et al. (2019) further show that HFs trade on the well-documented market anomalies and these arbitrage activities generate positive risk-adjusted returns. We join this strand of literature, but instead of looking at the identity of arbitrageurs and quantifying their gains, we focus on the flip side of HF equity trades. We set out to find who the counterparties of these professional arbitrageurs are and what the economic reasons behind their trading decisions might be.

Given that institutional investors hold around 80% ($18 trillion) of the S&P 500 stocks[2] and account for about 70% of daily trading volume[3], in this paper we mainly focus on potential institutional counterparties of HFs.[4] To understand the economics of the other side of HF equity trades, we need to recognize the heterogeneous objective functions and trading behaviour of HFs and non-HF investors. One possibility would be that other investors make random errors in their judgements of stock profitability, and HFs exploit these errors. If this is the case, there should not be any specific type of institutions which as a group consistently exhibit "negative skill" when trading in the opposite direction of HFs. Alternatively, there may

[1] Brunnermeier and Nagel (2004) are among the first ones to examine fund holdings. The authors conclude that HFs possess stock-picking and market timing abilities. HF demand shocks predict stock returns over the next few quarters (Sias et al., 2016). Informed stock demand of HFs predicts not only stock returns, but firms' fundamentals such as returns on assets (Jiao et al., 2016). HF trading often reduces stock mispricing, whereas mutual funds and other types of institutional investors either do not have any significant effect on mispricing or even exacerbate it (Jiao and Ye, 2014; Akbas et al., 2015; Kokkonen and Suominen, 2015; Ha and Hu, 2018). While HF stock holdings predict future stock returns, their option holdings predict both stock returns and volatility (Aragon and Martin, 2012).

[2] According to Pensions and Investments as of 2017, https://www.pionline.com/article/20170425/INTERACTIVE/170429926/80-of-equity-market-cap-held-by-institutions.

[3] According to Institutional Investor as of 2015, https://www.finra.org/investors/insights/institutional-investors-get-smart-about-smart-money.

[4] We recognize that individual investors could also be counterparties of HF equity trades (Ben-David et al., 2012). In our empirical analysis, we evaluate trades made by HFs against other investors too. However, given the dominating market presence of the institutional investors, and the limited available data on individuals, we leave the detailed analysis of the economics of individual decision making for future research.

be groups of investors that do not have an alpha-maximizing objective functions (see, e.g., Baker et al., 2011; Christoffersen and Simutin, 2017). For such investors, forgoing an alpha may be a natural consequence of their optimal trades. Such investors may constitute systematic counterparties of HFs, facilitating their abnormal gains. In this paper, we set out to establish if any type of institutional investors consistently provides HFs with profitable trading opportunities, and if yes, what the economic reasons behind such behaviour might be.

The group of institutional investors is heterogeneous. Passive and active mutual funds, index funds and exchange-traded funds, pension funds and insurance companies all have different objective functions, investment horizons, compensation schemes, and trading strategies. Their trading has been extensively studied in the literature,[5] and all of them can be potential direct or indirect counterparties of HF equity trades. However, even within the same nominal type, the investment behaviour of institutions can be substantially different (Bushee, 2001). In his influential work Bushee (2001) suggests classifying institutions according to their actual trading behaviour, and not according to nominal labelling. Such a "revealed" classification scheme provides more insights into preferences and investment goals of the institutions. In particular, Bushee (2001) subdivides institutions into three big categories, (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) dedicated holders (DEDs). A quasi-indexer is defined as an institutional investor exhibiting high portfolio diversification and low turnover, and also pursuing index-based buy-and-hold strategies. A transient institution also holds a highly-diversified portfolio but has a high turnover, and follows predominantly short-term trading strategies. A dedicated holder invests in concentrated portfolios and has low turnover, focusing on long-term trading strategies with low sensitivity to current firm earnings.[6] For

[5]From the trading skill perspective, active mutual funds are often found to underperform index-tracking funds (Blake et al., 1993; Malkiel, 1995; Elton et al., 1996; French, 2008; Guercio and Reuter, 2014; Crane and Crotty, 2018). In terms of market impact, institutional trading may play a positive role in price discovery and mitigate market anomalies (Gompers and Metrick, 2001; Nagel, 2005; Israel and Moskowitz, 2013), but it can also destabilize stock prices (Frazzini and Lamont, 2008; Dasgupta et al., 2011).

[6]This classification has been also used in, for example, Ke and Ramalingegowda (2005); Cella

example, Vanguard group is classified as QIX, Fidelity International is TRA, while Apollo Investment Management is classified as DED.

We find empirical evidence that QIXs significantly underperform when trading in the opposite direction of HFs. On average, stocks sold by HFs and simultaneously purchased by QIXs exhibit a significantly negative alpha of -0.35% per month relative to the CAPM, whereas stocks purchased by HFs and sold by QIXs earn a significantly positive alpha of $+0.57\%$ per month over the following quarter. This pattern is also pronounced when the abnormal returns are calculated using the characteristic-based approach of Daniel et al. (1997). Other investors do not exhibit such patterns, when trading in the opposite direction of HFs.

QIXs usually have limited potential to lock in alpha due to leverage and short-selling restrictions. They are often constrained by the need to keep the tracking error within certain bounds, and their performance is benchmarked with respect to that of market indices. In order to achieve higher expected returns and beat the index, they optimally choose stocks with higher market betas, and thus depart from alpha-maximizing portfolios. Such reasoning is supported by Christoffersen and Simutin (2017), who show that mutual fund managers tend to increase their exposure to high-beta stocks to boost expected returns while maintaining tracking errors around the benchmark. We find that the average market beta of stocks sold by HFs and purchased by QIXs is 1.34, whereas the average beta of stocks purchased by HFs and sold by QIXs is 1.10, with the difference being highly statistically significant and persistent over time as well as for longer holding periods.

The beta-over-alpha preferences explain the negative abnormal returns on stock bought by QIXs and simultaneously sold by HFs. When we control for the betting against beta factor of Frazzini and Pedersen (2014), the negative alpha of this portfolio loses significance, as its underperformance in now absorbed by the negative factor loading. The positive abnormal return of stocks bought by HFs and sold by QIXs remains significant even after controlling for the beta preferences of QIXs and

et al. (2013); Fang et al. (2014); Boone and White (2015); Appel et al. (2016).

stock illiquidity, suggesting some extra stock-picking skills of HFs.

Our approach allows us also to contribute to the extensive literature on the relation between institutional ownership and market anomalies.[7] McLean and Pontiff (2016) show that market anomalies tend to decline after their publication dates. They suggest two competing explanations: (1) the very existence of the anomalies is questionable and may be a result of inappropriate statistical analysis (see, e.g., Harvey et al., 2016), hence, the anomalies should not persist; and (2) the anomalies exist because of stock mispricing, and sophisticated arbitrageurs correct them over time. Directly looking at institutional trading on market anomalies, Edelen et al. (2016) report, however, a negative relation between the change in aggregate institutional holding and the stocks' ex-post abnormal returns. At the same time, Chen et al. (2018) find that HFs earn positive abnormal returns by trading on anomaly stocks, and Ha and Hu (2018) show that the HF daily order flow is positively correlated with previous daily market anomalies. Our paper complements these studies and shows that the overall poor performance of institutional anomaly trading is mainly driven by QIXs, taking the "wrong" side of an anomaly trade due to the general beta-over-alpha preferences. HFs buy low-beta stock while QIXs sell them and vice versa, which results in a positive alpha for HFs, even when trading can be linked to return predictability based on well-documented market anomalies.

The total asset size of QIXs is far larger than that of other types of institutional investors and HFs together, that is, the vast amount of capital is invested in strategies that are not risk-adjusted return maximizing. Proactive arbitrageurs, such as HFs, have plentiful opportunities of delivering alpha to their investors, exploiting trading preferences of other institutions. This pattern is not likely to be reversed soon, since large investment firms keep launching low-cost index-tracking vehicles.[8]

[7]See Gompers and Metrick (2001); Nagel (2005); Frazzini and Lamont (2008); Green et al. (2011); Israel and Moskowitz (2013); McLean and Pontiff (2016); Calluzzo et al. (2019), among others.

[8]Fidelity, for example, launched the first index-tracking stock fund without any fees for investors on 3 August 2018. See "Asset managers shares dive after no-fee fund launch", *Financial Times*, August 2, 2018.

1.2. Research Design

To identify possible counterparties of HF equity trades, we need to classify different types of investors first. Previous studies usually employ one of the two systems: institutional investors are classified either according to their business registration type (e.g., mutual funds, banks, insurance companies, etc.) or according to their actual trading behaviour (Bushee, 2001). While considering both systems in our study, we believe the trading-behaviour based classification is more relevant to our research target. According to Bushee (2001), institutional investors can be divided into QIXs, TRAs, and DEDs.[9] We also add to the list of potential HF counterparties other investors (OTH), with stock holding not included in the previous groups.

Key "suspects" in our investigation of the other side of HF equity trades are QIXs. These institutions may constitute a systematic counterparty of HFs, as they are less likely to have alpha-maximizing objective functions. Instead, they may be more concerned with minimizing the tracking error with respect to their benchmark index, while still trying to beat it. Harris and Gurel (1986) show that when indices adjust their company lists, large index funds frequently buy stocks that are newly added to indices and sell stocks deleted from the indices, leading to substantial demand shifts. Even in the absence of any index adjustment, an important feature of the trading of institutions that face benchmarking is that they tilt their portfolios to high-beta stocks, in order to beat the benchmark. Buffa et al. (2019) develop an equilibrium framework in which choosing higher-beta investments is optimal for a benchmarking manager. Christoffersen and Simutin (2017) empirically show that those mutual funds that have a large share of investment from pension funds and, thus, are more likely to be benchmarked, invest disproportionally into high-beta stocks, and stocks with high market betas tend to have low alphas (Frazzini and Pedersen, 2014). Additionally, QIXs do not seem to closely monitor firms they invest into. They do not have any effect on innovation in firms they hold, while other types of institutional investors have positive association with innovation (Aghion

[9] More details are provided in Section 2.2.

et al., 2013). Another important feature of QIXs is that they tend to prefer more liquid stocks (Gompers and Metrick, 2001), whereas HFs are known for earning high returns by trading less liquid assets and providing market liquidity (Teo, 2011; Jylhä et al., 2014). These leads to our "swap" hypotheses as follows:

α swap:	*HFs earn positive abnormal returns when trading in the opposite direction of QIXs.*
	The abnormal returns are driven by:
β swap:	*HFs selling high-beta and buying low-beta stocks,*
Liquidity swap:	*HFs selling more liquid and buying less liquid stocks.*

To test our hypothesis, we first split all institutions into HFs and non-HF investors, and then, following Bushee (2001), we subdivide non-HF investors into QIXs, TRAs, and DEDs. We obtain institutional holdings from the 13F filings, and compute the holdings of OTHs following Ben-David et al. (2012) as the difference between 100% and the percentage holding of all other reporting institutional investors.[10]

Second, for each type of trader we compute quarterly change in their holding of each stock i, expressed as a fraction of the total common shares outstanding by the company at the end of the previous quarter $(\mathrm{q}-1)$.

For example, the change in holding of stock i by HFs during quarter q ($\Delta \mathrm{StockHold}_{\mathrm{i,q}}^{\mathrm{HF}}$) is given by:

$$\Delta \mathrm{StockHold}_{\mathrm{i,q}}^{\mathrm{HF}} = \frac{\mathrm{StockHold}_{\mathrm{i,q}}^{\mathrm{HF}} - \mathrm{StockHold}_{\mathrm{i,q\text{-}1}}^{\mathrm{HF}}}{\mathrm{TSO}_{\mathrm{i,q\text{-}1}}}, \tag{1.1}$$

[10]Holdings of OTH include holdings of individual investors, small US-based investors, and foreign institutions which do not need to comply with 13F filing requirements, as well as small holdings of large US-based investors, which are below the reporting threshold or for which confidential treatment was requested by reporting institutions (French, 2008; Ince and Kadlec, 2020).

where $\text{StockHold}^{\text{HF}}_{\text{i,q}}$ is the holding of stock i by all HFs at the end of quarter q, i.e.

$$\text{StockHold}^{\text{HF}}_{\text{i,q}} = \sum_{\text{j}} \text{StockHold}^{\text{HF}_\text{j}}_{\text{i,q}}, \tag{1.2}$$

and $\text{TSO}_{\text{i,q-1}}$ is the total number of outstanding shares of firm i at the end of quarter $\text{q} - 1$. $\Delta\text{StockHold}^{\text{HF}}_{\text{i,q}}$ is considered to be a missing value if any of $\text{StockHold}^{\text{HF}}_{\text{i,q}}$, $\text{StockHold}^{\text{HF}}_{\text{i,q-1}}$, or $\text{TSO}_{\text{i,q-1}}$ is missing. All holding and numbers of shares outstanding are adjusted for stock splits.

Third, we construct a set of swap portfolios, which include stocks heavily traded by HFs and simultaneously traded in the opposite direction by QIXs, TRAs, DEDs, or OTHs. We rank stocks based on the change in holding during each quarter in year t within stocks of two size groups – above or below the NYSE size median at the end of year $\text{t} - 1$ – following Fama and French (1993). We consider stocks with the change in holding below the 20^{th} percentile as those that investors significantly sell, and those above the 80^{th} percentile as those that investors significantly buy. The swapped stocks are those which belong to the intensively traded stocks for two types of investors, but in different directions. We form a set of swap portfolios as an equal-weighted average across different size groups of the value-weighted average returns of the chosen swapped stocks.[11] The portfolios are then held for one quarter until the end of the following quarter and then rebalanced. To capture the longer-term performance of swapped stocks, we also consider annual holding periods. We form swap portfolios every quarter and hold them for the following year. Every month we compute the average return of the previously formed portfolios which are still being held at that month to obtain the time series of long-term holding portfolio returns.

Last but not least, we evaluate the performance of these portfolios. We compute monthly average excess returns over the risk-free rate (measured as the 3-month T-bill rate) as well as the abnormal returns (α-s) and market factor loadings (β-s)

[11] As a robustness check, we also used 10% and 30% cutoffs. The results remain qualitatively the same and are reported in an Online Appendix.

relative to CAPM model.[12] We then compute the average Amihud (2002) illiquidity measure to check if HFs swap liquid to illiquid stocks with QIXs. Our swap hypotheses imply that the alpha of stocks bought by HFs and simultaneously sold by QIXs should be larger than that of stocks sold by HFs and bought by QIXs, while the relation of their market betas is the opposite. Stocks bought by HFs and sold by QIXs are also expected to be less liquid than stocks sold by HFs and bought by QIXs.

To take into account other stock characteristics that may impact performance in potentially nonlinear manner, we follow the procedure of Daniel et al. (1997) (hereafter DGTW) and construct the DGTW-adjusted monthly excess returns. At the end of each June, we assign stocks into one of 125 portfolios constructed based on market capitalization using NYSE breakpoints, the industry-adjusted book-to-market ratio using the Fama-French 48 industries, and the prior 12-month return. Portfolios are held for one year and then rebalanced. For each of the 125 portfolios, we calculate the value-weighted monthly returns as the benchmark. The DGTW-adjusted monthly excess return is the difference between the stock's monthly return and the return of the benchmark portfolio to which it belongs. We compare the monthly average DGTW-adjusted excess returns of stocks swapped by HFs and other types of investors. Similar to the CAPM abnormal returns, we expect the DGTW-adjusted excess returns to be higher of stocks bought by HFs and sold by QIXs, compared to excess returns of the opposite swap.

If the superior HF performance on swapped stocks is indeed driven by the β- and liquidity-swap, one should observe that the abnormal returns of HFs on swap portfolios to disappear after the differences in stock betas and liquidity are accounted for. In doing so, we use the betting against beta factor (hereafter BAB) of Frazzini and Pedersen (2014),[13] who find that high-beta assets earn low alphas due to funding

[12] As a robustness check we also use the Fama-French 3-factor model and Carhart 4-factor model (Carhart, 1997).

[13] The time series values of the factor are obtained from the authors' web-page https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly.

constraints, and the traded liquidity factor (hereafter LIQ) of Pástor and Stambaugh (2003), who show that liquidity risk is an important determinant of HF returns.[14] We evaluate the alphas from the regressions of the DGTW-adjusted excess returns of the swapped portfolios on these two factors.

To assess the stability of the results during different market conditions, we repeat the analysis before, during, and after the financial crisis of 2007–2008, and also run a rolling window regression using a three-year window and quarterly steps. We also assess the long-term performance of the swapped stocks and use an annual holding period instead of a quarterly one, as described above.

1.3. Data Sources and Sample Construction

Stock returns are from the Center for Research in Security Prices (CRSP) Monthly Stock File. We consider the monthly returns of common stocks (those with CRSP share codes of 10 or 11) traded on the NYSE, AMEX or NASDAQ (those with CRSP exchange codes of 1, 2 or 3) from April 1994 to December 2018. Stock returns are adjusted for split and delisting. We only consider the stocks with monthly prices above \$5 at the beginning of each quarter, in order to purge the estimation noise from the minimum tick effect (Harris, 1994; Amihud, 2002) and to make sure that all institutional investors can trade them. We exclude the stocks of utility firms (those with standard industrial classification (SIC) codes from 4900 to 4999) and financial firms (those with SIC codes from 6000 to 6999). Panel A of Table 1.1 reports the descriptive statistics of all of the stocks in our sample. We also collect the data for the standard market factors from Ken French's data library.[15]

Our data on institutional holding are from the Thomson Reuters Institutional (13f) Holding database (CDA/Spectrum s34). The 13f mandatory reports of institutional holding are filed with the Securities and Exchange Commission (SEC) and are

[14] The time series values of the factor are obtained from the authors' web-page http://finance.wharton.upenn.edu/~stambaug/.

[15] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

compiled by Thomson Reuters. According to the 1978 amendment to the Securities and Exchange Act of 1934, institutions with aggregate fair market values over $100 million must file their forms within 45 days after the end of a calendar quarter. The managers are allowed to omit their "small" holding (if they hold fewer than 10,000 shares and less than $200,000 in terms of their market values). Thus, most of the disclosed holding data come from relatively large positions of large firms.

To identify HFs, we use a union of three major HF databases – EurekaHedge, TASS Lipper, and Morningstar – for the period from 1994 to 2017.[16] We merge the databases following the procedure described in Joenväärä et al. (2016). We then create a list of HFs' 13f identifiers, i.e. manager numbers (hereafter MGRNOs), by matching the HF company name and the names of the institution reporting to the 13f database. We manually check that the identified companies do not have any other business (e.g., a mutual fund, insurance, banking etc.), ensuring that we obtain a list of pure HF companies. Altogether, we identify 734 HF companies that report to the 13f databases. Next, we use Brian Bushee's database[17] to identify 2,906 QIXs, 1,448 TRAs and 161 DEDs for our sample. We consider only those institutions which have a unique identifier of permanent classification provided in the Bushee's database. We remove institutions without a permanent classification or those with several permanent classifications. Overall, the 5,278 institutions in our final sample cover 74.92% of all institutions from the database existing between 1994 and 2017. As of the end of 2017, the overall portfolio size of QIXs was $9.72 trillion, whereas it was $2.83 trillion for TRAs, $0.29 trillion for DEDs, and $1.59 trillion for HFs.

[Place Table 1.1 about here]

Panel B of Table 1.1 reports the descriptive statistics of the institutional portfolios. The largest group of institutions are QIXs, with on overage 1,352 institutions

[16] Starting from 1994, most databases keep the information on defunct HFs: a potential survivorship bias in the data is thereby ameliorated.

[17] http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html

reporting holding per quarter compared to 319 HFs. The smallest group is DEDs with only 69 institutions reporting per quarter, on average. QIXs are also the most diversified institutions, holding on average 170 different stocks in a quarter, followed by TRAs with 166 stocks per quarter, compared to 118 of HFs and only 52 of DEDs. QIXs have the smallest turnover, on average 6.57% per quarter, compared to over 22.04% per quarter for HFs and 23.73% for TRAs. Turnover for quarter q is calculated as the minimum of purchases and sales during quarter q, divided by the average market value of the portfolio at the end of quarter q and the previous quarter.

Table 1.2 reports the descriptive statistics of the holding and the change in holding of all types of investors in our sample across three periods: the pre-crisis period 1994q2 to 2007q2, the crisis period 2007q3-2009q1, and the post-crisis period 2009q2-2017q4. The changes in holdings are winsorized at the 1% and 99% quantiles.[18] The descriptive statistics of the holdings are broadly similar to those reported in Jiao et al. (2016). QIXs hold a substantial share of the market. Their average holdings of shares in listed non-financial and non-utility companies have increased from 29% in the pre-crisis period to around 40% in the later periods. The average holdings of HFs and TRAs in these firms also have increased from 6% and almost 10% pre-crises to 10% and nearly 14% in the later sample, respectively. DEDs hold below 2% of the stocks in all the sub-samples. Before the crisis, QIXs had the largest average changes in the position of 0.87% per quarter, compared to 0.30% for HFs, 0.28% for TRAs, and 0.04% for DEDs. During the crisis period, QIXs kept purchasing stocks on average, although at a slower pace (the average change of 0.40%), while HFs as a group kept their holdings largely unchanged (the average change of 0.02%), and TRAs and DEDs have been selling stocks on average (the corresponding change are -0.30% and -0.20% respectively). Post-crisis, TRAs, QIXs, and HFs are net buyers in the stock market, with the average changes of 0.33%, 0.30%, and 0.15%, while DEDs are net sellers (the average change in holdings of -0.11%). Given

[18]We exclude from the sample those quarter-stock data points for which the sum of the reported institutional holding exceeds 100%.

how few DEDs exist per quarter, the small share of their holding, and a particular investment style of long-term holding of concentrated portfolios, we exclude these institutions from the further analysis.

[Place Table 1.2 about here]

1.4. Empirical Results

1.4.1. Institutional trading: α-, β- and liquidity-swap

Panel A of Table 1.3 reports the excess returns over the risk-free rate, the CAPM alphas and betas[19], and Amihud illiquidity measures for stocks swapped between HFs and other types of investors.

Consistent with our expectations, the stocks sold by HFs and simultaneously bought by QIXs exhibit negative future alphas of -0.35% per month, have high beta of 1.34, and are more liquid (Amihud illiquidity of 0.70×10^{-6}), compared to stocks bought by HFs and sold by QIXs. The latter exhibit a positive alpha of 0.57% per month, have smaller beta of 1.10, and higher illiquidity (1.10×10^{-6}), with all the differences being highly statistically significant. In contrast, stocks swapped between HFs and TRAs do not exhibit any statistically significant alphas in either direction. The differences between betas and illiquidity measures are not significant, either. Stocks sold by HFs and purchased by OTHs exhibit significantly negative alpha with respect to the CAPM, but no difference in beta or illiquidity can be seen for stocks swapped in different directions between HFs and OTHs.

Even after controlling for other factors via DGTW-adjusted returns (Panel B of Table 1.3), the excess return of stocks sold by HFs and purchased by QIXs remains negative of -0.19% per month and significant at the 10% level, whereas the DGTW-adjusted excess return of stocks bought by HFs and sold by QIXs is 0.50% per month, significant at the 1% level. The swaps between HFs and TRAs or OTHs do

[19]The results based on the Fama-French 3-factor model and Carhart 4-factor model are qualitatively the same and are reported in Online Appendix.

not generate any significant adjusted returns.

Controlling for LIQ and BAB factors reveals that stocks swaps between HFs and QIXs in opposite directions do not exhibit significant differences in their exposure to the liquidity factor, thus, differential liquidity risk does not contribute to underperformance of stocks bought by QIXs relative to stocks sold. At the same time, the difference in exposures to BAB factors is highly statistically signifiant, providing further support to our β-swap hypotheses. Importantly, the negative abnormal returns of stocks sold by HFs and simultaneously bought by QIXs lose significance, after controlling for BAB. Remarkably, abnormal returns on stocks purchased by HFs and simultaneously sold by QIXs remain large positive (0.47% per month) and statistically significant at the 1% level, even after LIQ and BAB factors are controlled for, suggesting a different source of superior HF performace in this case.

Combined together, the results suggest that QIXs trade in the alpha for the market beta when making purchasing decisions. Trying to beat the benchmark while remaining within admissible tracking error bounds, QIXs tilt their portfolios to high-beta stocks, which tend to be associated with low alphas. HFs exploit this opportunity and provide liquidity for such trades.

[Place Table 1.3 around here]

Despite similarities in the levels of portfolio diversification and rebalancing frequencies, the group of QIXs is heterogeneous. Passive mutual funds that track an index are more likely to be benchmarked relative to it, as compared, for example, to insurance companies. This may lead to differences in their preferences for stocks with high market beta. We refine the analysis by splitting the sample of QIXs into three categories of investors. The first one is independent investment advisors (IIAs), the largest group capturing 73.64% of QIXs in our sample, which contains, for example, mutual funds. The second is banks (BNKs) capturing 11.98% of the sample. The remaining 14.38% are other QIXs (OTQIXs), including pensions plans, insurance companies, and university endowments.

The beta-over-alpha preferences discussed above can be seen for all three types of QIXs (Table 1.4). The worst performance in terms of the abnormal returns seems to be generated by BNKs. The CAPM alpha spread between the portfolio of stocks bought by HFs and sold by BNKs, and sold by HFs while purchased by BNKs is 1.15% per month. The corresponding difference in the DGTW-adjusted excess returns is 0.88% per month. It is 0.59% for IIAs and 0.58% for OTQIXs. All the differences are significant at the 1% level. The difference in CAPM betas is the strongest for IIAs of -0.36, significant at the 1% level. It is substantially larger than -0.24 reported in Table 1.3 for all QIXs.

[Place Table 1.4 around here]

An alternative explanation for the significant ex-post alphas associated with HF/QIX swaps may be position reversals by QIXs and/or herding by investors after HF trades. If various investors sell a substantial amount of the stocks that have been bought by QIXs but sold by HFs during the previous quarter, the selling pressure would reduce the abnormal returns. The abnormal returns would increase if investors follow previous HF purchases. To check if such a mechanism is supported by the data, we compute the average change in holdings of HF/QIX swapped stocks during each quarter and the average quarterly change in holdings of HFs and non-HF investors of these stocks during the subsequent quarter (Table 1.5). During trading quarters, the change in holding of HFs is smaller in absolute value than the corresponding change in holdings of QIXs. HFs do not seem to fully exploit potential arbitrage opportunities, which may be due to the relatively small total size of the HF industry as compared to the overall market value. We find no evidence of substantial trade reversals or herding, however. QIXs, moreover, tend to keep buying during quarter q+1 stocks they purchased during the previous quarter and that were sold by HFs. On the HF buying side, HFs and TRAs increase their holdings in stocks swapped between HFs and QIXs, but these changes are small (0.33% and 0.35% respectively) as compared to the initial HF purchase size of 3.43%. Thus, we cannot find empirical support for trade reversals of QIXs or institutional herding into swapped stocks, which can lead to the observed abnormal return patterns.

[Place Table 1.5 about here]

1.4.2. Institutional trading swap: time-series variation and long-term performance

To assess the stability of our results across different market conditions, we repeat the analysis for three sample periods separately: pre-crisis (1994q1–2007q2), crisis (2007q3–2009q2), and post-crisis (2009q3–2017q4) periods (Ben-David et al., 2012).

The difference in CAPM alpha between stocks sold by HFs/bought by QIXs, and those bought by HFs/sold by QIXs is persistent across all three periods (Table 1.6). In the pre-crisis and crisis periods, HFs were gaining significantly by buying future winners. The effect is especially strong during the crisis period, where the ex-post alpha of stocks bought by HFs and sold by QIXs relative to the CAPM reaches 1.92% per month. During the post-crisis period, the performance differences are generated predominantly by HFs selling future losers. As for market betas, QIXs have been buying especially high-beta stocks during the pre-crisis periods, but not during the crisis, when the difference in betas between stock sold by HFs/bought by QIXs, and those bought by HFs/sold by QIXs is not statistically significant. This result is consistent with the intuition that QIXs tilt their portfolios towards high-beta stocks when trying to beat the benchmark. This strategy works, however, only as long as the benchmark has a positive expected return. During the crisis period the market returns were negative, and retreating from high-beta stocks was optimal for benchmarked institutions.

Similar pattern is observed when DGTW-adjusted returns are used (Table 1.7). The largest spread between two swapped portfolios (in terms of the DGTW-adjusted returns and their alphas relative to LIQ and BAB factors) is generated during the crisis period. In the post-crisis period, although stocks bought by HFs and simultaneously sold by QIXs still significantly outperform those sold by HFs/bought by

QIXs, the magnitude of the difference is only about one third of that during the crisis period.

[Place Tables 1.6 and 1.7 around here]

Figure 1.1 further plots the time series of alphas and market betas relative to the CAPM for stocks swapped between HFs and other investors estimated using three-year rolling windows. The alphas of stocks bought by HFs/sold by QIXs are almost always positive and above those sold by HFs/bought by QIXs, which are in most cases negative. The betas of the stocks purchased by HFs, on the other hand, are almost always smaller than those of sold stocks, apart from the crisis period, consistent with the previous discussion. As for the swaps between HFs and other investors, no persistent difference can be seen for either alphas or market betas over time.

[Place Figure 1.1 about here]

Long-term performance of the swapped stocks (Table 1.8) reveals that the alpha losses of QIXs that buy stocks which are sold by HFs are predominantly associated with the short-term performance over the first quarter, and the losses are not statistically significant over the annual horizon. It turns almost zero when LIQ and BAB are taken into account with DGTW-adjusted returns. At the same time, the gains which HFs make by purchasing stocks sold by QIXs remain positive and statistically significant even on the annual horizon, although their magnitude decreases. This findings is consistent with HFs being shorter-term investors with high turnover, capitalising predominantly on their skills to predict short-term returns (see Agarwal and Naik, 2000; Edwards and Caglayan, 2001; Jagannathan et al., 2010, among others). The difference in market betas and in loadings on the BAB factor remains statistically significant, with HFs selling/QIXs buying high-beta stocks, and this swap portfolio having a significantly negative exposure to the BAB factor. No statistical difference can be found for other counterparties of HFs.

[Place Table 1.8 around here]

1.4.3. Implications for market anomalies

Over the past decades, an increasing number of firm characteristics that predict future stock returns have been discovered (so-called market anomalies). The trading behaviour of institutional investors associated with these anomalies has attracted a great deal of scholarly attention (see Fama and French, 2008; Campbell et al., 2009; Israel and Moskowitz, 2013; Hou et al., 2015; Edelen et al., 2016, among others).

Calluzzo et al. (2019) show that HFs and other high turnover institutions do trade on market anomalies and exploit return predictability, especially over short-term. Edelen et al. (2016), however, show that on aggregate institutional investors trade against market anomalies. They incur abnormal losses when wrongly purchasing "anomaly" stocks that theoretically should belong to the short side of the anomaly trade. Thus, similar to our main findings, these equilibrium results suggest that HFs may be profiting by trading in the opposite direction other investors even if the trades are related to known features of return predictability. Our previous empirical results indicate that QIXs seem to have a different objective function from other institutional investors, and swap portfolio alphas for portfolio betas – the strategy being exploited by HFs. We now extend this analysis to portfolios of "anomaly" stocks.

We consider nine well-known market anomalies discussed in Fama and French (2008) and Stambaugh et al. (2012), including the operating profit (OP), gross profitability (GP), O-Score, investment-to-assets (IVA), investment growth (IK), net operating assets (NOA), net stock issues (NSI), accrual (ACR), and asset growth (AG) anomalies.[20]

To guarantee that all of the firm specific information related to the market anomalies is available to all institutional investors, we consider the institutional trading during the second quarter of year t. This ensures that the annual reports for the fiscal year ending in calendar year t − 1 are readily available.The portfolio holding period is the following four quarters starting from the third quarter of year

[20]The anomalies are described in detail in the supplementary Online Appendix.

t. The anomaly portfolios constructed during the institutional trading window of year t are held until the end of the next trading window of year t + 1.

Similar to our main analysis and following Fama and French (1993, 2008), we construct ten portfolios from the intersection of two size groups (above or below the NYSE size median at the end of calendar year t − 1) and five anomaly groups (using NYSE breakpoints for the quintiles). To reduce the dominance of micro-cap stock returns (Edelen et al., 2016), we compute the monthly value-weighted returns for each portfolio and calculate the equal-weighted returns of portfolios in different size groups but the same anomaly group. The resulting portfolios characterize the average performance of the anomaly-related stocks in our sample. We call portfolios "underpriced" if they contain the top 20% of stocks according to the gross profit and gross profitability, or the bottom 20% of stocks according to other anomalies. The underpriced portfolios are expected to have positive abnormal returns, and they belong to the long leg of a trade. We call portfolios "overpriced" if they contain the bottom 20% of stocks according to the gross profit and gross profitability, or the top 20% stocks according to other anomalies. The overpriced portfolios are expected to have negative abnormal returns and they belong to the short leg of a trade.

We then construct a set of institutional swaps on market anomalies portfolios. During the institutional trading window (the second quarter of year t), we conduct independent triple sorts of all stocks based on (1) stock sizes at the end of calendar year t − 1 using the NYSE median, (2) each of the nine market anomalies evaluated for the fiscal year ending in calendar year t − 1 using the 20% and 80% NYSE breakpoints, and (3) the change in holding during the second quarter of calendar year t using the 20^{th} and 80^{th} percentiles. For each portfolio, we compute the monthly value-weighted returns and calculate the equal-weighted returns of portfolios in different size groups but the same anomaly group, ranking variables and the change in holding. Then, we calculate the equal-weighted returns of nine anomaly portfolios for each pair of investors. Altogether, we end up with four swap portfolios for each pair of investors. For example, if HFs exploit market anomalies and QIXs make "wrong-side" trades, we would expect to find significantly negative abnormal returns for stocks in the short leg of the anomaly that are sold by HFs and bought by QIXs.

We collect the accounting information from the CRSP/Compustat Merged Database Fundamentals Annually from 1993 to 2016.[21] We only use firms with the minimum of two years of data available, starting from their second reporting year.

Panel A of Table 1.9 reports the descriptive statistics of the firm performance measures, related to the nine market anomalies in our sample. All of the anomaly measures are winsorized at the 1% and 99% levels. Panel B of Table 1.9 reports the CAPM alphas for portfolios sorted on each of the nine anomalies under study and the equal-weighted portfolio of nine anomaly portfolios (EW-Avg); Panel C reports the corresponding DGTW-adjusted excess returns. The results substantiate the existence of these anomalies in our sample, with the GP and NOA anomalies being the most pronounced. By investing in the corresponding long-short portfolios investors can obtain up to 0.65% per month in terms of abnormal returns relative to the CAPM, and 0.56% per month in terms of DGTW-adjusted returns, both signifiant at the 1% level (the NOA anomaly).

[Place Table 1.9 about here]

Table 1.10 reports CAPM alphas, betas, and liquidity for swapped stocks related to the equal-weighted combination of the market anomalies under consideration during the entire holding period, and Table 1.11 reports the DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas, and factor loadings. Swaps in which HFs sell/QIXs buy overpriced stocks deliver a significantly negative alpha of -0.46% per month, while swaps in which HFs buy/QIXs sell underpriced stocks exhibit a positive alpha of 0.51% per month. The differences in alphas of stocks bought by HFs/sold by QIXs and sold by HFs/bought by QIXs are positive

[21] The accounting information we used is this study is related to year t − 1. Thus, our last calendar year for the accounting data is 2016; based on this information our last holding period is from July 2017 to June 2018, that is, until the end of our return sample.

and highly statistically significant for both short leg and long leg of market anomalies. In terms of market betas in each sub-group of stocks (overpriced/underpriced relative to market anomalies), QIXs buy stocks with significantly higher market betas than those of stocks they sell. Swaps between HFs and other types of investors do not exhibit such patterns in either alpha or beta.

Similar to our main results, the negative abnormal returns of swapped stock in the short leg of anomaly trades which HFs sell and QIXs buy lose their significance when DGTW-adjusted returns are used and LIQ and BAB factors are controlled for, but the positive abnormal returns for the long leg of anomaly portfolios for stocks bought by HFs/sold by QIXs are still positive and significant.

[Place Tables 1.10 and 1.11 about here]

Overall, the results suggest that HFs are able to exploit return predictability associated with different market anomalies because they are able to find a willing counterparty – QIXs – investors that tilt their portfolios towards high-beta stocks and do not seem to be directly motivated to exploit return predictability.

The QIXs are the dominant group of institutional investors in our sample according to their asset size. Thus, as QIXs do not exploit the profitable opportunities arising from the market anomalies due to the peculiar objective function of these traders, and the total portfolio size of other institutions is not sufficient to offset the impact of the trading of QIXs, the market anomalies are still strongly pronounced nowadays, despite the availability of theoretical research explaining their nature and accounting information underlying the corresponding portfolio choice.

1.5. Conclusion

Hedge funds earn positive abnormal returns and avoid negative abnormal returns when they trade in the opposite direction of quasi-indexers – highly-diversified and low turnover institutions. Stocks bought by hedge funds and simultaneously sold by quasi-indexers exhibit significantly positive future alphas relative to various benchmark models, while stocks sold by hedge funds and bought by quasi-indexers exhibit negative future alphas. The seemingly negative stock-picking skills of quasi-indexers are likely to be related to their trading strategy, which is not explicitly alpha-maximizing. Being motivated by benchmarking relative to the market index, these institutions tend to purchase stocks with higher market betas, and sell stocks with low market betas, and hence, trading in alpha. Hedge funds provide liquidity for such trades, earning abnormal returns for their own investors. Other types of investors do not exhibit such patterns: hedge funds do not earn significant abnormal returns when trading with them.

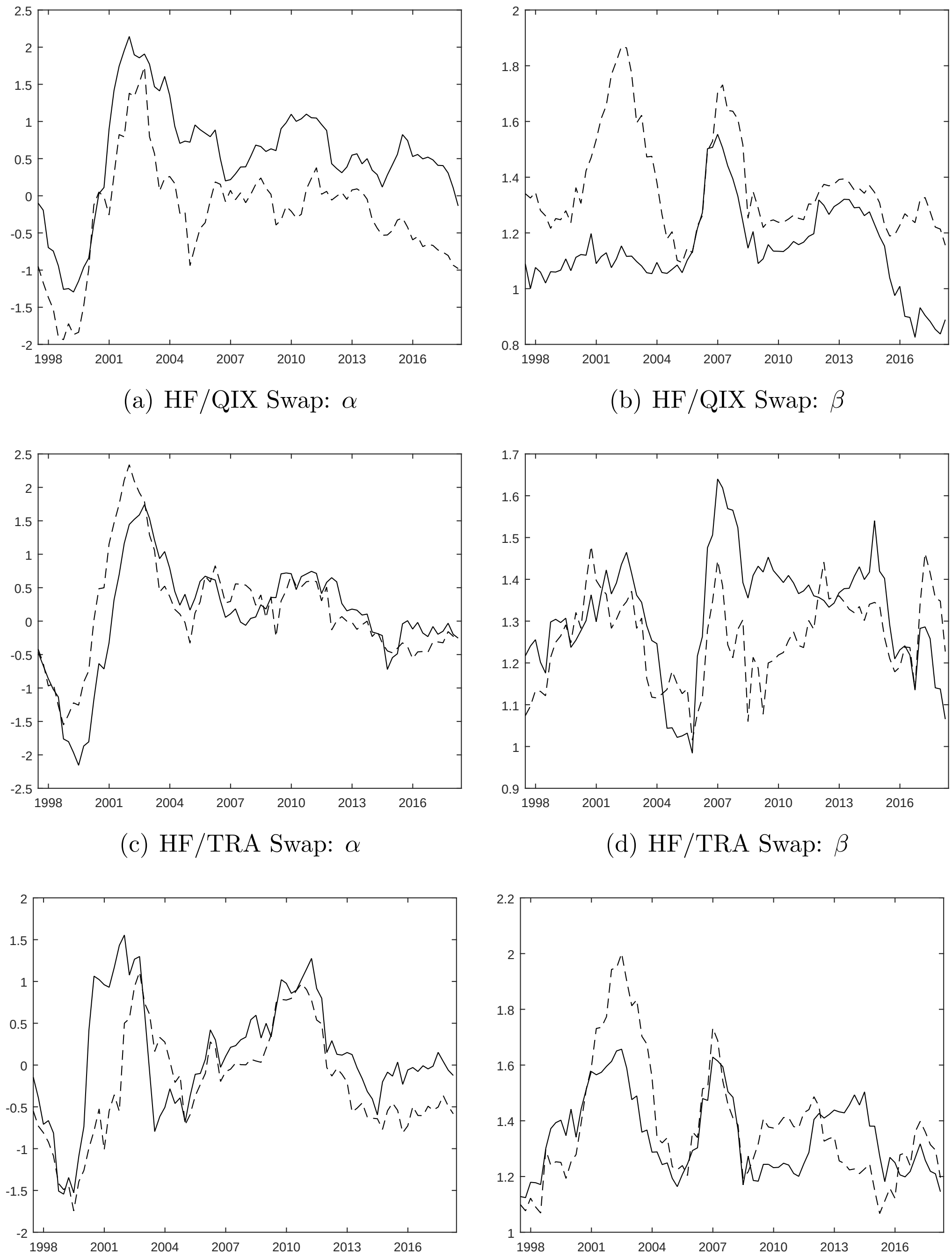
The beta-over-alpha preferences seem to keep quasi-indexers from trading against well-established market anomalies, too. Even conditional on the anomaly-related accounting information being publicly available, quasi-indexers still invest into high-beta and low-alpha stocks. They do not exploit return predictability, and allow hedge funds that trade against them to earn abnormal returns. This finding echoes Giannetti and Kahraman (2017), who show that open-end investment structures may hamper the trading against mispricing. It also extends the work of Edelen et al. (2016) by showing that the negative relation between change in institutional holding and ex-post abnormal returns for anomaly stocks is mainly driven by quasi-indexers, trading in the alpha for the market beta.

Our paper suggests that, as long as the largest amount of investible capital is allocated to traders that are not explicitly motivated to deliver high risk-adjusted expected returns, various profit-making opportunities (including but not limited to market anomalies) will persist in the market. More active and properly-motivated investors, such as hedge funds, will exploit these opportunities at the expense of individuals who delegate their money management to quasi-indexers.

1.6. Figures

Figure 1.1: Time series of alphas and market betas for trading swaps

The figure plots the time series of alphas and market betas from the CAPM model of stocks bought (solid line) by HFs from different groups of non-HF investors and sold (dashed line) by HFs to different groups of non-HF investors from 1994q2 to 2017q4. Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). The estimation is performed over three-year rolling windows.



(a) HF/QIX Swap: α

(b) HF/QIX Swap: β

(c) HF/TRA Swap: α

(d) HF/TRA Swap: β

(e) HF/OTH Swap: α

(f) HF/OTH Swap: β

1.7. Tables

Table 1.1: Descriptive statistics: stocks traded and portfolios

This table reports the summary statistics of characteristics of stocks traded and different groups of investors from 1994q2 to 2018q4. Panel A reports the monthly returns, prices, and Amihud illiquidity (Amihud, 2002). We only consider common stocks (those with CRSP share codes of 10 or 11) traded on the NYSE, AMEX or NASDAQ (those with CRSP exchange codes of 1, 2 or 3) with monthly prices above $5 at the end of previous quarter. We exclude the stocks of utility firms (those with standard industrial classification (SIC) codes from 6000 to 6999) and financial firms (those with SIC codes from 4900 to 4999). Panel B reports the portfolio characteristics of HF and non-HF institutional investors, including portfolio assets (PortAssets, in $million), numbers of stock held per quarter (No.StockHold), and the turnover (Turnover, in % per quarter). Non-HF institutional investors are classified following Bushee (2001) into (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) dedicated holders (DEDs).

Panel A: Characteristics of Stocks Traded

	Mean	Std.Dev	P5	P25	Median	P75	P95
Adjusted Return (% per month)	0.95	15.44	-21.64	-6.40	0.50	7.56	24.23
Price or Bid/Ask Average ($)	28.22	55.88	5.00	10.25	18.76	34.04	72.94
Amihud Illiquidity ($\times 10^{-6}$)	4.19	19.11	0.00	0.04	0.16	0.94	18.78

Panel B: Portfolio Charactistics of Different Groups of Institutional Investors

	Mean	Std.Dev	P5	P25	Median	P75	P95	No.Investors (per quarter)
PortAssets^{HF} ($m)	2392	11243	12	94	323	1278	8423	319
PortAssets^{QIX} ($m)	3434	24136	20	91	220	815	10648	1352
PortAssets^{TRA} ($m)	2591	24020	7	74	246	975	7873	489
PortAssets^{DED} ($m)	3470	17839	11	102	344	1297	11548	69
No.StockHold^{HF}	118	227	3	15	36	105	516	319
$\text{No.StockHold}^{QIX}$	170	326	8	37	67	137	735	1352
$\text{No.StockHold}^{TRA}$	166	295	3	24	62	160	706	489
$\text{No.StockHold}^{DED}$	52	174	1	4	10	33	186	69
Turnover^{HF} (% per quarter)	22.04	17.97	0.21	8.36	17.27	32.19	57.76	306
Turnover^{QIX} (% per quarter)	6.57	6.98	0.11	2.08	4.68	8.85	18.72	1293
Turnover^{TRA} (% per quarter)	23.73	17.73	0.46	10.73	19.80	33.45	58.79	462
Turnover^{DED} (% per quarter)	7.30	11.19	0.00	0.00	3.03	9.65	29.58	62

Table 1.2: Descriptive statistics: ownership and trading of different groups of investors

This table reports the summary statistics of the stock holding (StockHold, in %) and change in holding (ΔStockHold, in % per quarter) of HFs, non-HF institutional investors, and other investors (OTHs) from 1994q2 to 2017q4. Non-HF institutional investors are classified following Bushee (2001) into (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) dedicated holders (DEDs). Characteristics of OTHs are calculated following Ben-David et al. (2012).

Panel A: Pre-Crisis (1994q2-2007q2)							
	Mean	Std.Dev	P5	P25	Median	P75	P95
StockHold^{HF} (% per quarter)	6.04	6.50	0.00	0.61	4.17	9.36	18.61
StockHold^{QIX} (% per quarter)	29.18	17.78	2.76	13.99	28.55	42.85	58.92
StockHold^{TRA} (% per quarter)	9.89	8.96	0.00	2.87	7.71	14.55	27.45
StockHold^{DED} (% per quarter)	1.94	4.68	0.00	0.00	0.03	1.61	10.25
StockHold^{OTH} (% per quarter)	52.29	26.09	11.35	30.95	51.57	74.16	94.03
$\Delta\text{StockHold}^{HF}$ (% per quarter)	0.30	2.36	-3.30	-0.61	0.10	1.09	4.40
$\Delta\text{StockHold}^{QIX}$ (% per quarter)	0.87	4.28	-5.73	-1.15	0.44	2.70	8.45
$\Delta\text{StockHold}^{TRA}$ (% per quarter)	0.28	3.61	-5.43	-1.12	0.06	1.49	6.65
$\Delta\text{StockHold}^{DED}$ (% per quarter)	0.04	1.35	-1.72	-0.07	0.00	0.10	2.02
$\Delta\text{StockHold}^{OTH}$ (% per quarter)	-0.07	6.51	-10.10	-2.92	-0.26	2.18	10.84
Panel B: Crisis (2007q3-2009q1)							
	Mean	Std.Dev	P5	P25	Median	P75	P95
StockHold^{HF} (% per quarter)	10.89	7.85	0.54	5.25	9.45	15.11	25.60
StockHold^{QIX} (% per quarter)	40.49	19.77	5.28	25.41	43.13	55.77	69.79
StockHold^{TRA} (% per quarter)	12.63	8.50	0.82	6.30	11.49	17.65	28.15
StockHold^{DED} (% per quarter)	1.72	5.06	0.00	0.00	0.00	0.22	10.54
StockHold^{OTH} (% per quarter)	33.08	25.84	1.22	12.18	25.93	50.15	85.01
$\Delta\text{StockHold}^{HF}$ (% per quarter)	0.02	2.55	-4.16	-1.14	-0.02	1.06	4.36
$\Delta\text{StockHold}^{QIX}$ (% per quarter)	0.40	4.36	-6.66	-1.69	0.21	2.36	8.12
$\Delta\text{StockHold}^{TRA}$ (% per quarter)	-0.30	3.54	-6.27	-1.87	-0.18	1.19	5.56
$\Delta\text{StockHold}^{DED}$ (% per quarter)	-0.20	1.81	-3.80	-0.21	-0.01	0.04	2.34
$\Delta\text{StockHold}^{OTH}$ (% per quarter)	0.59	5.54	-7.88	-1.91	0.27	2.87	9.53
Panel C: Post-Crisis (2009q2-2017q4)							
	Mean	Std.Dev	P5	P25	Median	P75	P95
StockHold^{HF} (% per quarter)	10.51	7.56	0.42	5.17	9.26	14.47	24.45
StockHold^{QIX} (% per quarter)	40.08	19.52	2.25	26.03	44.13	55.03	67.04
StockHold^{TRA} (% per quarter)	13.79	8.20	0.11	7.92	13.81	19.28	27.36
StockHold^{DED} (% per quarter)	1.33	5.25	0.00	0.00	0.00	0.01	8.27
StockHold^{OTH} (% per quarter)	33.26	27.33	2.87	12.18	24.24	48.59	94.07
$\Delta\text{StockHold}^{HF}$ (% per quarter)	0.15	2.24	-3.17	-0.78	0.01	0.89	3.99
$\Delta\text{StockHold}^{QIX}$ (% per quarter)	0.30	3.55	-5.03	-1.21	0.10	1.67	6.06
$\Delta\text{StockHold}^{TRA}$ (% per quarter)	0.33	2.99	-4.18	-0.91	0.07	1.39	5.67
$\Delta\text{StockHold}^{DED}$ (% per quarter)	-0.11	1.45	-2.34	-0.10	0.00	0.04	1.52
$\Delta\text{StockHold}^{OTH}$ (% per quarter)	-0.05	4.64	-6.74	-1.77	-0.07	1.49	6.37

Table 1.3: Trading swaps and possible counterparties of hedge fund trades

This table reports monthly ex-post excess returns over the risk-free rate (measured as the 3-month T-bill rate), ex-post CAPM alphas and market betas, Amihud illiquidity (Amihud, 2002), DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas and factor loadings for the short-term portfolios of quarterly trading swaps between HFs and non-HF investors from 1994q2 to 2017q4. Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed at the end of each quarter and held for the following quarter. Stocks with the change in holding below (above) the bottom (top) 20^{th} percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. Factors considered in the 2-factor model are betting-against-beta (Frazzini and Pedersen, 2014) and liquidity (Pástor and Stambaugh, 2003). *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in brackets.

Panel A: Risk-Free Excess Returns, CAPM Alphas, CAPM Betas, and Amihud Illiquidity

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	0.58	0.89**	0.62*	-0.35**	0.03	-0.34*	1.34***	1.24***	1.37***	0.70***	0.59***	1.09***
	(1.49)	(2.51)	(1.68)	(-2.28)	(0.15)	(-1.81)	(26.36)	(29.49)	(20.59)	(7.03)	(7.99)	(9.30)
B/S	1.34***	0.97***	1.04***	0.57***	0.07	0.13	1.10***	1.29***	1.30***	1.10***	0.74***	1.13***
	(4.40)	(2.70)	(2.73)	(2.88)	(0.40)	(0.68)	(29.68)	(32.54)	(26.52)	(6.53)	(6.58)	(9.47)
B/S − S/B	0.75***	0.08	0.42**	0.92***	0.05	0.47**	-0.24***	0.05	-0.07	0.40***	0.15	0.04
	(3.76)	(0.54)	(2.31)	(5.04)	(0.32)	(2.53)	(-4.04)	(1.23)	(-1.53)	(3.09)	(1.59)	(0.35)

Panel B: DGTW-Adjusted Excess Returns, 2-Factor Alphas, and Factor Loadings on LIQ and BAB

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.19*	0.09	-0.06	-0.11	0.14	0.11	0.11**	0.10**	0.13***	-0.17***	-0.13	-0.29***
	(-1.66)	(0.70)	(-0.53)	(-0.86)	(1.00)	(0.98)	(2.28)	(2.30)	(3.66)	(-2.89)	(-1.46)	(-5.62)
B/S	0.50***	0.18	0.19	0.47***	0.18	0.25	0.10***	0.08	0.06	-0.02	-0.04	-0.11
	(3.77)	(1.60)	(1.39)	(3.83)	(1.49)	(1.35)	(3.32)	(1.51)	(0.96)	(-0.39)	(-1.11)	(-1.02)
B/S − S/B	0.69***	0.09	0.25	0.58***	0.04	0.15	-0.01	-0.03	-0.07	0.15***	0.09	0.17
	(4.15)	(0.60)	(1.51)	(3.39)	(0.22)	(0.65)	(-0.30)	(-0.43)	(-1.18)	(2.71)	(1.19)	(1.38)

Table 1.4: Trading swaps: QIXs sub-groups

This table reports monthly ex-post excess returns over the risk-free rate (measured as the 3-month T-bill rate), ex-post CAPM alphas and market betas, Amihud illiquidity (Amihud, 2002), DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas and factor loadings for the short-term portfolios of quarterly trading swaps between HFs and different groups of QIXs from 1994q2 to 2017q4. QIXs include independent investment advisors (IIA), banks (BNK), and other QIXs like insurance companies, pension funds and endowments (OTQIX). Portfolios are constructed at the end of each quarter and held for the following quarter. Stocks with the change in holding below (above) the bottom (top) 20$^{\text{th}}$ percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. Factors considered in the 2-factor model are betting-against-beta (Frazzini and Pedersen, 2014) and liquidity (Pástor and Stambaugh, 2003). *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in brackets.

Panel A: Risk-Free Excess Returns, CAPM Alphas, CAPM Betas, and Amihud Illiquidity												
	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX
S/B	0.60	0.42	0.67	-0.37**	-0.52**	-0.29	1.39***	1.35***	1.37***	0.74***	0.43***	0.51***
	(1.47)	(0.97)	(1.58)	(-2.12)	(-2.40)	(-1.46)	(23.09)	(20.68)	(21.62)	(6.48)	(5.29)	(5.29)
B/S	1.38***	1.38***	1.30***	0.66***	0.63***	0.47**	1.03***	1.08***	1.18***	1.10***	0.70***	0.78***
	(4.80)	(4.53)	(3.76)	(2.85)	(2.71)	(2.24)	(24.33)	(25.13)	(28.05)	(5.49)	(5.43)	(5.35)
B/ S− S/B	0.78***	0.96***	0.62**	1.04***	1.15***	0.76***	-0.36***	-0.26***	-0.19***	0.36**	0.27***	0.26*
	(3.26)	(3.41)	(2.47)	(5.04)	(4.37)	(3.11)	(-5.05)	(-3.04)	(-2.75)	(2.55)	(3.01)	(1.92)
Panel B: DGTW-Adjusted Excess Returns, 2-Factor Alphas, and Factor Loadings on LIQ and BAB												
	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX
S/B	-0.17	-0.34*	-0.10	-0.06	-0.23	0.00	0.09	0.12*	0.12	-0.20***	-0.22**	-0.19**
	(-1.07)	(-1.86)	(-0.66)	(-0.33)	(-1.10)	(-0.00)	(1.58)	(1.69)	(1.55)	(-2.82)	(-2.28)	(-2.43)
B/S	0.41***	0.54***	0.48***	0.39***	0.52***	0.49***	0.08***	0.09**	0.12**	-0.02	-0.03	-0.07
	(2.71)	(3.65)	(2.95)	(2.62)	(3.74)	(2.75)	(2.89)	(2.27)	(2.22)	(-0.28)	(-0.64)	(-1.49)
B/S − S/B	0.59***	0.88***	0.58***	0.45**	0.74***	0.49**	-0.01	-0.03	0.00	0.18***	0.19*	0.12**
	(2.90)	(3.73)	(2.87)	(2.04)	(2.89)	(2.45)	(-0.12)	(-0.42)	(0.04)	(2.95)	(1.80)	(1.99)

Table 1.5: Average change in holdings of trading-swap stocks

This table reports the average quarterly change in holding (ΔStockHold, in % per quarter) of trading-swap stocks between HFs and quasi-indexers (QIXs) in trading quarters (q) and corresponding average quarterly change in holding of HFs and non-HF investors of the same stocks in quarters following trading (q+1) from 1994q2 to 2017q4. In trading quarter, stocks with the change in holding below (above) the bottom (top) 20th percentile are considered as those that investors significantly sell (buy). Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012).

	ΔStockHold (%) in q		ΔStockHold (%) in q+1			
	HF/QIX		HF	QIX	TRA	OTH
S/B	-2.88***	5.80***	0.04	0.86***	-0.01	0.33**
	(-61.39)	(34.68)	(0.79)	(9.15)	(-0.14)	(2.06)
B/S	3.43***	-4.65***	0.33***	0.11	0.35***	-0.11
	(57.99)	(-44.56)	(7.19)	(0.86)	(4.17)	(-0.84)

Table 1.6: Impact of financial crisis on trading swaps: risk-free excess return, alpha, market beta, and Amihud illiquidity

This table reports monthly ex-post excess returns over the risk-free rate (measured as the 3-month T-bill rate), ex-post CAPM alphas and market betas, Amihud illiquidity (Amihud, 2002) for the short-term portfolios of quarterly trading swaps between HFs and non-HF investors in pre-crisis (1994q2-2007q2), crisis (2007q3-2009q1), and post-crisis (2009q2-2017q4) periods (Ben-David et al., 2012). Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed at the end of each quarter and held for the following quarter. Stocks with the change in holding below (above) the bottom (top) 20$^{\text{th}}$ percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in brackets.

Panel A: Pre-Crisis (1994q2-2007q2)

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	0.64	0.92**	0.48	-0.33	0.06	-0.55**	1.43***	1.25***	1.50***	0.83***	0.67***	1.20***
	(1.34)	(2.11)	(1.02)	(-1.41)	(0.23)	(-2.51)	(17.02)	(18.10)	(15.81)	(5.87)	(6.52)	(7.95)
B/S	1.43***	0.92**	0.98*	0.68**	0.03	0.03	1.10***	1.29***	1.38***	1.39***	0.86***	1.14***
	(3.75)	(2.17)	(1.90)	(2.14)	(0.12)	(0.11)	(18.03)	(19.79)	(20.93)	(5.69)	(5.50)	(6.81)
B/S − S/B	0.79**	0.00	0.50*	1.01***	-0.03	0.58*	-0.33***	0.04	-0.12*	0.56***	0.19**	-0.06
	(2.49)	(-0.01)	(1.69)	(3.47)	(-0.14)	(1.97)	(-3.39)	(0.68)	(-1.80)	(4.06)	(2.19)	(-0.64)

Panel B: Crisis (2007q3-2009q1)

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-2.52	-1.68	-0.68	-0.06	0.71*	1.95**	1.24***	1.21***	1.33***	0.38***	0.33***	1.03***
	(-1.08)	(-0.80)	(-0.28)	(-0.15)	(1.90)	(2.37)	(29.77)	(24.08)	(24.31)	(5.42)	(3.38)	(3.11)
B/S	-0.40	-1.25	-1.01	1.92***	1.54***	1.41***	1.17***	1.41***	1.22***	0.48***	0.78***	1.13***
	(-0.21)	(-0.51)	(-0.49)	(6.35)	(4.02)	(3.78)	(41.40)	(31.24)	(45.77)	(4.85)	(3.92)	(3.24)
B/S − S/B	2.12***	0.43	-0.33	1.98***	0.83**	-0.54	-0.07	0.20***	-0.11*	0.10	0.45*	0.10
	(3.55)	(1.01)	(-0.50)	(4.25)	(2.85)	(-0.86)	(-1.31)	(2.89)	(-2.05)	(0.69)	(2.07)	(0.24)

Panel C: Post-Crisis (2009q2-2017q4)

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	1.11**	1.36***	1.09***	-0.44**	-0.24	-0.45***	1.24***	1.27***	1.22***	0.58***	0.53***	0.94***
	(2.49)	(3.18)	(2.63)	(-2.05)	(-1.39)	(-3.02)	(20.36)	(23.11)	(23.10)	(3.72)	(4.41)	(4.76)
B/S	1.54***	1.49***	1.54***	0.14	-0.08	-0.03	1.12***	1.26***	1.25***	0.79***	0.56***	1.12***
	(4.04)	(3.62)	(3.58)	(0.83)	(-0.38)	(-0.15)	(19.67)	(19.21)	(15.99)	(3.41)	(3.06)	(5.87)
B/S − S/B	0.43***	0.14	0.45***	0.58***	0.16	0.41**	-0.13**	-0.02	0.03	0.21	0.04	0.18
	(3.03)	(0.84)	(2.71)	(3.62)	(0.92)	(2.03)	(-2.47)	(-0.34)	(0.45)	(0.80)	(0.16)	(0.65)

Table 1.7: Impact of financial crisis on trading swaps: DGTW-adjusted excess return, 2-factor alpha, and factor loading

This table reports DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas and factor loadings for the short-term portfolios of quarterly trading swaps between HFs and non-HF investors in pre-crisis (1994q2-2007q2), crisis (2007q3-2009q1), and post-crisis (2009q2-2017q4) periods (Ben-David et al., 2012). Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed at the end of each quarter and held for the following quarter. Stocks with the change in holding below (above) the bottom (top) 20th percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. Factors considered in the 2-factor model are betting-against-beta (Frazzini and Pedersen, 2014) and liquidity (Pástor and Stambaugh, 2003). *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in brackets.

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
Panel A: Pre-Crisis (1994q2-2007q2)												
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.10	0.13	-0.15	0.12	0.27	0.11	0.04	0.04	0.13***	-0.24***	-0.17	-0.35***
	(-0.59)	(0.65)	(-0.90)	(0.76)	(1.22)	(0.57)	(0.59)	(0.65)	(2.87)	(-4.04)	(-1.45)	(-6.50)
B/S	0.67***	0.27	0.21	0.68***	0.35*	0.43	0.04	0.00	-0.03	-0.04	-0.07	-0.18
	(3.44)	(1.55)	(0.92)	(3.52)	(1.79)	(1.40)	(0.76)	(-0.04)	(-0.37)	(-0.60)	(-1.56)	(-1.25)
B/S − S/B	0.78***	0.14	0.36	0.55**	0.08	0.32	0.00	-0.04	-0.16**	0.21***	0.10	0.17
	(2.89)	(0.55)	(1.33)	(2.10)	(0.31)	(0.83)	(0.02)	(-0.49)	(-2.27)	(3.86)	(1.04)	(1.07)
Panel B: Crisis (2007q3-2009q1)												
	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.67	0.06	0.91**	-0.55	0.01	0.91**	0.18***	0.21***	0.11**	0.08	-0.04	0.00
	(-1.37)	(0.15)	(2.21)	(-1.14)	(0.01)	(2.15)	(5.01)	(3.90)	(2.83)	(1.53)	(-0.52)	(-0.07)
B/S	0.80	0.17	0.43	0.85	0.32	0.49	0.18***	0.16	0.19**	0.03	0.10*	0.04
	(1.20)	(0.32)	(1.08)	(1.13)	(0.80)	(1.33)	(4.27)	(1.49)	(2.41)	(0.35)	(1.94)	(0.38)
B/S − S/B	1.47***	0.11	-0.48	1.40***	0.31	-0.42	0.00	-0.05	0.09	-0.05	0.14*	0.04
	(4.13)	(0.22)	(-0.90)	(3.26)	(0.67)	(-0.73)	(-0.10)	(-0.45)	(1.06)	(-0.62)	(1.74)	(0.85)
Panel C: Post-Crisis (2009q2-2017q4)												
	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.23*	0.02	-0.12	-0.20	0.10	-0.04	0.09	0.08	0.05	-0.01	-0.08	-0.09*
	(-1.87)	(0.21)	(-1.10)	(-1.46)	(0.76)	(-0.37)	(1.50)	(1.58)	(0.77)	(-0.24)	(-0.99)	(-1.96)
B/S	0.17	0.05	0.12	0.19*	0.15	0.05	0.11***	0.08**	0.03	0.01	-0.11	0.10
	(1.60)	(0.42)	(0.99)	(1.70)	(1.07)	(0.38)	(3.86)	(2.37)	(0.69)	(0.10)	(-1.53)	(1.63)
B/S − S/B	0.40***	0.02	0.24*	0.39**	0.05	0.09	0.02	0.00	-0.01	0.02	-0.03	0.19***
	(3.05)	(0.15)	(1.69)	(2.49)	(0.24)	(0.69)	(0.29)	(0.01)	(-0.19)	(0.24)	(-0.28)	(2.95)

Table 1.8: Trading swaps: long-term

This table reports monthly ex-post excess returns over the risk-free rate (measured as the 3-month T-bill rate), ex-post CAPM alphas and market betas, Amihud illiquidity (Amihud, 2002), DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas and factor loadings for the long-term portfolios of quarterly trading swaps between HFs and non-HF investors from 1994q2 to 2017q4. Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed at the end of each quarter and held for the following four quarters. Stocks with the change in holding below (above) the bottom (top) 20$^{\text{th}}$ percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. Factors considered in the 2-factor model are betting-against-beta (Frazzini and Pedersen, 2014) and liquidity (Pástor and Stambaugh, 2003). *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in brackets.

Panel A: Risk-Free Excess Returns, CAPM Alphas, CAPM Betas, and Amihud illiquidity

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	0.68*	0.72*	0.64*	-0.19	-0.11	-0.24	1.32***	1.26***	1.34***	0.73***	0.60***	1.07***
	(1.87)	(1.96)	(1.74)	(-1.37)	(-0.75)	(-1.65)	(35.10)	(39.24)	(26.11)	(7.23)	(7.87)	(10.72)
B/S	1.05***	0.92***	0.85**	0.30**	0.10	-0.01	1.15***	1.25***	1.31***	1.15***	0.75***	1.12***
	(3.34)	(2.71)	(2.23)	(1.99)	(0.70)	(-0.07)	(32.66)	(40.38)	(33.59)	(6.82)	(6.72)	(10.05)
B/S − S/B	0.37***	0.20**	0.21**	0.48***	0.20**	0.23**	-0.17***	-0.01	-0.03	0.41***	0.15**	0.05
	(3.83)	(2.05)	(2.01)	(4.79)	(2.05)	(2.24)	(-3.57)	(-0.21)	(-0.99)	(3.96)	(2.07)	(0.63)

Panel B: DGTW-Adjusted Excess Returns, 2-Factor Alphas, and Factor Loadings on LIQ and BAB

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.07	-0.03	-0.05	0.00	-0.01	0.04	0.10***	0.09**	0.11***	-0.15***	-0.07	-0.18***
	(-0.79)	(-0.29)	(-0.60)	(0.00)	(-0.11)	(0.56)	(2.64)	(2.49)	(4.11)	(-2.69)	(-1.13)	(-4.85)
B/S	0.23***	0.14**	0.11	0.18**	0.13	0.16	0.10***	0.09**	0.09**	0.01	-0.04	-0.12
	(3.15)	(2.05)	(0.95)	(2.03)	(1.49)	(1.11)	(3.24)	(2.31)	(2.11)	(0.19)	(-0.72)	(-1.24)
B/S − S/B	0.30***	0.17**	0.16*	0.18**	0.15*	0.12	0.00	0.00	-0.02	0.16***	0.03	0.06
	(3.58)	(2.12)	(1.83)	(1.98)	(1.83)	(0.96)	(0.04)	(-0.13)	(-0.48)	(4.04)	(1.40)	(0.75)

Table 1.9: Market anomalies: descriptive statistics and portfolio performance

This table reports the descriptive statistics, portfolio CAPM alphas and DGTW-adjusted excess returns (Daniel et al., 1997) from 1994q3 to 2018q2 for nine market anomalies, including the OP (operating profit), GP (gross profitability), O-Score, IVA (investment-to-assets), IK (investment growth), NOA (net operating assets), NSI (net stock issues), ACR (accrual), and AG (asset growth) anomalies. Portfolios are constructed in the second quarter of year t using anomaly information for the fiscal year ending in calendar year t-1 and are held for the following one year. Short (Long) leg is defined as portfolios that expect to have negative (positive) ex-post alphas, which comprise stocks at the bottom (top) 20% of OP and GP anomaly and those at the top (bottom) 20% of O-Score, IVA, IK, NOA, NSI, ACR, or AG anomaly. EW-Avg refers to the equal-weighted portfolio of portfolios for nine anomalies. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 12 lags. t-statistics are reported in brackets.

Panel A: Descriptive Statistics of Market Anomalies

	Mean	Std.Dev	P5	P25	Median	P75	P95
OP	0.20	0.37	-0.38	0.10	0.22	0.33	0.66
GP	0.36	0.27	0.00	0.20	0.33	0.50	0.85
O-Score	-3.16	2.52	-6.63	-4.67	-3.41	-2.01	1.04
IVA	0.10	0.21	-0.07	0.01	0.05	0.13	0.45
IK	0.58	1.73	-0.61	-0.18	0.13	0.64	3.14
NOA	0.68	0.45	0.07	0.45	0.65	0.82	1.37
NSI	0.12	0.39	-0.06	0.00	0.01	0.05	0.60
ACR	0.01	0.25	-0.26	-0.04	0.01	0.07	0.30
AG	0.37	1.00	-0.16	0.00	0.10	0.28	1.76

Panel B: CAPM Alphas of Anomaly Portfolios

	OP	GP	O-Score	IVA	IK	NOA	NSI	ACR	AG	EW-Avg
Short Leg	-0.27	-0.27*	-0.22	-0.34**	-0.12	-0.40***	-0.24	-0.21	-0.09	-0.24*
	(-1.27)	(-1.72)	(-1.20)	(-2.02)	(-0.71)	(-3.04)	(-1.40)	(-1.28)	(-0.52)	(-1.72)
Long Leg	0.18	0.36***	0.13	0.12	0.20	0.25	0.28	0.15	0.16	0.20*
	(1.21)	(3.08)	(1.00)	(0.78)	(1.09)	(1.60)	(1.45)	(1.17)	(0.92)	(1.79)
Long − Short	0.45	0.64***	0.35**	0.46**	0.31**	0.65***	0.53*	0.35**	0.26	0.44***
	(1.45)	(3.78)	(2.29)	(2.45)	(2.44)	(3.50)	(1.79)	(2.13)	(0.96)	(3.67)

Panel C: DGTW-Adjusted Excess Returns of Anomaly Portfolios

	OP	GP	O-Score	IVA	IK	NOA	NSI	ACR	AG	EW-Avg
Short Leg	-0.12	-0.15	-0.09	-0.24**	-0.05	-0.35***	-0.09	-0.16**	-0.01	-0.14
	(-0.68)	(-1.25)	(-0.59)	(-2.23)	(-0.51)	(-3.44)	(-0.77)	(-2.12)	(-0.07)	(-1.46)
Long Leg	0.05	0.23***	0.06	0.07	0.21	0.21*	0.01	0.11	0.07	0.11*
	(0.58)	(2.63)	(0.74)	(0.99)	(1.56)	(1.78)	(0.15)	(1.11)	(1.07)	(1.92)
Long − Short	0.17	0.38**	0.16	0.31**	0.26**	0.56***	0.10	0.27**	0.08	0.25***
	(0.76)	(2.58)	(1.08)	(2.37)	(2.26)	(3.66)	(0.59)	(2.22)	(0.59)	(3.01)

Table 1.10: Trading swaps for market anomalies: risk-free excess return, alpha, market beta, and Amihud illiquidity

This table reports the monthly ex-post excess returns over the risk-free rate (measured as the 3-month T-bill rate), ex-post CAPM alphas and market betas, Amihud illiquidity (Amihud, 2002) for the equal-weighted portfolio of trading-swap portfolios from 1994q3 to 2018q2 for nine anomalies, including the operating profit, gross profitability, O-Score, investment-to-assets, investment growth, net operating assets, net stock issues, accrual, and asset growth anomalies. Trading swaps are between HFs and Non-HF investors, which include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed in the second quarter of year t using the change in holding information in the same quarter and the anomaly information for the fiscal year ending in calendar year t-1, and are held for the following one year. Stocks with the change in holding below (above) the bottom (top) 20^{th} percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. Short (Long) leg is defined as portfolios that expect to have negative (positive) ex-post alphas, which comprise stocks at the bottom (top) 20% of OP and GP anomaly and those at the top (bottom) 20% of O-Score, IVA, IK, NOA, NSI, ACR, or AG anomaly. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 12 lags. t-statistics are reported in brackets.

Panel A: HF/QIX Swap

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	0.65	1.44***	0.79**	-0.46**	0.46	0.92***	1.41***	1.24***	-0.16**	0.85***	1.06***	0.21
	(1.50)	(3.33)	(2.13)	(-2.07)	(1.28)	(2.62)	(25.56)	(25.63)	(-2.34)	(3.21)	(4.57)	(0.85)
Long Leg	1.06***	1.37***	0.31*	0.09	0.51***	0.43***	1.23***	1.08***	-0.15***	0.67***	0.90***	0.23
	(2.86)	(5.03)	(1.75)	(0.37)	(2.73)	(2.63)	(36.65)	(32.08)	(-5.90)	(2.83)	(3.63)	(1.64)
Long − Short	0.41**	-0.07	-0.48	0.55***	0.05	-0.49	-0.17***	-0.16***	0.01	-0.18*	-0.16	0.02
	(2.26)	(-0.30)	(-1.42)	(3.08)	(0.24)	(-1.49)	(-3.32)	(-2.71)	(0.20)	(-1.82)	(-1.24)	(0.13)

Panel B: HF/TRA Swap

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	0.99**	0.97**	-0.02	-0.11	-0.18	-0.07	1.40***	1.46***	0.06	0.72***	0.68***	-0.04
	(2.15)	(2.23)	(-0.10)	(-0.43)	(-0.64)	(-0.27)	(20.40)	(17.54)	(0.51)	(3.54)	(3.49)	(-0.28)
Long Leg	1.09***	1.33***	0.24	0.16	0.37*	0.20	1.17***	1.22***	0.05	0.52***	0.92***	0.41*
	(3.15)	(4.29)	(1.15)	(0.59)	(1.68)	(0.77)	(23.75)	(16.17)	(0.45)	(3.64)	(3.45)	(1.75)
Long − Short	0.10	0.36*	0.26	0.27	0.55***	0.27	-0.22***	-0.24***	-0.01	-0.21**	0.24	0.45**
	(0.42)	(1.76)	(1.12)	(1.24)	(3.02)	(1.11)	(-3.58)	(-4.39)	(-0.16)	(-2.00)	(1.30)	(2.03)

Panel C: HF/OTH Swap

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	0.65	1.19***	0.53*	-0.50	0.06	0.56	1.45***	1.42***	-0.03	1.43***	0.91***	-0.52*
	(1.26)	(2.90)	(1.74)	(-1.64)	(0.21)	(1.57)	(12.69)	(25.28)	(-0.29)	(4.84)	(4.54)	(-1.70)
Long Leg	1.04***	1.29***	0.25	0.04	0.29	0.25	1.26***	1.26***	0.00	1.36***	0.68***	-0.68**
	(2.95)	(3.69)	(1.12)	(0.19)	(1.06)	(0.94)	(15.70)	(15.85)	0.00	(3.73)	(3.59)	(-2.20)
Long − Short	0.39	0.10	-0.28	0.54**	0.23	-0.31	-0.19***	-0.16	0.03	-0.07	-0.23**	-0.15
	(1.62)	(0.56)	(-1.36)	(2.19)	(1.13)	(-1.44)	(-2.92)	(-1.62)	(0.31)	(-0.20)	(-2.27)	(-0.37)

Table 1.11: Trading swaps for market anomalies: DGTW-adjusted excess return, 2-factor alpha, and factor loading

This table reports the DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas and factor loadings for the equal-weighted portfolio of trading-swap portfolios from 1994q3 to 2018q2 for nine anomalies, including the operating profit, gross profitability, O-Score, investment-to-assets, investment growth, net operating assets, net stock issues, accrual, and asset growth anomalies. Trading swaps are between HFs and Non-HF investors, which include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed in the second quarter of year t using the change in holding information in the same quarter and the anomaly information for the fiscal year ending in calendar year t-1, and are held for the following one year. Stocks with the change in holding below (above) the bottom (top) 20th percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. Short (Long) leg is defined as portfolios that expect to have negative (positive) ex-post alphas, which comprise stocks at the bottom (top) 20% of OP and GP anomaly and those at the top (bottom) 20% of O-Score, IVA, IK, NOA, NSI, ACR, or AG anomaly. Factors considered in the 2-factor model are betting-against-beta (Frazzini and Pedersen, 2014) and liquidity (Pástor and Stambaugh, 2003). *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 12 lags. t-statistics are reported in brackets.

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
Panel A: HF/QIX Swap												
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	-0.24	0.39	0.63*	-0.21	0.37	0.58*	0.03	0.29***	0.26***	-0.06	-0.13	-0.07
	(-1.51)	(1.47)	(1.95)	(-1.20)	(1.24)	(1.82)	(0.41)	(2.81)	(2.93)	(-0.86)	(-0.79)	(-0.62)
Long Leg	0.11	0.39***	0.28*	0.14	0.34***	0.20	0.06	0.00	-0.06*	-0.08	0.07	0.15**
	(0.68)	(3.45)	(1.69)	(0.83)	(2.97)	(1.17)	(1.35)	(-0.02)	(-1.69)	(-1.19)	(0.83)	(2.39)
Long − Short	0.35*	0.00	-0.35	0.35*	-0.03	-0.38	0.03	-0.29***	-0.32***	-0.02	0.20*	0.22*
	(1.89)	(-0.00)	(-1.04)	(1.93)	(-0.13)	(-1.14)	(0.64)	(-3.26)	(-3.61)	(-0.53)	(1.76)	(1.88)
Panel B: HF/TRA Swap												
	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	0.07	-0.01	-0.08	0.02	0.17	0.16	0.05	0.13	0.08	0.05	-0.34*	-0.39***
	(0.37)	(-0.03)	(-0.40)	(0.07)	(0.63)	(0.82)	(0.60)	(1.24)	(1.01)	(0.37)	(-1.71)	(-2.83)
Long Leg	0.12	0.39**	0.27	0.07	0.50***	0.43**	0.05	0.06	0.02	0.05	-0.19**	-0.24*
	(0.67)	(2.30)	(1.31)	(0.41)	(2.68)	(2.18)	(0.92)	(1.26)	(0.27)	(0.44)	(-2.17)	(-1.77)
Long − Short	0.05	0.40**	0.35	0.05	0.32	0.27	-0.01	-0.07	-0.06	0.00	0.15	0.15
	(0.25)	(2.08)	(1.57)	(0.26)	(1.47)	(1.26)	(-0.09)	(-0.70)	(-0.78)	(-0.03)	(1.10)	(1.52)
Panel C: HF/OTH Swap												
	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	-0.27	0.16	0.43	-0.15	0.24	0.39	0.03	0.15*	0.12	-0.20***	-0.21	-0.01
	(-1.22)	(0.75)	(1.58)	(-0.73)	(1.00)	(1.24)	(0.56)	(1.68)	(1.11)	(-2.95)	(-1.31)	(-0.05)
Long Leg	-0.01	0.31**	0.32	0.11	0.34*	0.23	0.01	0.08	0.08	-0.18***	-0.08	0.10
	(-0.08)	(2.12)	(1.55)	(0.81)	(1.83)	(0.96)	(0.21)	(1.28)	(0.91)	(-3.34)	(-0.57)	(0.79)
Long − Short	0.26	0.16	-0.11	0.26	0.09	-0.16	-0.03	-0.07	-0.04	0.02	0.13	0.11
	(1.60)	(0.87)	(-0.58)	(1.65)	(0.58)	(-0.78)	(-0.55)	(-1.32)	(-0.74)	(0.38)	(1.46)	(1.21)

1.8. Online Appendix

Table 1.1a: Trading swaps and possible counterparties of hedge fund trades: different models

This table reports monthly ex-post alphas and market betas based on Fama-French 3-factor model (Fama and French, 1993) and Carhart 4-factor model (Carhart, 1997) for the short-term portfolios of quarterly trading swaps between HFs and non-HF investors from 1994q2 to 2017q4. Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed at the end of each quarter and held for the following quarter. Stocks with the change in holding below (above) the bottom (top) 20^{th} percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in brackets.

Panel A: Fama-French 3-Factor Alphas and Market Betas						
	3-Factor Alphas			3-Factor Market Betas		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.32***	0.04	-0.30**	1.20***	1.12***	1.27***
	(-3.15)	(0.31)	(-2.00)	(37.01)	(37.02)	(26.60)
B/S	0.53***	0.05	0.17	1.04***	1.21***	1.15***
	(3.46)	(0.38)	(1.38)	(30.80)	(33.95)	(33.60)
B/S − S/B	0.86***	0.01	0.47**	-0.17***	0.09**	-0.11**
	(4.94)	(0.10)	(2.46)	(-3.88)	(2.29)	(-2.18)
Panel B: Carhart 4-Factor Alphas and Market Betas						
	4-Factor Alphas			4-Factor Market Betas		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.26**	0.01	-0.13	1.17***	1.14***	1.18***
	(-2.29)	(0.08)	(-0.92)	(39.33)	(38.55)	(23.57)
B/S	0.64***	0.19	0.13	0.98***	1.14***	1.18***
	(4.27)	(1.40)	(1.01)	(28.38)	(31.04)	(31.10)
B/S − S/B	0.91***	0.18	0.26	-0.19***	0.01	-0.01
	(5.02)	(1.23)	(1.38)	(-4.53)	(0.18)	(-0.13)

Table 1.2a: Trading swaps and possible counterparties of hedge fund trades: 10% cutoff

This table reports monthly ex-post excess returns over the risk-free rate (measured as the 3-month T-bill rate), ex-post CAPM alphas and market betas, Amihud illiquidity (Amihud, 2002), DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas and factor loadings for the short-term portfolios of quarterly trading swaps between HFs and non-HF investors from 1994q2 to 2017q4. Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed at the end of each quarter and held for the following quarter. Stocks with the change in holding below (above) the bottom (top) 10^{th} percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. Factors considered in the 2-factor model are betting-against-beta (Frazzini and Pedersen, 2014) and liquidity (Pástor and Stambaugh, 2003). *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in brackets.

Panel A: Risk-Free Excess Returns, CAPM Alphas, CAPM Betas, and Amihud Illiquidity

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	0.40	0.70*	0.56	-0.58**	-0.15	-0.48	1.41***	1.22***	1.49***	0.85***	0.69***	1.01***
	(0.86)	(1.69)	(1.15)	(-2.31)	(-0.59)	(-1.47)	(21.90)	(17.62)	(17.70)	(5.46)	(4.86)	(7.80)
B/S	1.08***	0.87**	1.03**	0.30	-0.10	0.05	1.11***	1.39***	1.40***	0.93***	0.76***	1.33***
	(3.25)	(2.06)	(2.24)	(1.59)	(-0.44)	(0.17)	(24.48)	(19.84)	(18.83)	(4.54)	(5.37)	(7.07)
B/S − S/B	0.67***	0.17	0.46	0.88***	0.05	0.53	-0.30***	0.17*	-0.09	0.08	0.07	0.33
	(2.71)	(0.64)	(1.28)	(4.04)	(0.19)	(1.47)	(-4.20)	(1.90)	(-1.39)	(0.39)	(0.35)	(1.62)

Panel B: DGTW-Adjusted Excess Returns, 2-Factor Alphas, and Factor Loadings on LIQ and BAB

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.36*	-0.21	-0.13	-0.18	-0.15	0.08	0.11	0.16**	0.22***	-0.29***	-0.17	-0.40***
	(-1.85)	(-1.00)	(-0.55)	(-0.76)	(-0.65)	(0.33)	(1.58)	(2.30)	(3.53)	(-2.75)	(-1.38)	(-5.56)
B/S	0.05	0.14	0.17	0.04	0.16	0.21	0.05	0.05	0.1	-0.02	-0.06	-0.12
	(0.33)	(0.71)	(0.70)	(0.24)	(0.75)	(0.73)	(1.02)	(0.65)	(1.04)	(-0.30)	(-0.88)	(-0.87)
B/S − S/B	0.42*	0.35	0.30	0.23	0.32	0.13	-0.05	-0.12	-0.11	0.27**	0.11	0.28**
	(1.73)	(1.22)	(0.88)	(0.80)	(0.95)	(0.35)	(-0.77)	(-1.23)	(-1.19)	(2.30)	(0.87)	(2.49)

Table 1.3a: Trading swaps and possible counterparties of hedge fund trades: 30% cutoff

This table reports monthly ex-post excess returns over the risk-free rate (measured as the 3-month T-bill rate), ex-post CAPM alphas and market betas, Amihud illiquidity (Amihud, 2002), DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas and factor loadings for the short-term portfolios of quarterly trading swaps between HFs and non-HF investors from 1994q2 to 2017q4. Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs), following Bushee (2001) and Ben-David et al. (2012). Portfolios are constructed at the end of each quarter and held for the following quarter. Stocks with the change in holding below (above) the bottom (top) 30^{th} percentile are considered as those that investors significantly sell (buy); they are denoted by S (B) respectively. Factors considered in the 2-factor model are betting-against-beta (Frazzini and Pedersen, 2014) and liquidity (Pástor and Stambaugh, 2003). *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in brackets.

Panel A: Risk-Free Excess Returns, CAPM Alphas, CAPM Betas, and Amihud Illiquidity

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	0.67*	0.84**	0.57	-0.23*	0.01	-0.34***	1.28***	1.18***	1.29***	0.79***	0.64***	1.17***
	(1.88)	(2.50)	(1.59)	(-1.70)	(0.10)	(-2.65)	(32.00)	(31.53)	(30.97)	(8.53)	(7.86)	(10.77)
B/S	1.19***	1.02***	1.02***	0.43***	0.17	0.14	1.09***	1.22***	1.25***	1.09***	0.81***	1.32***
	(3.97)	(3.01)	(2.79)	(2.60)	(1.06)	(0.93)	(31.71)	(37.80)	(34.22)	(7.61)	(8.67)	(9.64)
B/S − S/B	0.53***	0.18	0.45***	0.66***	0.15	0.48***	-0.19***	0.04	-0.04	0.30***	0.17***	0.14
	(3.57)	(1.32)	(3.35)	(4.60)	(1.16)	(3.56)	(-3.89)	(0.97)	(-0.89)	(3.16)	(2.75)	(1.21)

Panel B: DGTW-Adjusted Excess Returns, 2-Factor Alphas, and Factor Loadings on LIQ and BAB

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.13	0.02	-0.07	-0.06	0.04	0.01	0.08**	0.08**	0.12***	-0.13**	-0.07	-0.17***
	(-1.59)	(0.20)	(-0.95)	(-0.63)	(0.28)	(0.13)	(2.00)	(2.03)	(4.00)	(-2.33)	(-0.78)	(-5.12)
B/S	0.36***	0.23***	0.21*	0.31***	0.20***	0.24	0.08**	0.08**	0.06	0.01	-0.01	-0.08
	(3.75)	(2.87)	(1.85)	(3.19)	(2.62)	(1.60)	(2.58)	(2.37)	(1.55)	(0.26)	(-0.39)	(-0.78)
B/S − S/B	0.49***	0.21*	0.28**	0.37***	0.16	0.23	0.00	0.00	-0.05	0.15***	0.05	0.09
	(4.34)	(1.66)	(2.49)	(3.10)	(1.16)	(1.48)	(0.02)	(0.08)	(-1.29)	(3.16)	(0.88)	(1.06)

Table 1.4a: Market anomalies: description

This table describes the market anomalies used in this study. “Positive” predictability means that stocks with high value of the anomaly-related characteristic are expected to have positive future abnormal returns, whereas “negative” predictability means that the expected abnormal returns are negative. The variable names (items) are as used in COMPUSTAT.

Market anomaly	Variable	Predictability	Construction	Reference
Gross profitability	GP	Positive	Total revenue (item REVT) minus the cost of goods sold (item COGS), divided by total assets (item AT).	Novy-Marx (2013)
Operating profit	OP	Positive	Total revenue minus the cost of goods sold, minus selling, general, and administrative expenses (item XSGA) if available, minus interest expense (item XINT) if available, divided by book equity. Book equity is stockholders' book equity (item SEQ), plus balance sheet deferred taxes (Compustat item ITCB) and investment tax credit (TXDB) if available, minus the book value of preferred stock (zero if missing). Book value of preferred stock is redemption value (PSTKRV), liquidating value (PSTKL), or par value (PSTK).	Fama and French (2015)
O-Score	O-Score	Negative	$\text{O-Score} = -0.407\text{SIZE} + 6.03\text{TLTA} - 1.43\text{WCTA} + 0.076\text{CLCA} - 1.72\text{OENEG} - 2.37\text{NITA} - 1.83\text{FUTL} + 0.285\text{INTWO} - 0.521\text{CHIN} - 1.32$, where SIZE is the log of total assets, TLTA is the book value of debt (item DLC plus item DLTT) divided by total assets, WCTA is working capital (item ACT minus item LCT) divided by total assets, CLCA is current liabilities (item LCT) divided by current assets (item ACT), ONEEG is 1 if total liabilities (item LT) exceed total assets and is zero otherwise, NITA is net income (item NI) divided by total assets, FUTL is funds provided by operations (item PI) divided by total liabilities, INTWO is equal to 1 if net income (item NI) is negative for the last 2 years and zero otherwise, CHIN is $(\text{NI}_j - \text{NI}_{j-1})/(\lvert\text{NI}_j\rvert + \lvert\text{NI}_{j-1}\rvert)$, in which NI_j is the income (item NI) for year j.	Ohlson (1980)
Investment-to-assets	IVA	Negative	The change in gross property, plant, and equipment (item PPEGT) plus the change in inventory (item INVT), divided by lagged total assets.	Titman et al. (2004)
Investment growth	IK	Negative	The change in capital expenditure (item CAPX) divided by lagged capital expenditure.	Xing (2008)
Net operating assets	NOA	Negative	Debt included in current liabilities (item DLC, zero if missing), plus long-term debt (item DLTT, zero if missing), plus common equity (item CEQ), plus minority interests (item MIB), plus book value of preferred stocks, minus cash and short-term investment (item CHE), divided by lagged total assets.	Hirshleifer et al. (2004)
Net stock issues	NSI	Negative	The annual log change in split-adjusted shares outstanding. Split-adjusted shares outstanding equals shares outstanding (item CSHO) times the adjustment factor (item AJEX).	Fama and French (2008)
Accrual	ACR	Negative	The change in operating working capital per split-adjusted share, divided by book equity per split-adjusted share. Operating working capital is computed as current assets, minus cash and short-term investments, minus the difference of current liability and debt included in current liabilities if available.	Fama and French (2008)
Asset growth	AG	Negative	The change in total assets divided by lagged total assets.	Cooper et al. (2008)

Chapter 2

Do Outflows Drive Hedge Fund Stock-Picking Skills?

Keywords: Flows, Trading Skills, Hedge Funds.

Hedge funds are widely considered to be sophisticated institutional investors with superior stock-picking skills and advanced trading strategies (see Brunnermeier and Nagel, 2004; Kosowski et al., 2007; Agarwal et al., 2013, among others), which often improve market efficiency (Akbas et al., 2015; Kokkonen and Suominen, 2015; Cao et al., 2018). In this paper, we test if hedge fund superior stock-picking skills flourish also under tighter constraints, such as outflows. For mutual funds, for example, Coval and Stafford (2007) and Lou (2012) show that in extreme financial situations, the times when investors face large outflows/inflows, mutual funds make immediate but suboptimal trading decisions, such as fire sales, moving stock prices away from their fundamental values and ultimately losing money for remaining investors.

Using company-level data of hedge funds from TASS Lipper, we document superior stock-picking skills of hedge funds, pronounced upon strong changes in investor flows. In particular, we observe a remarkable "trading against the flow" pattern in hedge funds. Those stocks, in which hedge funds increase their holdings[1], despite

[1]As the Form 13F only reports the long side holdings of institutional investors, we are not able to investigate funds' short positions.

experiencing large outflows, deliver a significant ex-post abnormal return of +0.06% per month, revealing stock-picking skills of hedge funds. One potential explanation of this phenomenon is that hedge funds tend to put more effort in adjusting their portfolios when facing large outflows. Such trading against the flow pattern is even more pronounced after the 2007-2008 financial crisis, when flows to the hedge fund industry as a whole decrease, further supporting the argument that managers seem to perform better in more adverse conditions. These findings are consistent with Theory X of management style (McGregor, 1957) and managerial reputation concerns (Li et al., 2011; Guerrieri and Kondor, 2012).

We identify several sources that contribute to the success of hedge fund stock-picking upon outflows. First is the flow-related change in managerial income: managers of larger funds or with higher management fee income exhibit better stock-picking skills when facing large outflows. Second is the portfolio illiquidity: trading against the flow is more successful for funds with higher return serial correlation, which tend to hold more illiquid assets. Third is the time frame for decision marking: managers of funds with longer notice period prior to redemption deliver higher abnormal returns on purchased stocks upon outflows. Last but not least, the effect is further amplified for managers that are more motivated to put effort into work. Younger funds that need to build up a track record display superior stock-picking skills upon outflows.

Those funds that engage in trading agains the flow successfully ameliorate the adverse effect of outflows on their survival, and reduce the liquidation probability over the following quarter.

2.1. Literature Review

Our paper builds upon a large body of literature on hedge fund trading skills, with majority of works documenting stock-picking, market-timing, or volatility-timing skills of hedge funds. Hedge funds largely held technology stocks during the technology bubble and reduced their holdings before the bubble burst (Brunnermeier and Nagel, 2004). Performance of top hedge funds cannot be attributed to pure luck, and these managers possess asset-selection skills (Kosowski et al., 2007). Hedge funds' directional option positions predict future stock returns and their non-directional positions predict future market volatility (Aragon and Martin, 2012). Hedge funds also possess ability in timing market liquidity (Cao et al., 2013). Aggregate hedge fund demand shocks predict subsequent returns (Sias et al., 2016). Hedge funds seem to be sophisticated arbitrageurs. After controlling for the changes in stock volatility, liquidity, and turnover, only hedge fund trading (and not trading by other institutional investors) significantly improves market efficiency (Cao et al., 2018). Style-shifting hedge funds are able to time the outperforming new styles and have skills in trading in both new and old styles (Jiang et al., 2019).

Griffin and Xu (2009), on the contrary, find that controlling for past quarterly returns, hedge fund trading does not have any predictive power for future stock returns, similar to that of mutual funds, hence, little stock-picking skill. This can be driven, however, by hedge funds not disclosing all of their tradings. Hedge funds' confidential holdings significantly outperform the normally disclosed ones (Agarwal et al., 2013), suggesting that hedge funds stock-picking skill may be driven by private information and hidden for some time due to confidential treatment of such trades.

Comparing the impact of trading by hedge funds and mutual funds on stock prices, Akbas et al. (2015) find that aggregate flows to hedge funds correct the aggregate market mispricing, whereas aggregate flows to mutual funds exacerbate it. Other studies also confirm beneficial impact of flow-related hedge fund trading on financial markets. Hedge fund aggregate flows are negatively correlated with changes in the misvaluation spread (Kokkonen and Suominen, 2015). They are also negatively related to the changes in bond yields, and reduce profitability of various bond-related arbitrage strategies (Kolokolova et al., 2018). Hedge fund order flows have positive and permanent impact on future stock prices, whereas those of other institutional investors cause only temporary price pressure (Ha and Hu, 2018).

Hedge fund skill, however, is not displayed all the time. Chen and Liang (2007) document that market-timing ability in hedge funds at both the aggregate and fund levels is especially pronounced when the market is in decline and when it is more volatile. Lu et al. (2016) test the limited attention hypothesis and show that when hedge fund managers go through turbulent periods in personal life, such as marriages and divorces, they invest in more conventional stocks and their funds' alphas decrease around the events.

In this paper, we build upon this literature and set out to identify if during more stressful periods such as times of outflows managers are able to show some extra skill, by possibly being more focused on managing their portfolios.

Prior literature suggests that mutual funds with past inflows outperform their peers with past outflows (Lou, 2012). The authors also show that past-winning funds expand their existing holdings in past-winning stocks, while past-losing funds liquidate their holdings in past-losing stocks, leading to a stock price momentum. Mutual funds trading, however, leads to a substantial price pressure when mutual funds face outflows (Coval and Stafford, 2007). The cumulative average abnormal returns of stocks that experience fire sales by mutual funds are significantly negative during the selling period, which turn to significantly positive afterwards. At the same time, Alexander et al. (2006) show that mutual funds make successful purchases if their trades are motivated by stock valuation, and happen during times of outflows. Trades linked to the need to deploy excess investor liquidity at times of inflows are not so profitable.

2.2. Data

Our hedge fund data are from TASS Lipper database, and data on institutional holdings are from Thomson Reuters Institutional (13f) Holdings database (CDA/Spectrum s34). To identify hedge fund companies (hereafter HFCs), we create a list of HFCs' 13f identifiers, i.e. manager numbers, by matching the names of HFCs and those of the institutions reporting to 13f. We manually check that the identified companies do not have any mutual fund or insurance business as side-business, thus assuring that we obtain a list of pure HFCs. In total, from TASS Lipper merged database, we identify 324 HFCs that report to the 13f database from 1994q1 to 2017q4.

To ensure the quality of our data, we impose two requirements following previous literature. First, we exclude extremely small HFCs with the total net asset (hereafter TNA) below \$1 million (Lou, 2012). Second, following Coval and Stafford (2007), we exclude observations with the extreme monthly percentage changes of the TNA of HFCs, and keep only observations in the following range:

$$-0.5 \leq \frac{\mathrm{TNA_{j,t}} - \mathrm{TNA_{j,t\text{-}1}}}{\mathrm{TNA_{j,t\text{-}1}}} \leq 2, \tag{2.1}$$

Stock return data are collected from the Center for Research in Security Prices (CRSP) Monthly Stock File. We use monthly returns of common stocks (those with CRSP share codes of 10, or 11) traded on NYSE, AMEX, or NASDAQ (those with CRSP exchange codes of 1, 2, or 3) from 1994/01 to 2018/03. Stock returns are adjusted to the stock splits and delistings. In each quarter q, we only consider the stocks with the price above \$5 at the end of quarter q-1 to purge the estimation noise from minimum tick effect (Harris, 1994; Amihud, 2002). We exclude the stocks of utility firms (those with standard industrial classification (SIC) codes from 4900 to 4999) and financial firms (those with SIC codes from 6000 to 6999).

Next, we calculate monthly flows. For HFC j at the end of month t, the flow ($\mathrm{flow_{j,t}}$) is computed as

$$\mathrm{flow_{j,t}} = \frac{\mathrm{TNA_{j,t}} - \mathrm{TNA_{j,t\text{-}1}} \times (1 + \mathrm{R_{j,t}})}{\mathrm{TNA_{j,t\text{-}1}}}, \tag{2.2}$$

where $\mathrm{R_{j,t}}$ is the TNA-weighted hedge fund return in month t, calculated as

$$\mathrm{R_{j,t}} = \frac{\sum_{k=1}^{N} \mathrm{TNA_{j,k,t}} \times \mathrm{R_{j,k,t}}}{\sum_{k=1}^{N} \mathrm{TNA_{j,k,t}}}, \tag{2.3}$$

and $\mathrm{TNA_{j,k,t}}$ and $\mathrm{R_{j,k,t}}$ are the TNAs and the monthly return, respectively, of hedge fund k managed by HFC j in month t.

We start our sample in 2000q1, when the number of HFCs, for which we are able to compute flows and which report holdings, exceeds 50 for the first time. Panel A of Table 2.1 reports the descriptive statistics[2] for our sample of 324 HFCs from 2000q1 to 2017q4. HFCs, on average, control 2.35 funds, charge 1.31% management fee and 18.36% incentive fee. 80% of hedge funds have the high-water mark (hereafter HWM), and 68% report using leverage. The average monthly flow of HFCs is 1.68%, consistent with hedge fund market growth over the period, despite the shrinkage of the industry during the financial crisis 2007-2008. The average alpha relative to the Fung and Hsieh (2004) seven factors is 1.13% per month, indicating the presence of some skill in the industry. It is, however, quite disperse with the 5th percentile of -23.20% and 95th percentile of 24.77%.

[Place Table 2.1 about here]

2.3. Research Design and Hypotheses

The goal of this paper is to assess the quality of decision making by HFC facing extreme outflows or inflows. Being sophisticated investors, when suddenly experiencing large outflows, HFCs should sell most liquid stocks to obtain the required amount of cash to meet redemptions without a substantial price impact, and avoid selling underpriced stocks with high expected returns. Thus, stocks sold by HFCs upon outflows should not exhibit positive future abnormal returns, if the trades are correctly managed. At the same time, some HFCs may still be willing to buy stocks even experiencing outflows to maintain future fund profitability, if managers have confidence in future good stock returns. The trading against the flow strategy should lead to positive ex-post abnormal returns, if it truly reflects managerial skill and informed buying. Such valuation-based trades are found to be profitable even

[2] Except for fund age, HFCs' characteristics in quarter q are computed as the mean of the monthly TNA-weighted characteristics in this quarter. The calculation of first-order serial correlation and past alpha is detailed in Section 2.5.2.

for mutual funds (Alexander et al., 2006).

But should not one expect all stocks purchased by HFCs to deliver (on average) positive abnormal returns if HFC managers are skilful? We hypothesise that a HFC manager may put different levels of effort into managing their portfolios depending on the level of investor flows, with strong outflows inducing higher effort. This would be one of the implications of Theory X of management style (McGregor, 1957), suggesting that when employees are more self-interested and individual-goal oriented, they tend to work more efficiently under the threat of punishment as motivation (Hersey et al., 2000). Since in the context of HFCs, the main tool for investors to express their dissatisfaction with the managers is to redeem their shares, outflows can perform this disciplinary role and induce higher managerial effort.

At the same time, flows are directly related to managerial compensation stemming from management fees. Management fees represent a large share of the overall expected present value of managerial compensation. According to the model of Lan et al. (2013), management fee accounts for 75% of the total managerial surplus. When hedge fund size increases due to inflow, the expected compensation of managers goes up, even if the expected returns remain unchanged. Upon outflows, however, the expected fee income decreases. Thus, in order to assure the same level of expected compensation, managers need to increase the expected returns, which can be achieved, for example, by proactively searching for more profitable stocks.

Moreover, outflows increase probability of hedge fund liquidation (see, e.g., Kolokolova, 2011, among others), which can lead to reputation loss and career concerns of managers. Li et al. (2011) document that hedge fund managers who face pressure of establishing their careers tend to put more effort than established ones. A theoretical model built by Guerrieri and Kondor (2012) suggests that fund managers earn reputation premium for investing in risky bonds. Higher default risk is linked to higher premium, which compensates managers for the risk of being fired.

Our key hypothesis is, thus, as follows:

Trading against the flow: *Stocks purchased by HFCs experiencing large outflows exhibit positive ex-post abnormal returns.*

To test our hypothesis, we first, rank HFCs based on their average monthly flows in quarter q. HFCs with the lowest 30th percentile of flows are those with large outflows[3]; HFCs with average flows between 30th and 70th percentiles are those having moderate flows; and those HFCs with average flows above 70th percentile experience strong inflows[4]. Then, for HFCs with different levels of flows, we calculate the aggregate change in holding, a commonly-used trading measure (see Nofsinger and Sias, 1999; Gompers and Metrick, 2001; Griffin and Xu, 2009, among others). For each HFC j, stock i, and quarter q, we calculate the change in holding ($\Delta \mathrm{Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}}$) as follows:

$$\Delta \mathrm{Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}} = \frac{\mathrm{Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}} - \mathrm{Holding}_{\mathrm{i,q\text{-}1}}^{\mathrm{HFC_j}}}{\mathrm{SHROUT}_{\mathrm{j,q\text{-}1}}}, \tag{2.4}$$

where $\mathrm{Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}}$ is the number of stock i held by HFC j in quarter q, and $\mathrm{SHROUT}_{\mathrm{i,q\text{-}1}}$ is the total number of outstanding shares of stock i at the end of quarter q-1. We then sum the change in holding of all HFCs that trade the same stock, and obtain the aggregate change in holding for stock i in quarter q ($\mathrm{Trade}_{\mathrm{i,q}}$), i.e.

$$\mathrm{Trade}_{\mathrm{i,q}} = \sum_{\mathrm{j=1}}^{\mathrm{K}} \Delta \mathrm{Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}}, \tag{2.5}$$

where K is the number of HFCs that trade stock i in quarter q. Stocks with aggregate change in holding below (above) the bottom (top) 30th percentile are considered as those that HFCs significantly sell (buy)[5].

We evaluate the performance of these stocks using the adjusted abnormal returns following Daniel et al. (1997) (hereafter DGTW). At the end of each June, we assign stocks into one of 125 portfolios constructed based on market capitalization using

[3] We also require the "large outflows" to be smaller than zero. If the 30th percentile is positive in some quarters, only negative flows are classified as "large outflows".

[4] Likewise, we also require the "strong inflows" to be larger than zero.

[5] We also require the aggregate change in holding to be smaller (larger) than zero for stocks classified as "sell (buy)".

NYSE breakpoints, the industry-adjusted book-to-market ratio using the Fama-French 48 industries, and the prior 12-month return. Portfolios are held for one year and then rebalanced. For each of the 125 portfolios, we calculate the value-weighted monthly returns as the benchmark. The DGTW-adjusted monthly return is the difference between the stock's monthly return and the return on the benchmark portfolio which this stock belongs to. We then regress the DGTW-adjusted monthly return in quarter q+1 on a set of dummy variables capturing HFC trading upon different flow levels in quarter q. For example, a dummy variable $\text{Buy}^{\text{Outflow}}$ for stock i during months of quarter q+1 takes a value of one if this stock is among significantly bought ones (Trade > 70th) in quarter q by HFCs experiencing large outflows (Flow $\leq$ 30th).

2.4. Empirical Results: Trading Against the Flow

Panel B of Table 2.1 reports the equal-weighted average of HFC monthly flows within different flow-level groups during the whole sample period (2000q1-2017q4), as well as pre-crisis (2000q1-2007q2), crisis (2007q3-2009q1), and post-crisis (2009q2-2017q4) periods (Ben-David et al., 2012). Overall, HFCs attract around twice larger inflows than outflows. This pattern, however, varies during different periods. Before the financial crisis of 2007-2008, the average large inflow of HFCs is 12.22%, almost four times larger in absolute value than the average large outflow of -3.71%. After the crisis, the average large inflow of HFCs significantly shrinks to 5.53%, while the average large outflow increases in absolute value to -4.46% per month.

Table 2.2 reports the regression results. According to the full-sample results in Columns (1)-(3), stocks sold by HFCs upon large outflows do not exhibit any significant abnormal returns. Even facing larger redemptions, HFCs do not seem to make "bad deals" and do not lose money for their investors. They also do not seem to exhibit a substantial price pressure while selling stocks, as no positive ex-post abnormal return can be documented. In this respect they are quite different from the mutual funds, which move stock prices substantially away from their fundamental values when trading in response to outflows (Coval and Stafford, 2007).

The stocks that HFCs buy when facing large outflows exhibit an abnormal return of 0.06% per month, on average, which is highly statistically significant. Purchasing decisions at times when HFCs face redemptions are, thus, more likely to be driven by HFC stock-picking skills and expectations of higher future profits. Remarkably, such stock-picking skills cannot be detected for stocks bought upon inflows, consistent with our hypothesis. The abnormal returns are not statistically significant in this case. When capital is abundant, HFCs seem to take less efficient decisions, potentially investing in more "conventional" shares or paying less attention to their portfolios, contributing to a negative flow-performance relation found in Berk and Green (2004), Naik et al. (2007), and Joenväärä et al. (2018) among others.

An interesting pattern emerges in this setting, however. The abnormal returns of stock sold upon inflow are negative and highly statistically significant of approximately -0.14% per month. That is, even if HFC managers do not take efficient purchasing decisions when capital is in abundance upon large inflows, they still monitor their existing portfolios and sell future losing stocks.

One can expect some variation in trading performance around the financial crisis of 2007-2008. Schaub and Schmid (2013), for example, find that hedge funds with more stringent share restrictions hold more illiquid assets and earn an illiquidity premium during the period before the financial crisis. However, during the financial crisis, these funds experience lower returns and lower alphas. Columns (4)-(12) of Table 2.2 indicate that the trading against the flow pattern indeed varies across different time periods, and it is mostly pronounced during the post-crisis period (2009q2-2017q4). During the pre-crisis period (2000q1- 2007q2) stocks purchased by HFCs experiencing strong outflows, on the contrary to our expectations, exhibit smaller abnormal returns, while we cannot document any abnormal returns related to flow-induced trading during the crisis period. During the post-crisis period, HFCs with both strong inflows and outflows exhibit extra stock-picking skills. This is likely to be driven by the generally lower flows into the hedge fund industry and the increasing competition between managers.

[Place Table 2.2 about here]

We further check if HFCs tend to trade stocks with different characteristics upon inflows and outflows. We run a regression similar to that in Column (3) of Table 2.2 using different stock characteristic as dependent variables. In particular, we compute Amihud illiquidity measure using daily returns in quarter q (Amihud, 2002), average market capitalisation during quarter q, holdings of the stock by large diversified institutional investors – quasi-indexers (Bushee, 2001), as well as holdings of non-institutional investors (Ben-David et al., 2012) at the end of quarter q-1. We further use stock CAPM beta, and loadings on size, value, and momentum factors from the Carhart (1997) model. The results reported in Table 2.3 show that HFCs in general sell more liquid (less illiquid) stocks than they buy (Column (1)), and buy stocks with relatively larger holdings of non-institutional investors compared to stocks they sell (Column (3)). Upon both strong inflows and outflows HFCs trade low CAMP-beta stocks (Column (5)). Hedge funds tend to trade stocks that are smaller than an average listed firm in the market, what can be seen from all negative loadings in Column (2). Remarkably, upon large outflows HFCs tent to buy somewhat larger firms than they do upon inflow.

[Place Table 2.3 about here]

2.5. Determinants of Trading Against the Flow

In order for HFCs to display higher skills under "pressure" of outflows, they need to be motivated to put extra effort in managing the fund, and also be able to do so. We consider several aspects that contribute to manager's motivation and ability to trade. Direct financial losses of managers due to outflows, their compensation structure, and career concerns all contribute to managerial motivations while illiquidity of assets, flexibility in decision making and access to capital facilitate potentially profitable trades. We extend the panel regression from Column (3) of Table 2.2 by interacting $\text{Buy}^{\text{Outflow}}$ with dummies capturing particular types of HFCs that trade this stock. For example, $\text{Buy}^{\text{Outflow}} \times \text{TNA}^{\text{Low}}$ captures the abnormal returns of stocks bought by HFCs experiencing large outflows with TNAs below median. We discuss each group of determinants in detail below.

2.5.1. Direct losses of managers

Management fee is an important source of managerial compensation. According to Lan et al. (2013), management fee accounts for 75% of the total expected life-long present value of managerial compensation. Funds with higher management fees tend to perform better; within a HFC, performance difference between the first and consequently launched funds is greater for funds with relatively higher management fees (Fung et al., 2018). Management fee also plays a role in strategic decisions, such as fund liquidation and risk taking. Funds with higher management fees within their families are less likely to be liquidated (Kolokolova, 2011). High-management-fee funds take a less aggressive risk-taking approach. Having poor performance at the beginning of a year, they tend to reduce their risk taking to increase the chances of survival (Kolokolova and Mattes, 2018).

A substantial portion of managerial income of profitable funds is also generated by incentive fees. Funds with higher incentive fees are often perceived as more motivated and skilled (Ackermann et al., 1999; Edwards and Caglayan, 2001; Agarwal et al., 2009). Outflows reduce the fee-base, having an immediate effect on managerial compensation. The higher the fees, the higher compensation losses are for a given level of outflow.[6]

Fund size is another component directly linked to the absolute value of managerial compensation. The same percentage outflow implies much larger absolute losses for managers of large funds as opposed to small funds. In order to restore

[6]Flow-related indirect incentives in hedge fund industry are found to be 1.4 times higher than direct incentives stemming from nominal fees (Lim et al., 2016).

the expected level of compensation to at least the pre-outflow level, managers would need to adjust their strategies and may be putting more effort in managing the portfolios and searching for more profitable opportunities. Inflows, on the contrary, do not provide such incentives to the managers. Inflows immediately increase expected managerial compensation (related to management fees at least) without the need of fast trading. The new capital can be gradually invested in the existing products, which would not require extra search/research cost for managers. Hence, we expect that funds with higher management and incentive fees and larger size to exhibit stronger trading against the flow patterns.

Column (1)-(6) of Table 2.4 report the regression results associated with each of the factors, as well as the sum of the coefficients on $\text{Buy}^{\text{Outflow}}$ and the products of the fund classification dummy variables and $\text{Buy}^{\text{Outflow}}$ (labeled as "Joint coefficients"). According to the joint coefficients, the trading against the flow is more profitable for HFCs with larger size and higher incentive fees (Columns (4) and (6)), consistent with our expectation. Stocks bought by large HFCs earn an additional abnormal return of +0.11% per month significant at the 1% level, which is largely driven by the fund size effect based on the significance of corresponding coefficients on the interaction $\text{Buy}^{\text{Outflow}} \times \text{TNA}^{\text{High}}$. HFC with higher-than-the-median incentive fees incentive fees (that is, fees above 20%) exhibit an impressive 0.58% of additional abnormal return per month on the stocks they buy during times of outflow.

[Place Table 2.4 about here]

2.5.2. Career concerns

Career concerns generally motivate managers to put more effort into their work (Li et al., 2011; Guerrieri and Kondor, 2012). This is especially true for younger funds which still need to establish a reliable track record and reputation, and which are more likely to experience outflows (Getmansky et al., 2019). Thus, younger funds may be more likely to engage in trading against the flow to boost their performance in tough times. In the regression, we consider HFCs with above-median ages as older funds.

Career concerns can be further amplified for managers with poor past performance. When experiencing large outflows, HFCs with low recent alpha may be under much more pressure to perform, as they not only need to respond to the outflow, but also to make up for past losses to assure long-term survival. Thus, they may be expected to put more effort into managing their funds.

To measure the alpha, for each HFC in each quarter q, we use its past 24-month returns (from q-8 to q-1)[7] and estimate their alphas relative to the seven-factor model of Fung and Hsieh (2004). As before, monthly returns on a company level is the TNA-weighted average of monthly returns of individual funds belonging to the company:

$$\frac{\sum_{k=1}^{N} \mathrm{TNA_{j,k,t}} \times \mathrm{R_{j,k,t}}}{\sum_{k=1}^{N} \mathrm{TNA_{j,k,t}}} = \alpha_{\mathrm{j,Q}} + \beta_{\mathrm{j}}^{1}\mathrm{SNPMRF_t} + \beta_{\mathrm{j}}^{2}\mathrm{SCMLC_t} \tag{2.6}$$

$$+ \beta_{\mathrm{j}}^{3}\mathrm{BD10RET_t} + \beta_{\mathrm{j}}^{4}\mathrm{BAAMTSY_t} + \beta_{\mathrm{j}}^{5}\mathrm{PTFSBD_t} \tag{2.7}$$

$$+ \beta_{\mathrm{j}}^{6}\mathrm{PTFSFX_t} + \beta_{\mathrm{j}}^{7}\mathrm{PTFSCOM_t} + \varepsilon_{\mathrm{j}}, \tag{2.8}$$

where SNPMRF is the Standard & Poors 500 index monthly total return (Datastream item: S&PCOMP RI), SCMLC is the difference between Russell 2000 index monthly total return (item: FRUSS2L RI) and Standard & Poors 500 monthly total return (item: S&PCOMP RI), BD10RET is the monthly change in the Federal Reserve's 10-year treasury constant maturity yield[8] (month end-to-month end), BAAMTSY is the monthly change in the difference between Moody's Baa yield[9] and the Federal Reserve's 10-year treasury constant maturity yield (month end-to-month end), PTFSBD, PTFSFX, and PTFSCOM are correspondingly the returns on portfolios of lookback straddles on bond, currency, and commodity futures.[10] We rank HFCs based on their past alpha in quarter q. HFCs with past above-median alphas

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[7] We only consider the HFCs with more than 18 monthly returns over past 24 months.

[8] https://fred.stlouisfed.org/series/DGS10.

[9] https://fred.stlouisfed.org/series/DBAA.

[10] http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.

are considered as past-winning HFCs, otherwise they are considered as past-losing ones.

Column (7)-(10) of Table 2.4 report the regression results associated with determinants of career concerns. According to the joint coefficients, stocks purchased by HFCs with younger ages or lower past alphas earn abnormal returns of +0.19% or +0.10% per month, respectively, supporting our hypothesis that career concerns are indeed a motivating factor for managerial productivity. Looking at the coefficients on each intersection variable, we can see that the trading against the flow pattern is especially strong for HFCs with younger age.

2.5.3. Asset illiquidity and decision making flexibility

To meet redemptions, especially large ones, fund managers may have to sell most liquid stocks to obtain the required amount of cash. This may be harder to achieve for those funds, that hold illiquid portfolios. If selling the assets leads to additional losses, funds are adversely impacted through both channels – investor outflows and trading losses. Therefore, managers of illiquid funds may be expected to experience even more pressure than those of liquid funds and hence put further effort into managing the portfolios.

We measure HFC asset illiquidity using return serial correlation following Getmansky et al. (2004), who argue that funds with higher return serial correlation tend to be more illiquid. For each quarter q and each HFC in our sample, we calculate the first-order return serial correlation using past 24-month returns (from q-8 to q-1)[11]. HFCs with above-median first-order serial correlations are classified as those holding less liquid assets.

Fund illiquidity is closely related to share restrictions. Aragon (2007) find a positive relation between share restrictions of HFCs and fund asset illiquidity, suggesting that HFCs with more stringent share restrictions tend to manage illiquid assets more efficiently and earn illiquidity premium. Hence, illiquid HFCs tend to

[11] We use only HFCs with more than 18 monthly returns over past 24 months.

have more share restrictions, but HFC with tighter restrictions have higher flexibility and are able to trade more efficiently. Investors in hedge funds with shorter notice periods have easier access to their money, and such funds are more likely to experience sudden capital outflows. Agarwal et al. (2015) find that funds of funds tend to liquidate holdings in individual funds with few redemption constraints when experiencing large outflows. HFCs with longer notice periods receive the information on the coming outflows earlier. They have more time to adjust their portfolios and avoid fire sales even if their holdings are less liquid, which can lead to better trading against the flow results for these HFs. We use a notice period prior to redemption as a proxy for outflow share restrictions.[12] In each quarter q, we classify HFCs as having a long notice period, if the reported notice period is longer than 30 days.

To finance an investment programme, a manager needs capital. During times of outflow, new purchases can be financed either by portfolio rebalancing and selling more assets than required to meet investor redemptions, or though borrowing.[13] Stable relations with prime brokers are important for HFCs to be able to finance their strategies, borrowing assets for short selling or getting leverage for their long positions. Healthy prime brokers facilitate trading, and adverse shocks to prime brokers are harmful for hedge fund performance (Boyson et al., 2010; Brunnermeier and Pedersen, 2008; Kruttli et al., 2018). At the same time, individual shocks to prime brokers are diversified and not propagated to their client hedge funds, if hedge funds have multiple prime brokers (Dahlquist et al., 2019). Thus, having multiple prime brokers makes a HFCs "immune" to individual shocks to prime brokers and allows them to diversify borrowing opportunities. To capture borrowing flexibility, we classify HFCs into those reporting only a single prime broker and those reporting multiple prime brokers. We expect trading agains the flow to be more profitable for HFCs with multiple prime brokers.

[12] According to Getmansky et al. (2019), share restrictions can be classified into two key groups: outflow restrictions (e.g. lockup period, redemption frequency, and notice period) and inflow restrictions (e.g. subscription period, closure to new investors).

[13] HFs can also use their cash reserves to finance the extra purchases. The data on cash reserves of HFs is, however, not available.

Table 2.5 reports the regression results associated with HFC asset illiquidity and flexibility. Consistent with our expectation, the trading against the flow pattern is more pronounced among HFCs with higher return serial correlation and a longer notice period. Stocks bought by those HFCs earn abnormal returns of +0.12% and +0.22% per month, respectively. These returns are highly statistically significant, suggesting that managers of illiquid funds display better stock-picking skills upon large outflows. Remarkably, however, stocks purchases upon outflows earn a negative abnormal return of -0.06% for HFCs with shorter notice periods. For trading against the flow to be successful, managers need to have enough time to make optimal decisions. In this respect, a longer notice period provides managers with this time and flexibility and enables profitable trading decisions when facing outflows.

In terms of the number of prime brokers, even thought the signs of the interaction terms of $\text{Buy}^{\text{Outflow}} \times \text{PrimeBroker}^{=1}$ and $\text{Buy}^{\text{Outflow}} \times \text{PrimeBroker}^{>1}$ point into the expected direction of more profitable trading by HFCs with multiple prime brokers, the effects are not statistically significant.

[Place Table 2.5 about here]

2.6. Implications for liquidation probability

During times of outflows, less resilient funds are more likely to be liquidated. The documented superior performance of trading against the flow is associated with those funds that are able to sustain outflows and then redirect their trading based on their stock-picking abilities. This can come at a cost of, for example, increasing leverage, investing in riskier stocks or stocks in which HFC managers do not have much expertise. In this section we test if HFCs survival probability is affected by their trading against the flow.

We estimate a logit model for HFC liquidation probability over the following quarter. We control for the known characteristics that can impact the liquidation probability, including quarterly returns, return standard deviation, fund size, and investor restrictions among others. We control for average monthly fund flow during quarter q (Flow) and also include the flow if it is smaller than 30th percentile during this quarter ($\mathrm{Flow}^{\leq 30\mathrm{th}}$) to check for possible non-linearity of the effect of net flows.[14] We also include year fixed effects to capture potential systematic time variation in the HFC liquidation probability.

The key question to answer here is if trading against the flow affects chances of HFC survival. To quantify the level of such trading, we introduce a HFC-level *Trading Intensity* (TI) measure. For HFC j, stock i, and quarter q, we calculate the proportional change in value holding ($\Delta\mathrm{Value\ Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}}$) as follow:

$$\Delta\mathrm{Value\ Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}} = \frac{\left(\mathrm{Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}} - \mathrm{Holding}_{\mathrm{i,q\text{-}1}}^{\mathrm{HFC_j}}\right) \times \overline{\mathrm{P}}_{\mathrm{i,q}}}{\mathrm{TNA}_{\mathrm{j,q\text{-}1}}}, \tag{2.9}$$

where $\overline{\mathrm{P}}_{\mathrm{i,q}}$ is the average daily price of stock i in quarter q, and $\mathrm{TNA}_{\mathrm{j,q\text{-}1}}$ is the TNAs of HFC j at the end of quarter q-1. We then average the proportional change in value holding across all stocks traded by the same HFC, and obtain the trading intensity measure for HFC j ($\mathrm{TI}_{\mathrm{j,q}}$), i.e.

$$\mathrm{TI}_{\mathrm{j,q}} = \frac{1}{\mathrm{K}} \sum_{\mathrm{i=1}}^{\mathrm{K}} \Delta\mathrm{Value\ Holding}_{\mathrm{i,q}}^{\mathrm{HFC_j}}, \tag{2.10}$$

where K is the number of stocks traded by HFC j in quarter q.

Next, we calculate the against-the-flow trading intensity ($\mathrm{ATF\text{-}TI}_{\mathrm{j,q}}$) for each HFC facing large outflows. For each HFC j with Flow $\leq$ 30th in quarter q, we compute its TI measure only for stocks with aggregate change in HFC holding above the top 30th percentile in quarter q ($\mathrm{Trade}_{\mathrm{i,q}} >$ 70th). HFCs with other level of flows or that do not trade any stocks with $\mathrm{Trade}_{\mathrm{i,q}} >$ 70th will have zero ATF-TI.[15] We include the product of $\mathrm{ATF\text{-}TI}_{\mathrm{j,q}}$ and $\mathrm{Flow}^{\leq 30\mathrm{th}}$ in the final specification of the

[14] Jorion and Schwarz (2015) find evidence that funds receiving higher inflows have higher future performance and a lower probability of failure. However, they do not find evidence that outflows predict poor performance or fund failure. Their findings indicate an asymmetric smart money effect in the hedge fund industry.

[15] Note, that the ATF-TI measure can be negative. For example, if a HFC with llarge outflows sells a stock, which is simultaneously bought by other HFCs who trade against the flow.

model. If HFCs that do trade against the flow are more likely to survive (less likely to be liquidated), we should observe a positive coefficient for this interaction term, since $\text{Flow}^{\leq 30\text{th}}$ is negative.

The estimation results (Table 2.6) reveal that, as expected, flows are negatively related to the liquidation probability. The corresponding coefficient of -1.823 is highly statistically significant in Column (1). However, the effect seems to be driven completely by strong outflows. The coefficients for $\text{Flow}^{\leq 30\text{th}}$ are highly statistically significant and range from -5.664 to -8.516 in Columns (2)-(3), and when we control for large outflows, the general flow variable loses significance.[16] The product $\text{Flow}^{\leq 30\text{th}} \times$ ATF-TI is positive and significant at 1% level. The values of the coefficient is 1.007 in Columns (3). Therefore, by trading against the flow, HFCs significantly decreases their liquidation probability through ameliorating the adverse impact of outflows. Such trading seems to be an effective strategy for managers with stock-picking skills to weather financial distress.

[Place Table 2.6 about here]

2.7. Conclusion

We analyze trading patterns of HFCs, facing substantial inflows or outflows of capital and find that HFC managers are likely to reveal their skills under "pressure". Some HFCs display a trading against the flow pattern: despite facing outflows and requiring cash to meet redemptions, they still purchase stocks. The purchased stocks exhibit a positive and significant ex-post abnormal return adjusted using DGTW methodology. Large outflows reduce the base for fees and may put the very survival of the fund at risk. Such financial and reputation concerns seem to motivate managers to put higher effort into managing the funds, innovate, and search for especially profitable opportunities.

[16] We also consider a different specification, in which flows below 30th percentile, between 30th and 70th percentiles, and above 70th percentile are used as separate variables. The results are almost identical to those discussed in this section. Only $\text{Flow}^{\leq 30\text{th}}$ is negative and significant, whereas other two flow variables are not significant.

The abnormal returns associated with trading against the flow are more pronounced after 2007-2008 financial crisis, and for HFCs with large size or higher fees – HFCs for which managerial compensation is relatively more strongly affected by outflows. Abnormal returns are significantly higher for funds that manage more illiquid assets and have more time to adjust their portfolios due to longer notice periods. The purchasing decisions upon large outflows are also more successful for those funds that are motivated to perform because of additional reasons, such as a need to establish track record for young funds. These findings further support our intuition that some extra pressure is required to induce managers to put more effort into their day-to-day investment job, echoing Theory X of management style of McGregor (1957). The extra effort put into trading against the flow by fund managers pays off and reduces the next-quarter liquidation probability of the funds facing outflows.

Our findings call for devising a new generation of theoretical models of managerial decision in HFCs, building upon the existing works (Hodder and Jackwerth, 2007; Lan et al., 2013; Buraschi et al., 2014, among others) but allowing for the choice of the effort level managers put into their work, similar to the approach pioneered by Holmström (1999) and further developed in, for example, Dewatripont et al. (1999). From an investor's point of view, the question arises of how to incentivise a manager to perform during good times and not only during bad times, as the existing compensation structure of a management plus incentive fee does not seem to be sufficient for that task.

2.8. Tables

Table 2.1: Descriptive statistics for hedge fund companies

This table reports the numbers of observations, means, standard deviations, minimums, medians, maximums, and the 5th, 25th, 75th, and 95th percentiles of characteristics for 324 hedge fund companies (HFCs) from 2000q1 to 2017q4, including flows, total net assets (TNAs), high-water mark (HWM), and past alphas, as well as the equal-weighted average of HFC monthly flows within different flow-level groups during the whole sample period (2000q1-2017q4), as well as pre-crisis (2000q1-2007q2), crisis (2007q3-2009q1), and post-crisis (2009q2-2017q4) periods (Ben-David et al., 2012). Except for fund age, HFCs' characteristics of quarter q are proxied as the mean of the monthly TNA-weighted characteristics in quarter q. Fund age is computed since inception of HFC. Flow and past alpha are winsorized at 1% and 99% levels.

Panel A: Characteristics of HFCs

	N	Mean	Std Dev	Minimum	P5	P25	P50	P75	P95	Maximum
Fund age (month)	10037	91.92	65.09	2.00	12.00	42.00	78.00	128.00	217.00	389.00
No. funds in HFC	10037	2.36	2.02	1.00	1.00	1.00	2.00	3.00	6.33	17.00
Flow (% per month)	10037	0.02	0.08	-0.16	-0.08	-0.01	0.00	0.03	0.16	0.48
Management fee (%)	10021	1.31	0.42	0.00	0.90	1.00	1.22	1.50	2.00	3.31
TNA ($million)	10037	746.26	2829.12	1.00	7.29	44.67	148.33	528.00	2811.23	51166.67
Incentive fee (%)	10019	18.38	4.63	0.00	7.13	20.00	20.00	20.00	20.00	50.00
HWM	10021	0.80	0.36	0.00	0.00	0.78	1.00	1.00	1.00	1.00
Leveraged	10037	0.67	0.43	0.00	0.00	0.09	1.00	1.00	1.00	1.00
Notice period (day)	10037	44.17	27.61	0.00	6.14	30.00	40.71	60.00	90.00	259.92
Lock-up period (day)	10037	5.13	6.59	0.00	0.00	0.00	0.50	12.00	12.00	36.00
Redemption frequency (day)	9960	90.13	81.56	1.00	30.00	30.00	90.00	90.00	360.00	360.00
No. prime brokers in HFC	8947	1.75	1.23	1.00	1.00	1.00	1.00	2.00	4.00	12.00
First-order serial correlation	8770	-0.04	0.22	-0.72	-0.41	-0.18	-0.04	0.11	0.31	0.64
Past alpha (% per month)	8770	1.06	15.30	-48.62	-23.34	-5.01	0.65	6.75	24.92	61.22

Panel B: Equal-weighted average flows of HFCs (% per month)

	Flow $\leq$ 30th	30th $<$ Flow $\leq$ 70th	Flow $>$ 70th
Full sample	-4.226%	0.517%	9.551%
Pre-crisis	-3.707%	1.026%	12.221%
Crisis	-6.196%	-0.255%	6.495%
Post-crisis	-4.461%	-0.156%	5.528%

Table 2.2: Trading against the flow: abnormal returns

This table reports the estimation results of panel regressions for DGTW-adjusted monthly returns (Daniel et al., 1997) in quarter q+1 on industry and year fixed effects, and a set of dummy variables capturing HFC trading upon different flow levels in quarter q during the whole sample period (2000q1-2017q4), as well as pre-crisis (2000q1-2007q2), crisis (2007q3-2009q1), and post-crisis (2009q2-2017q4) periods (Ben-David et al., 2012). "Sell" ("Buy") takes a value of 1 if the aggregate change in holding of the stock is below (above) the bottom (top) 30th percentile. Superscripts "Outflow" and "Inflow" indicate if corresponding HFCs experienced large outflows and inflows respectively. HFCs with the lowest 30th percentile of average flows are those with large outflows, and those HFCs with average flows above 70th percentile experience large inflows. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. Robust standard errors clustered by both HFC and year are in parentheses.

	Full sample			Pre-crisis			Crisis			Post-crisis		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\text{Sell}^{\text{Outflow}}$	-0.029		-0.039	-0.027		-0.053	-0.123		-0.104	-0.011*		-0.015
	(0.028)		(0.031)	(0.047)		(0.064)	(0.155)		(0.129)	(0.005)		(0.014)
$\text{Buy}^{\text{Outflow}}$	0.061***		0.051**	-0.011**		-0.037**	0.202		0.221	0.095**		0.090**
	(0.013)		(0.019)	(0.004)		(0.013)	(0.109)		(0.140)	(0.030)		(0.033)
$\text{Sell}^{\text{Inflow}}$		-0.140**	-0.138**		-0.192	-0.203		-0.014	0.005		-0.132**	-0.123**
		(0.059)	(0.063)		(0.128)	(0.135)		(0.090)	(0.111)		(0.040)	(0.043)
$\text{Buy}^{\text{Inflow}}$		0.046	0.047		-0.013	-0.024		0.132	0.151		0.073***	0.082***
		(0.037)	(0.040)		(0.074)	(0.079)		(0.189)	(0.191)		(0.012)	(0.020)
Constant	0.097***	0.109***	0.107***	0.117***	0.132***	0.142***	-0.003	-0.003**	-0.022**	0.104***	0.117***	0.108***
	(0.000)	(0.002)	(0.003)	(0.000)	(0.004)	(0.006)	(0.002)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)
$\text{Buy}^{\text{Outflow}} - \text{Sell}^{\text{Outflow}}$	0.090**		0.090**	0.016		0.016	0.325		0.325	0.106**		0.106**
	(0.041)		(0.041)	(0.051)		(0.062)	(0.209)		(0.217)	(0.035)		(0.037)
$\text{Buy}^{\text{Outflow}} - \text{Buy}^{\text{Inflow}}$			0.003			-0.013			0.070			0.009
			(0.034)			(0.086)			(0.135)			(0.021)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	952,040	952,040	952,040	426,475	426,475	426,475	108,187	108,187	108,187	417,378	417,378	417,378
R-squared	0.001	0.001	0.001	0.002	0.002	0.002	0.003	0.003	0.003	0.001	0.001	0.001

Table 2.3: Trading against the flow: stock characteristics

This table reports the estimation results of panel regressions for different stock characteristics on industry and year fixed effects, and a set of dummy variables capturing HFC trading upon different flow levels in quarter q during the whole sample period (2000q1-2017q4). "Sell" ("Buy") takes a value of 1 if the aggregate change in holding of the stock is below (above) the bottom (top) 30th percentile. Superscripts "Outflow" and "Inflow" indicate if corresponding HFCs experienced large outflows and inflows respectively. HFCs with the lowest 30th percentile of average flows are those with large outflows, and those HFCs with average flows above 70th percentile experience large inflows. The bottom panel reports the Wald test for the difference in the estimated coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. Robust standard errors clustered by both HFC and year are in parentheses.

	Amhud illiquidity ($\times 10^{-6}$)	Market Cap (in $billion)	Institutional holding (%)		Factor loading			
			Non-institutional investors	Quasi-indexers	CAPM Beta	Carhart SMB	Carhart HML	Carhart UMD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Sell}^{\text{Outflow}}$	-0.315***	-5.387***	-2.203***	-0.071	0.077***	0.097***	0.005	0.000
	(0.103)	(1.001)	(0.343)	(0.264)	(0.011)	(0.017)	(0.014)	(0.009)
$\text{Buy}^{\text{Outflow}}$	-0.095	-5.180***	-1.055**	-0.564*	0.063***	0.099***	0.014	0.011
	(0.087)	(1.000)	(0.373)	(0.280)	(0.011)	(0.016)	(0.015)	(0.009)
$\text{Sell}^{\text{Inflow}}$	-0.386***	-5.403***	-2.623***	0.413	0.087***	0.095***	-0.005	0.005
	(0.080)	(1.138)	(0.349)	(0.275)	(0.012)	(0.017)	(0.014)	(0.012)
$\text{Buy}^{\text{Inflow}}$	-0.124	-6.411***	-0.807*	-0.895**	0.051***	0.102***	0.036*	-0.018
	(0.085)	(1.262)	(0.455)	(0.348)	(0.010)	(0.017)	(0.019)	(0.013)
Constant	0.707***	9.839***	30.638***	45.252***	1.256***	0.685***	0.083***	-0.064***
	(0.023)	(0.392)	(0.091)	(0.056)	(0.000)	(0.002)	(0.001)	(0.000)
$\text{Buy}^{\text{Outflow}} - \text{Sell}^{\text{Outflow}}$	0.219***	0.207	1.148**	-0.492	-0.014	0.002	0.008	0.011
	(0.072)	(0.301)	(0.433)	(0.385)	(0.013)	(0.021)	(0.022)	(0.011)
$\text{Buy}^{\text{Outflow}} - \text{Buy}^{\text{Inflow}}$	0.029	1.232**	-0.248	0.331	0.012	-0.003	-0.022	0.029*
	(0.090)	(0.515)	(0.478)	(0.402)	(0.012)	(0.015)	(0.019)	(0.014)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	952,040	932,637	845,759	930,560	876,282	876,282	876,282	876,282
R-squared	0.005	0.053	0.089	0.090	0.107	0.027	0.057	0.018

Table 2.4: Determinants of trading against the flow: managerial income and incentives

This table reports the estimation results of panel regressions for DGTW-adjusted monthly returns (Daniel et al., 1997) in quarter q+1 on industry and year fixed effects, a set of dummy variables capturing HFC trading upon different flow levels with different levels of given characteristics in quarter q from 2000q1 to 2017q4. "Sell" ("Buy") takes a value of 1 if the aggregate change in holding of the stock is below (above) the bottom (top) 30th percentile. Superscripts "Outflow" and "Inflow" indicate if corresponding HFCs experienced large outflows and inflows respectively. HFCs with the lowest 30th percentile of average flows are those with large outflows, and those HFCs with average flows above 70th percentile experience large inflows. The dummy variables indicate if the HFCs belong to a group with a given characteristic above or below median, including management fee (ManFee), Incentive fee (IncentiveFee), total net assets (TNA), HFC age since inception (FundAge), and past alpha relative to the Fund and Hsieh (2004) seven factors (PastAlpha). "Joint coefficients" refers to the sum of the products of dummy variables containing $\text{Buy}^{\text{Outflow}}$ and $\text{Buy}^{\text{Outflow}}$ itself. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. Robust standard errors clustered by both HFC and year are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\text{Sell}^{\text{Outflow}}$	-0.039	-0.039	-0.039	-0.039	-0.039	-0.039	-0.039	-0.039	-0.039	-0.039
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
$\text{Buy}^{\text{Outflow}}$	0.077	0.043	0.140**	-0.064	0.614	0.040**	-0.160*	0.193***	-0.006	0.085*
	(0.095)	(0.048)	(0.064)	(0.041)	(0.592)	(0.019)	(0.079)	(0.053)	(0.043)	(0.044)
$\text{Sell}^{\text{Inflow}}$	-0.138**	-0.138**	-0.138**	-0.138**	-0.138**	-0.138**	-0.138**	-0.138**	-0.138**	-0.138**
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
$\text{Buy}^{\text{Inflow}}$	0.047	0.047	0.048	0.047	0.047	0.047	0.047	0.047	0.047	0.047
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$\text{Buy}^{\text{Outflow}} \times \text{ManFee}^{\text{Low}}$	-0.035									
	(0.119)									
$\text{Buy}^{\text{Outflow}} \times \text{ManFee}^{\text{High}}$		0.020								
		(0.130)								
$\text{Buy}^{\text{Outflow}} \times \text{TNA}^{\text{Low}}$			-0.181							
			(0.106)							
$\text{Buy}^{\text{Outflow}} \times \text{TNA}^{\text{High}}$				0.176**						
				(0.073)						
$\text{Buy}^{\text{Outflow}} \times \text{IncentiveFee}^{\text{Low}}$					-0.570					
					(0.603)					
$\text{Buy}^{\text{Outflow}} \times \text{IncentiveFee}^{\text{High}}$						0.542*				
						(0.300)				
$\text{Buy}^{\text{Outflow}} \times \text{FundAge}^{\text{Young}}$							0.349***			
							(0.119)			
$\text{Buy}^{\text{Outflow}} \times \text{FundAge}^{\text{Old}}$								-0.264**		
								(0.122)		
$\text{Buy}^{\text{Outflow}} \times \text{PastAlpha}^{\text{Low}}$									0.102	
									(0.067)	
$\text{Buy}^{\text{Outflow}} \times \text{PastAlpha}^{\text{High}}$										-0.062
										(0.080)
Constant	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Joint coefficients	0.042	0.063	-0.041	0.113***	0.044*	0.582*	0.190***	-0.071	0.097**	0.023
	(0.033)	(0.088)	(0.046)	(0.037)	(0.022)	(0.296)	(0.042)	(0.071)	(0.034)	(0.045)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	952,040	952,040	952,040	952,040	952,040	952,040	952,040	952,040	952,040	952,040
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Table 2.5: Determinants of trading against the flow: liquidity and managerial flexibility

This table reports the estimation results of panel regressions for DGTW-adjusted monthly returns (Daniel et al., 1997) in quarter q+1 on industry and year fixed effects, a set of dummy variables capturing HFC trading upon different flow levels with different levels of given characteristics in quarter q from 2000q1 to 2017q4. "Sell" ("Buy") takes a value of 1 if the aggregate change in holding of the stock is below (above) the bottom (top) 30th percentile. Superscripts "Outflow" and "Inflow" indicate if corresponding HFCs experienced large outflows and inflows respectively. HFCs with the lowest 30th percentile of average flows are those with large outflows, and those HFCs with average flows above 70th percentile experience large inflows. $\text{Notice}^{\text{Short}}$ ($\text{Notice}^{\text{Long}}$) is equal to one when the notice periods of HFCs are less (more) than 30 days. $\text{SerialCorr}^{\text{Low}}$ ($\text{SerialCorr}^{\text{High}}$) is equal to one when the first-order reported return serial correlation is below (above) the median. $\text{PrimeBroker}^{=1}$ ($\text{PrimeBroker}^{>1}$) equal to one if HFC reports having only a single prime broker (more than one prime brokers). "Joint coefficients" refers to the sum of the products of dummy variables containing $\text{Buy}^{\text{Outflow}}$ and $\text{Buy}^{\text{Outflow}}$ itself. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. Robust standard errors clustered by both HFC and year are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Sell}^{\text{Outflow}}$	-0.039	-0.039	-0.039	-0.039	-0.039	-0.039
	(0.032)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
$\text{Buy}^{\text{Outflow}}$	0.091*	-0.057	0.280***	-0.092**	0.076	0.045
	(0.045)	(0.058)	(0.063)	(0.043)	(0.070)	(0.035)
$\text{Sell}^{\text{Inflow}}$	-0.138**	-0.138**	-0.138**	-0.138**	-0.138**	-0.138**
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
$\text{Buy}^{\text{Inflow}}$	0.048	0.047	0.048	0.047	0.047	0.047
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$\text{Buy}^{\text{Outflow}} \times \text{SerialCorr}^{\text{Low}}$	-0.085					
	(0.094)					
$\text{Buy}^{\text{Outflow}} \times \text{SerialCorr}^{\text{High}}$		0.172*				
		(0.096)				
$\text{Buy}^{\text{Outflow}} \times \text{Notice}^{\text{Low}}$			-0.342***			
			(0.087)			
$\text{Buy}^{\text{Outflow}} \times \text{Notice}^{\text{High}}$				0.314**		
				(0.112)		
$\text{Buy}^{\text{Outflow}} \times \text{PrimeBroker}^{=1}$					-0.047	
					(0.101)	
$\text{Buy}^{\text{Outflow}} \times \text{PrimeBroker}^{>1}$						0.014
						(0.085)
Constant	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Joint coefficients	0.007	0.115**	-0.062**	0.222***	0.029	0.059
	(0.058)	(0.044)	(0.027)	(0.070)	(0.036)	(0.059)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	952,040	952,040	952,040	952,040	952,040	952,040
R-squared	0.001	0.001	0.001	0.001	0.001	0.001

Table 2.6: HFC liquidation probability

This table reports the estimation results for a logit model for HFC liquidation probability in quarter q+1 from 2000q1 to 2017q4. $\text{Flow}^{\leq 30th}$ is the flow if it is smaller than 30th flow percentile in quarter q. ATF-TI is the “against-the-flow” trading intensity. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. Standard errors are in parentheses.

	(1)	(2)	(3)
Flow	-1.983***	0.414	0.606
	(0.712)	(0.898)	(0.865)
$\text{Flow}^{\leq 30th}$		-5.315***	-8.390***
		(1.767)	(1.638)
AFT-TI			0.020
			(0.022)
$\text{Flow}^{\leq 30th}$ × ATF-TI			1.047***
			(0.237)
No.funds in HFC	-0.241***	-0.243***	-0.251***
	(0.058)	(0.058)	(0.059)
Past volatility	-0.036	-0.035	-0.034
	(0.035)	(0.034)	(0.034)
Past alpha	0.002	0.002	0.001
	(0.005)	(0.005)	(0.005)
Fund age	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Management fee	0.010	-0.022	-0.052
	(0.180)	(0.180)	(0.182)
TNA	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Incentive fee	0.028	0.027	0.024
	(0.021)	(0.021)	(0.021)
HWM	0.146	0.150	0.155
	(0.207)	(0.208)	(0.208)
Leveraged	-0.333**	-0.329**	-0.323*
	(0.165)	(0.165)	(0.166)
Notice period	-0.004	-0.003	-0.003
	(0.003)	(0.003)	(0.003)
Lock-up period	-0.007	-0.005	-0.004
	(0.011)	(0.011)	(0.011)
Redemption frequency	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
No.prime brokers in HFC	-0.179**	-0.191**	-0.188**
	(0.082)	(0.082)	(0.081)
Constant	-4.528***	-4.616***	-4.608***
	(0.950)	(0.951)	(0.952)
Strategy FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Pseudo R-squared	0.122	0.126	0.133
Observations	7,845	7,845	7,845

Chapter 3

Do Hedge Funds Still Manipulate Stock Prices?

Keywords: Stock Manipulation, Post-Publication, Hedge Funds.

3.1. Introduction

Many studies in finance and economics cannot be replicated[1]. The reasons of the lack of replicability may be either incorrect statistical inference, including p-hacking and short-sample biases (e.g. Harvey et al., 2016; Ioannidis et al., 2017; Harvey, 2017; Linnainmaa and Roberts, 2018; Chordia et al., 2019), or the actual change in the documented phenomenon. After an academic paper is published, new information is released and incorporated in prices in systematic way. It may be reflected in changing of financial regulations and behaviour of investors, thus, altering the observed patterns in prices and returns.

One of the examples of such changes is the case of market anomalies. After

[1] For example, Camerer et al. (2016) show that the keys findings of at least 7 studies published in the American Economic Review and the Quarterly Journal of Economics between 2011 and 2014 cannot be statistically replicated. Furthermore, Chang and Li (2017) show that 30 out of 59 papers published in 13 well-regarded journals cannot be replicated due to (1) the authors not providing files to the journal replication archives, or (2) the provided files either not working or producing opposite results. More evidence is well concluded in Christensen and Miguel (2018).

an academic paper discussing a particular market anomaly is published, trading on this anomaly intensifies and consequently the anomaly weakens (McLean and Pontiff, 2016). Another example concerns mutual funds, that were found to engage in portfolio pumping (Carhart et al., 2002; Bhattacharyya and Nanda, 2013; Hu et al., 2014) and window dressing (Ng and Wang, 2004; Agarwal et al., 2014), but after the academic papers exposing them were published, the effect has become milder (Duong and Meschke, 2020).

Among professional investors, hedge funds tend to be seen as the most "skilful" in market timing (Brunnermeier and Nagel, 2004; Cao et al., 2013) and stock picking (Kosowski et al., 2007; Agarwal et al., 2013). The information available to researchers on hedge funds through commercial databases may be not completely accurate, however, since it is self-reported and thus may be subject to return manipulation. Hedge funds reporting to commercial databases outperform nonreporting funds (Aiken et al., 2013). Managers are more likely to list their small, best-performing funds in multiple outlets immediately, while keeping an option to list other funds in additional databases later (Jorion and Schwarz, 2014b). Hedge fund managers tend to strategically delay the release of poor returns. The delayed negative returns are often clustered with subsequent positive returns smoothing the performance (Aragon and Nanda, 2017).[2] Such potential "management of reported returns" can mislead investors and benefit fund managers[3], but it does not seem to directly affect

[2]Still, researchers up to date do not completely agree whether the documented stylized facts of hedge fund performance should be attributed to return misreporting or instead they are natural consequences of hedge fund trading strategies. High return serial correlation (Bollen and Pool, 2008), distribution-discontinuity (Bollen and Pool, 2009), and December spikes (Agarwal et al., 2011) suggest hedge fund return misreporting. But such patterns can be triggered by managers' pricing control (Cassar and Gerakos, 2011), incentive-fee mechanism (Jorion and Schwarz, 2014a), overvaluation of equity positions (Cici et al., 2016), and properties of the underlying assets (Cao et al., 2017).

[3]Return misreporting can temporarily improve the observed performance, attracting inflows and avoiding outflows (Berk and Green, 2004). Bollen and Pool (2008) find that funds with more volatile cash flows are more likely to "smooth" their returns. Agarwal et al. (2011) suggest that as incentive fees are often paid annually at the end of December, hedge funds are able to earn higher incentive fees by reporting higher December returns. Jylha (2011) concludes that hedge fund misreporting is mainly motivated by charging higher management fee, attracting more future inflow, and/or transferring wealth from new investors to the old ones.

financial markets.[4] At the same time, hedge funds were found to engage in actual stock price manipulation (and not only misreporting). With investors' flows chasing good performance, fund managers have incentives to manipulate stock prices at the end of a quarter (Bernhardt and Davies, 2009).

The starting point of our paper is the findings in Ben-David et al. (2013), which suggest clear stock price manipulation by hedge funds. The authors find a strong "blip" pattern among stocks held by hedge funds: stocks in the top quartile of hedge fund holding experience large abnormal returns on the last trading day of a quarter, most of which reverts the next day. This finding echoes Comerton-Forde and Putniņš (2011, 2014), who show similar patterns in the prosecuted market manipulation cases for mutual funds.

In this short paper[5], we re-examine the key findings in Ben-David et al. (2013) and ask if stock price manipulation by hedge funds has weakened after it has been exposed by the paper on Feb 17, 2011.[6] We, first, replicate the keying findings of Ben-David et al. (2013) using the same time period as in the original paper (2000q1 to 2010q3), and then show that the blip pattern substantially shrinks in magnitude and turns statistically insignificant in the post-publication period (2011q1 to 2018q4). Further, using the fund-level blip suggested by Ben-David et al. (2013), we find that after publication of that paper, the portfolio blip of hedge funds significantly decreases by approximately 6 percentage points per quarter, and the probability of large blips reduces too.

As an extension, we test if hedge funds benefit from stock price manipulation by attracting higher future flows and whether such benefits reduce after the academic "exposure". We find a concave relation between fund-level blip and future fund flow: moderate stock price manipulation is positively related to future flows, which

[4] In fact, some studies find that hedge funds improve market efficiency (e.g. Akbas et al., 2015; Kokkonen and Suominen, 2015; Cao et al., 2018).

[5] Without the extension part, this short paper is mainly targeted for the "Replications and Corrigenda" section of The Journal of Finance.

[6] This is the posted date when this paper was first published on the website of Social Science Research Network (SSRN) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1763225.

is reduced for extreme levels of manipulation. Interestingly, this pattern remains unchanged after the publication of the original paper. Further looking into the flow-performance sensitivity and its relation with fund-level blip, we find that before the publication flows were less sensitive to performance for high-blip funds, but they become more sensitive to fund performance afterwards. This finding suggests that in the earlier period poor performing funds were benefitting more from return manipulation, while in the later period, the beneficiaries are well-performed funds.

Overall, our findings suggest that after Ben-David et al. (2013) publication, stock price manipulation by hedge funds has reduced substantially on both the aggregate and individual levels, such that no significant pattern can be detected during recent years. An average hedge fund is not expected by investors to engage in return manipulation anymore. Consequently, those hedge funds that still do it to some degree receive higher flows in response to their good performance.

3.2. Hypothesis and Methodology

In this paper, we check if hedge funds still manipulate stock prices after the findings of Ben-David et al. (2013) became publicly available. If such academic "exposure" makes stock manipulation costly due to more regulatory scrutiny, hedge funds may choose to reduce stock price manipulation. Coincidently, on Feb 24, 2011, one week after the working paper was posted online, the Security and Exchange Commission (SEC) charged a hedge fund trader involved in a "portfolio pumping" scheme.[7] This leads to our key hypothesis:

HYPOTHESIS 1: *The stock manipulation pattern found in Ben-David et al. (2013) reduces after the findings of the paper become publicly avaiable.*

Throughout the paper, we use data from 2000q1 to 2010q3 as the benchmark

[7] See *SEC Charges Securities Professionals and Traders in International Hedge Fund Portfolio Pumping Scheme*, https://www.sec.gov/news/press/2011/2011-51.htm for more details. Besides, on Sep 8, 2014, SEC charged a Minneapolis-based hedge fund manager with "portfolio pumping". See *SEC Charges Minneapolis-Based Hedge Fund Manager With Bilking Investors and Portfolio Pumping*, https://www.sec.gov/news/press-release/2014-187 for more details.

sample matching the one from Ben-David et al. (2013), and data from 2011q1 to 2018q4 as the true out-of-sample period.[8] We closely follow the methodology of Ben-David et al. (2013) when investigating the link between the daily stock returns around a quarter end and hedge fund ownership.

We first construct DGTW-adjusted daily stock returns, following Daniel et al. (1997) (hereafter DGTW). At the end of each June, we assign stocks into one of 125 portfolios constructed based on market capitalization using NYSE breakpoints, the industry-adjusted book-to-market ratio using the Fama-French 48 industries, and the prior 12-month return. Portfolios are held for one year and then rebalanced. For each of the 125 portfolios, we calculate the value-weighted daily returns as the benchmark. The DGTW-adjusted daily return is the difference between the stock's daily return and the return on the benchmark portfolio which this stock belongs to.

We then regress last-day of a quarter DGTW-adjusted returns and last-day-plus-1 DGTW-adjusted returns on the indicators of ownership by hedge fund companies (hereafter HFCs). We split the stock universe according to the ownership quartiles and halves as in the original paper, and use robust standard errors in the regressions.

Next, following Ben-David et al. (2013), we calculate the fund-level "blip" measure. For HFC j, we calculate the dollar-holding-weighted adjusted returns of their long equity portfolio on the last trading day of quarter q and the first trading day of quarter q+1, $\text{DW-Return}_{\text{j,q}}^{\text{last}}$ and $\text{DW-Return}_{\text{j,q+1}}^{\text{first}}$. The portfolio returns are adjusted by subtracting corresponding daily market returns proxied by the value-weighted return of all CRSP firms incorporated in U.S. and listed on NYSE, AMEX, or NASDAQ. Then, for HFC j at the end of quarter q, we calculate the adjusted fund-level "blip" measure ($\text{Adj blip}_{\text{j,q}}$) as

$$\text{Adj blip}_{\text{j,q}} = \text{DW-Return}_{\text{j,q}}^{\text{last}} - \text{DW-Return}_{\text{j,q+1}}^{\text{first}}.$$

To control for the effect of stock return volatility on the size of the blip, the fund-

[8] As the stock manipulation is around quarter-end, we regard 2011q1 as the first quarter after the publication.

level blip measure is scaled by the portfolio daily volatility: Adj blip/$\mathrm{vol}_{j,q}$. The volatility is calculated using the daily returns of the long equity portfolio weighted by the quarter-end dollar holdings on all trading days of the quarter q except for the very last trading day, in order to prevent the potential manipulation from artificially inflating the volatility of the portfolio.

We compare the average sizes of blips in pre- and post-publication periods, and then assess the changes in a multivariate setting. We regress fund-level blips on various characteristics of HFCs (such as fees, past returns, flows etc., following the original paper) and the time dummy for the after-publication period. We use two different specifications for the dependent variable: (1) the volatility-adjusted blip, and (2) the volatility-adjusted blip if it is positive (and zero otherwise), which closer corresponds to potential stock price manipulation. Additionally, we test if the probability of large volatility adjusted blips – those above 50% – changes over time using a Logit model with the same set of control variables.

We expect the level of blip on stock- and fund-levels, as well as the probability of large blips to reduce in the post-publication period, if regulators and investors pay attention to the academic research and if hedge fund managers are aware of it.

3.3. Data

Our hedge fund data is from TASS database, and institutional holding data are from Thomson Reuters Institutional (13f) Holdings database (CDA/Spectrum s34). To identify HFCs that report to 13f, we create a list of HFCs' 13f identifiers (i.e. manager numbers, hereafter MGRNOs), by matching the names of HFCs and those of the institutions reporting to 13f. We manually check that the identified companies do not have any mutual fund or insurance business as side-business, thus assuring that we obtain a list of pure HFCs. In total, from 2000q1 to 2018q4, we identify 315 HFCs from TASS database. Figure 3.1 plots the time series of the numbers of matched HFCs with holding observations. The number of 13f-reporting HFCs in TASS database decreases after 2007-2008 financial crisis, consistent with Joenväärä et al. (2019).

[Place Figure 3.1 about here]

Note, the exact replication of the hedge fund sample used in Ben-David et al. (2013) is not feasible for us. The authors obtain a proprietary list of hedge funds directly from Thompson Reuters, which is not available for general research purpose. They also impose a weaker criterion to define a HFC. Any investment company with more than 50% of the asset in hedge fund business is classified as a HFC in Ben-David et al. (2013), whereas we require no other business apart from hedge fund business for the company to be included in the sample. Table 3.1 indicates that on average during the overlapping years we have around 50% of the HFCs compared to Ben-David et al. (2013). At the same time, as will be discussed later, we are able to replicate the results of Ben-David et al. (2013) even using our reduced, but available for every researcher, sample of HFCs.

[Place Table 3.1 about here]

To construct fund-level control variables, we calculate company-level total net assets (hereafter TNA) as the sum of TNA of all managed hedge funds. Other HFC characteristic are computed as the TNA-weighted company-level fund characteristics. To match the quarterly frequency of 13f holding reports, we further calculate within-quarter averages of the monthly TNA-weighted company-level fund characteristics.

Stock return data are from the Center for Research in Security Prices (CRSP) Monthly Stock File. We use daily returns of common stocks (those with CRSP share codes of 10, or 11) traded on NYSE, AMEX, or NASDAQ (those with CRSP exchange codes of 1, 2, or 3) from Jan 3, 2000 to Jan 2, 2019. We manually pick the last trading day of the quarter and the first trading day of the next quarter to exclude holidays or other market-closing days.[9] Stock returns are adjusted using

[9] For example, Mar 29, 2002, Mar 29, 2013, Mar 30, 2018 are Good Friday; Jan 02, 2006, Jan 02, 2012, Jan 02, 2017 are New Year Holiday; Jan 02, 2007 is Tribute to former US President Gerald Ford. On these weekday days, exchanges were closed.

the cumulative adjusted factor provided by CRSP.

To assure the comparability of the results, we try to match our stock sample as close as possible to that of Ben-David et al. (2013). The challenge here is that no details on the stock data filtering is provided in the original paper. For example, it is not specified if the returns are winsorized, or whether micro-caps are excluded from the sample. Thus we resort to matching the reported descriptive statistics, and are able to identify the following criteria:

1. Stocks with returns on the last day of a quarter or the first day of a quarter are included in the sample; they are not required to have both consecutive returns. This is informed by the fact that in Ben-David et al. (2013) the number of DGTW-adjusted daily stock returns on the last trading day of the quarter is 128,841, and it is not equal to the number of returns on the first trading day of the following quarter of 122,804 (Ben-David et al. (2013), Tables II).

2. The DGTW-adjusted daily stock returns are winsorized only from above at the 99% level using the complete sample. The maximum value of DGTW-adjusted daily stock returns on different days as reported in Ben-David et al. (2013) is always the same of 14.469%, whereas the minimum value varies depending on the day (Ben-David et al. (2013), Table I).

3. Small stocks with the price below USD 5 are excluded from the sample, matching well the mean market capitalization of 4.08E+09 and its 25th percentile of 1.60E+08 reported in Ben-David et al. (2013) Table I.

Table 3.2 reports the day-level summary statistics of stocks before and after the first publication of the paper. Panel A reproduces the data as reported in Ben-David et al. (2013). Panel B of Table 3.2 reports the descriptive statistics of our sample using only the first two criteria from 2000q1 to 2010q3. The number of last-day stock returns is 190,775, approximately 48% higher than that reported in the original paper. The 25th percentile of market capitalization on the last trading day of the quarter is 5.67E+07, which is approximately 35% of that in the original paper. Panel C of Table 3.2 removes small-cap stocks with unadjusted current prices smaller than $5, resulting in a much better alignment of the moments in our sample and in that used in Ben-David et al. (2013).

Panel D of Table 3.2 applies all three criteria to data from 2011q1-2018q4. The average last-day return after publication of 1.5 bps is a bit smaller than that before the publication. While the average last-day-plus-1 return shrinks by almost a half from -6.3 bps to -3.8 bps in the later sample. This points into the direction of a reduced manipulation pattern.

[Place Table 3.2 about here]

Table 3.3 reports the quarter-level summary statistics of HFCs before and after the first publication of the paper. Overall, the descriptive statistics of HFC are very similar during both sub-samples. The strongest difference is in the net fund flow, which reduces in the later period. It is likely to be driven by substantial outflows from the hedge fund industry during the recent years. Remarkably, the fund level adjusted blip decreases from 0.32% pre-publication to only 0.06% post-publication, and volatility adjusted blip drops from 19.52% to 7.09%. This also indicates a substantial reduction of potential return manipulation at the individual hedge fund level during the later period.

[Place Table 3.3 about here]

3.4. Empirical Results

Table 3.4 reports the stock-level results in pre- and post-publication samples. The last-day DGTW-adjusted returns and last-day-plus-1 DGTW-adjusted returns are regressed on the dummies indicating different levels of hedge fund ownership. Panel A uses ownership quartiles, and Panel B uses the indicator for hedge fund ownership being above the median. The results in the earlier sample are consistent with those in Ben-David et al. (2013). The daily returns of stocks in the top ownership quartile, on average, increase by 17.9 bps on the last trading day of the quarter, and decrease by 8.2 bps on the first trading day of the following quarter. The magnitude of the effect is somewhat smaller than in the original paper, but the corresponding t-statistics are equally high, reaching 7.23 for the last day return and high HFC ownership quartile compared to 6.80 reported in Ben-David et al. (2013). Similar pattern can be seen using the above-the-median hedge fund ownership indicator. After the publication, the patterns in abnormal returns completely disappear. The loadings on the dummies for top quartile and top half of ownership are closer to zero and not statistically significant.

[Place Table 3.4 about here]

Moving to the fund-level manipulation measure, we compare the average volatility-adjusted blip and positive volatility-adjusted blip before and after the publication (Table 3.5). The average volatility-adjusted blip is 19.92% before publication, which reduces to just 5.88% after the publication, with the difference being significant at the 5% level. Similarly, the average positive volatility-adjusted blip significantly decreases after the publication.

[Place Table 3.5 about here]

Table 3.6 reports the regression results for fund-level blips. The fund-level blip pattern is more pronounced for funds with poor performance, charging lower management fee, that are younger and with less frequent redemptions. Consistent with HYPOTHESIS 1, the volatility-adjusted blip significantly decreases by approximately 6 percentage points after the publication, and the likelihood of strong manipulation also significantly reduces after publication.

[Place Table 3.6 about here]

Overall, the stock-level and fund-level results indicate significant reduction of stock price manipulation by hedge funds in the period following the publication of Ben-David et al. (2013).

3.4.1. Extension: the impact on fund flow

One of the reasons why hedge funds may have engaged in stock return manipulation is that they have been benefiting from such practice by obtaining higher future capital flows from investors. The academic "exposure" of such behavior may have made regulators aware of such practices. Facing potential penalties from regulators, hedge funds have reduces portfolio pumping at quarter end. There can be a second mechanism here too, related to changing investor behavior. If prior to the publication investors rewarded hedge funds with higher inflow but stoped doing this after they have learned about the potential "dark sider" of hedge fund trades, hedge funds would have very little incentive to manipulate stocks. Such activity is turning costly from the regulatory cost point of view, and does not result in substantial benefits anymore.

We test if the effect of potential return manipulation on future fund flow has changed in the post-publication period. Net HFC flow in quarter q+1 is regressed on the fund-level blip a the end of the previous quarter, time dummy for the after-publication period, HFC past return, the interaction terms among them, as well as other controls that impact fund future capital flows. We include past quarter flow, natural logarithm of past quarter TNA of the HFC, incentive and management fees, HFC age, number of hedge funds in the HFC, the existence of the high-water mark, usage of leverage, and the length of the notice and lock-up periods. We also control for the aggregate fund flow in the hedge fund industry during quarter q+1.

To obtain the net fund flow of HFC j in month t, we first calculate the TNA-weighted monthly return of HFC j in month t and then use it for flow computation:

$$\mathrm{R_{j,t}} = \frac{\sum_{\mathrm{k=1}}^{\mathrm{N}} \mathrm{TNA_{j,k,t}} \times \mathrm{R_{j,k,t}}}{\sum_{\mathrm{k=1}}^{\mathrm{N}} \mathrm{TNA_{j,k,t}}}, \tag{3.1}$$

$$\mathrm{flow_{j,t}} = \frac{\mathrm{TNA_{j,t}} - \mathrm{TNA_{j,t\text{-}1}} \times (1 + \mathrm{R_{j,t}})}{\mathrm{TNA_{j,t\text{-}1}}}, \tag{3.2}$$

where $TNA_{j,k,t}$ and $R_{j,k,t}$ are the TNA and the monthly return, respectively, of hedge fund k managed by HFC j in month t, and N is the total number of hedge funds managed by HFC j.

Fund-level blip is measured using a positive volatility-adjusted blip (Adj $blip^+/vol$). To control for potential non-linearities in the relation between return manipulation and flow, we first include the quadratic term of fund-level blip (Adj $blip^+/vol)^2$, and then use two different measures for large and very large blips: a dummy taking a value of one if the volatility-adjusted blip is larger than the 25th percentile, and a dummy taking the value of one if the volatility-adjusted blip is larger than the 75th percentile.

The estimation results (Tables 3.7) reveal that on average HFC stock manipulation is beneficial for HFCs. It is positively related to future fund flow, and the relation does not significantly change after the publication. This positive relation, however, weakens if the portfolio blip is too extreme as suggested by the negative and significant coefficient on the quadratic term of fund-level blip (Tables 3.7) and insignificant coefficients on Adj $blip^+/vol > 75$th percentile in columns (5) to (8) of Tables 3.8. The results may suggest that investors identify extremely high price changes at a quarter end as suspicious and do not reward such hedge funds with higher flows.

The flow-performance sensitivity decreased substantially in the post publication period.[10] More importantly, the shape of the flow-performance relation conditional on individual fund portfolio blip has changed. Funds with large blips exhibited lower flow-performance sensitivity in the pre-publication period, but a higher sensitivity after the publication. This suggests that, during the earlier period, poorly performing funds may have additionally benefited from return manipulation, as it reduced the effect of past poor returns on future flows. However after the publication, stock return manipulation benefits only well performing funds, attracting even

[10]Such overall decline in flow-performance sensitivity may not necessarily be related to the publication, however. Other factors could have impacted fund flow during this period, indulging, for example, regulatory changes in the US, restricting investment into hedge funds by banking institutions.

higher flows in response to good past performance. Using the insights from Ben-David et al. (2013) that poorly performing funds have been more likely to engage is stock price manipulation, it seems that post publication investors do not expect well performing funds to engage in this activity, thus, benefitting those well performing funds that still choose to manipulate stock prices, despite the overall reduction in such activities.

[Place Tables 3.7 and 3.8 about here]

3.5. Conclusion

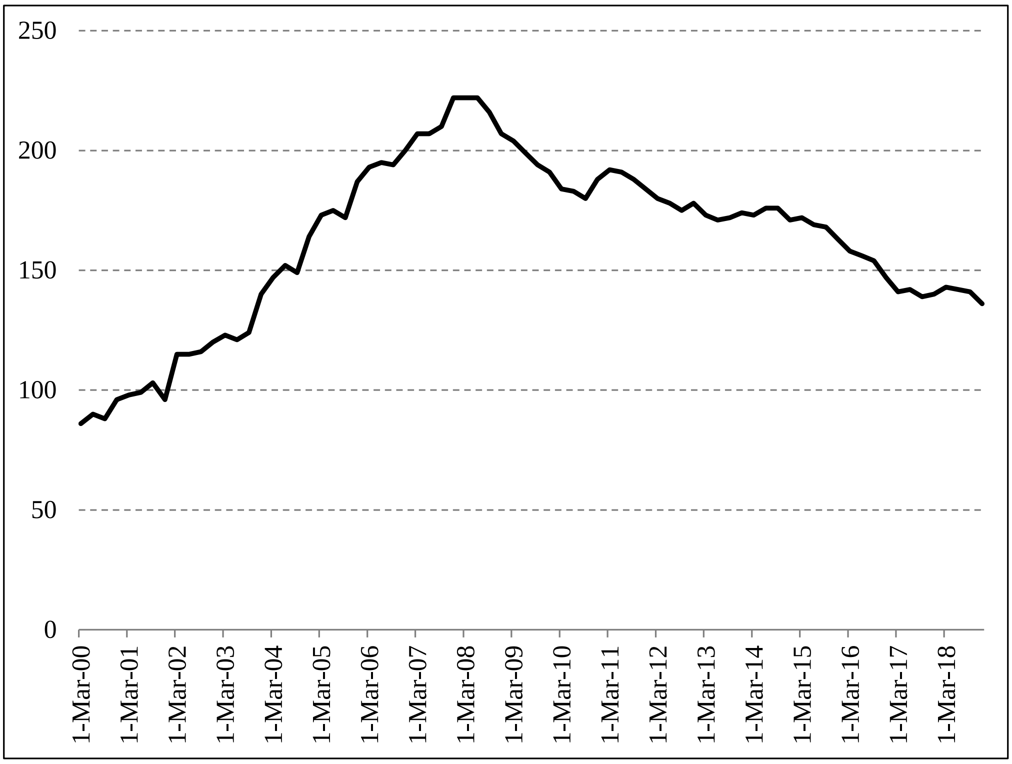
In early 2011, Ben-David et al. (2013) reported evidence that hedge funds manipulate stock prices at quarter ends in order to "pump" their portfolios. Stocks held by hedge funds exhibited high positive abnormal returns on the last trading day in a quarter, and a significant negative abnormal return during the first day of a quarter between 2000q1 and 2010q3, forming a so-called return "blip". We replicate this result using a somewhat different sample of hedge funds, and find a similarly strong pattern during the same time period. Applying the methodology during the period following the publication of the original paper (2011q1 to 2018q4) we can no longer detect a significant pattern of end-of-quarter abnormal returns at the stock level, suggesting that hedge funds as a group engage much less in portfolio pumping activities after this pattern was "exposed" though the academic publication. On a fund level, potential return manipulation, measured by the stock portfolio return blip around quarter end, also significantly decreases compared to the pre-publication level, making it not statistically significant on average.

Our findings contribute to the literature showing changes in investor behavior and various financial market phenomena after research exposing those become public knowledge (McLean and Pontiff, 2016; Duong and Meschke, 2020), and highlight a strong feedback loop between the financial market and financial research, when the latter studies the former but also shapes it.

3.6. Figures

Figure 3.1: Time series of the numbers of matched hedge fund companies

The figure plots the time series of the number of hedge fund companies (HFCs) from the TASS database from 2000q1 to 2018q4 and also report their holdings to SEC through 13f filings.



3.7. Tables

Table 3.1: Numbers of hedge fund company per year

This table reports the numbers of HFCs in the sample per year as reported in Ben-David et al. (2013) and those used in our paper.

Year	Number of Hedge Fund Companies in Ben-David at al. (2013)	Number of Hedge Fund Companies Our Sample	Percentage
2000	309	160	51.73%
2001	328	186	56.68%
2002	387	202	52.26%
2003	419	209	49.80%
2004	470	205	43.51%
2005	530	208	39.25%
2006	552	197	35.61%
2007	531	184	34.56%
2008	415	158	37.97%
2009	317	139	43.93%
2010	288	130	45.10%

Table 3.2: Summary statistics: stocks (day-level)

This table reports the summary statistics of the sample of stocks, including returns on the last trading day and the first trading day of a quarter, market capitalization on the last trading day of a quarter, and ownership of hedge fund companies (HFCs). We use common stocks (CRSP share codes of 10, or 11) traded on NYSE, AMEX, or NASDAQ (CRSP exchange codes of 1, 2, or 3). Returns are adjusted following procedures detailed in Daniel et al. (1997) (DGTW). Panel A reproduces the numbers reported in (Ben-David et al., 2013). Panel B uses our sample with returns winsorized at the 99% level from 2000q1 to 2010q3, the same period as used in Ben-David et al. (2013). Panel C reports the descriptive statistics statistics of the same sample excluding stocks with the market value below $5. Panel D reports the statistics of winsorized returns excluding small cap stocks from 2011q1 to 2018q4.

	N	Mean	Std.Dev	Min	P25	P50	P75	Max
	Panel A: 2000q1 to 2010q3 (Ben-David et al. (2013))							
Return last day (%, DGTW adjusted)	128,841	0.021	3.772	-74.251	-1.361	-0.067	1.260	14.469
Return first day (%, DGTW adjusted)	128,868	-0.126	3.728	-81.250	-1.539	-0.072	1.398	14.469
HF ownership (%)	128,910	2.615	3.803	0.000	0.440	1.258	3.246	100.000
Market capitalization last day	125,861	4.08E+09	1.77E+10	-1.03E+09	1.60E+08	5.40E+08	1.89E+09	5.71E+11
	Panel B: 2000q1 to 2010q3 (with small-cap stocks)							
Return last day (%, DGTW adjusted)	190,775	-0.040	4.278	-75.345	-1.534	-0.093	1.375	13.568
Return first day (%, DGTW adjusted)	189,694	-0.136	4.148	-80.757	-1.696	-0.095	1.495	13.568
HFC ownership (%)	190,775	3.058	5.581	0.000	0.000	1.318	4.039	100.000
Market capitalization	190,775	2.78E+09	1.45E+10	1.67E+05	5.67E+07	2.42E+08	1.07E+09	5.72E+11
	Panel C: 2000q1 to 2010q3 (without small-cap stocks)							
Return last day (%, DGTW adjusted)	142,979	0.017	3.118	-52.867	-1.260	-0.075	1.130	13.568
Return first day (%, DGTW adjusted)	141,897	-0.063	3.032	-64.121	-1.385	-0.054	1.300	13.568
HFC ownership (%)	142,979	3.356	5.180	0.000	0.301	1.820	4.557	100.000
Market capitalization	142,979	3.68E+09	1.67E+10	1.80E+06	1.43E+08	4.72E+08	1.67E+09	5.72E+11
	Panel D: 2011q1 to 2018q4 (without small-cap stocks)							
Return last day (%, DGTW adjusted)	84,482	0.015	1.859	-67.554	-0.829	-0.031	0.791	8.581
Return first day (%, DGTW adjusted)	84,000	-0.038	2.057	-55.228	-1.014	-0.050	0.922	8.581
HF ownership (%)	84,482	3.829	4.849	0.000	1.089	2.628	5.131	100.000
Market capitalization	84,482	7.45E+09	2.90E+10	2.22E+06	3.16E+08	1.10E+09	3.85E+09	1.07E+12

Table 3.3: Summary statistics: hedge funds (quarter-level)

This table reports the summary statistics of characteristics of hedge fund companies (HFCs). We calculate the mean of the monthly TNA-weighted company-level fund characteristics as the proxies of HFC characteristics in a quarter. Panel A reports the statistics from 2000q1 to 2018q4, whereas Panel B reports those from 2011q1 to 2018q4.

	N	Mean	Std.Dev	Min	P25	P50	P75	Max
	Panel A: 2000q1 to 2010q3							
Adj blip (%)	4,390	0.324	1.856	-35.746	-0.318	0.144	0.773	36.803
Adj blip/vol (%)	4,390	19.517	82.460	-206.234	-25.170	12.059	59.755	289.415
Adj blip$^+$/vol (%)	4,390	40.290	59.663	0.000	0.000	12.059	59.755	289.415
Fund return (%)	4,390	0.606	2.977	-21.497	-0.367	0.654	1.740	38.941
Net fund flow (%)	4,326	1.641	11.139	-25.237	-1.624	0.238	2.569	70.458
Ln(TNA)	4,390	19.003	1.734	0.693	17.983	19.074	20.182	24.216
Ln(#stock under management)	4,390	4.105	1.506	0.000	3.219	4.025	5.226	7.749
#Fund under management	4,390	2.488	2.175	1.000	1.000	2.000	3.000	16.333
Management fee (%)	4,381	1.282	0.412	0.000	1.000	1.136	1.500	3.308
Incentive fee (%)	4,381	18.576	4.199	0.000	20.000	20.000	20.000	40.000
HWM dummy	4,381	0.776	0.374	0.000	0.638	1.000	1.000	1.000
Levered dummy	4,390	0.678	0.426	0.000	0.156	1.000	1.000	1.000
Notice period (day)	4,390	43.495	25.069	0.000	30.000	41.881	60.000	259.916
Lockup period (month)	4,390	5.148	6.637	0.000	0.000	1.417	12.000	36.000
Redemption frequency (day)	4,368	98.231	87.019	1.000	30.000	90.000	90.000	360.000
Fund age (month)	4,390	84.330	51.399	1.000	44.000	76.069	117.244	281.000
	Panel B: 2011q1 to 2018q4							
Adj blip (%)	1,688	0.062	0.916	-8.269	-0.265	0.069	0.448	5.486
Adj blip/vol (%)	1,688	7.089	69.241	-207.520	-25.845	6.178	40.798	205.823
Adj blip$^+$/vol (%)	1,688	28.607	43.773	0.000	0.000	6.178	40.798	205.823
Fund return (%)	1,688	0.362	8.134	-15.322	-0.562	0.360	1.294	320.549
Net fund flow (%)	1,665	0.085	9.404	-28.665	-1.659	-0.172	0.633	62.838
Ln(TNA)	1,688	19.352	2.076	11.606	18.028	19.200	20.901	24.675
Ln(#stock under management)	1,688	4.096	1.587	0.000	2.996	4.025	5.257	7.779
#Fund under management	1,688	2.500	2.076	1.000	1.000	2.000	3.000	17.000
Management fee (%)	1,688	1.296	0.420	0.342	1.000	1.215	1.500	2.626
Incentive fee (%)	1,682	17.655	5.181	0.000	18.702	20.000	20.000	25.486
HWM dummy	1,688	0.792	0.370	0.000	0.769	1.000	1.000	1.000
Levered dummy	1,688	0.682	0.429	0.000	0.147	1.000	1.000	1.000
Notice period (day)	1,688	45.740	33.826	0.000	30.000	44.136	60.000	231.756
Lockup period (month)	1,688	5.209	6.370	0.000	0.000	0.000	12.000	24.000
Redemption frequency (day)	1,678	83.240	85.829	7.000	30.000	74.669	90.000	360.000
Fund age (month)	1,688	154.043	80.752	1.000	90.000	143.000	211.040	383.000

Table 3.4: Stock-level manipulation

This table reports the estimation results for the regression of stock abnormal returns during the last day or a quarter and the last-day-plus-1 day on indicators of hedge fund ownership quartiles (Panel A) and halves (Panel B) following Ben-David et al. (2013) using two time periods. First period is from 2000q1 to 2010q3, as used in Ben-David et al. (2013). The second period is from 2011q1 to 2018q4, starting after the first publication of the paper “Do Hedge Funds Manipulate Stock Prices?” (Ben-David et al., 2013) on Feb 17, 2011. T-statistics with robust standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

	2000q1-2010q3		2011q1-2018q4	
	Last Day	Last Day + 1	Last Day	Last Day + 1
	Panel A: Regression on Ownership Quartiles			
Ownership Q4 (high)	0.179***	-0.082***	0.019	0.001
	(7.229)	(-3.453)	(0.927)	(0.045)
Ownership Q3 (median)	0.119***	-0.006	0.022	0.014
	(4.933)	(-0.267)	(1.141)	(0.691)
Ownership Q2 (low)	0.077***	0.059***	0.004	0.042**
	(3.157)	(2.605)	(0.201)	(1.998)
Constant	-0.075***	-0.055***	0.004	-0.052***
	(-4.016)	(-3.216)	(0.281)	(-3.190)
Observations	142,979	141,897	84,482	84,000
R-squared	0.000	0.000	0.000	0.000
	Panel B: Regression on Ownership Halves			
Ownership (top half)	0.112***	-0.073***	0.018	-0.013
	(6.808)	(-4.510)	(1.431)	(-0.923)
Constant	-0.039***	-0.026**	0.006	-0.032***
	(-3.167)	(-2.299)	(0.656)	(-3.045)
Observations	142,979	141,897	84,482	84,000
R-squared	0.000	0.000	0.000	0.000

Table 3.5: Average fund-level blip

This table reports the descriptive statistics of volatility-adjusted blips and positive volatility-adjusted blips, as well as the corresponding differences. "Before" denotes the period from 2000q1 to 2010q3, as used in Ben-David et al. (2013), whereas "After" denotes the period from 2011q1 to 2018q4, the period after the first publication of the paper "Do Hedge Funds Manipulate Stock Prices?" (Ben-David et al., 2013) on Feb 17, 2011. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

	Number of quarter	Average #HFs per quarter	Average Adj blip/vol per quarter (%)	Average #HFs with positive Adj blip/vol per quarter	Average positive Adj blip/vol per quarter (%)
Before	43	158.512	19.916***	90.907	68.381***
			(4.5090)		(13.8764)
After	32	163.125	5.884	89.469	52.649***
			(1.3856)		(15.2029)
Before − After	11	-4.613	14.032**	1.438	15.732**
			(2.2281)		(2.4383)

Table 3.6: Fund-level blip: regression results

This table reports the estimation results of regressions for fund-level blips on the characteristics of HFCs and the time dummy for the after-publication period. Fund-level blip is measured using: (1) volatility-adjusted blip, and (2) positive volatility-adjusted blip. Column (3) reports the estimation results for the Logit model for the probability of the volatility-adjusted blip being larger than 50%. Standard error are corrected for heteroskedasticity and fund-level clustering with t-statistics reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

	OLS		Logit
	Adj blip/vol	Adj blip$^+$/vol	Adj blip/vol > 50%
	(1)	(2)	(3)
After publication dummy	-5.397**	-6.067***	-0.214**
	(-2.325)	(-2.879)	(-2.254)
Fund return	-0.343*	-0.189*	-0.030***
	(-1.753)	(-1.654)	(-2.781)
Log(TNA)	0.655	0.154	0.012
	(1.006)	(0.248)	(0.462)
Net fund flow	14.179	8.848	0.185
	(1.492)	(1.238)	(0.588)
#Fund under management	0.201	0.333	0.020
	(0.243)	(0.523)	(0.826)
Management fee	-11.354***	-8.627***	-0.298**
	(-3.715)	(-3.080)	(-2.444)
Incentive fee	0.394	0.386	0.018
	(1.138)	(1.080)	(1.086)
HWM dummy	-1.208	-3.778	-0.136
	(-0.350)	(-1.177)	(-1.069)
levered dummy	6.817**	5.761**	0.135
	(2.418)	(2.321)	(1.432)
Notice period	-0.093***	0.025	0.001
	(-2.688)	(0.642)	(0.694)
Lock-up period	-0.210	0.039	0.001
	(-1.106)	(0.227)	(0.152)
Redemption frequency	0.055***	0.057***	0.002***
	(2.957)	(3.428)	(4.326)
Fund age	-0.074***	-0.056***	-0.002**
	(-3.571)	(-2.868)	(-2.354)
Constant	15.837	36.941***	-1.226**
	(1.229)	(2.976)	(-2.183)
Observations	6,031	6,031	6,031
R-squared	0.014	0.023	0.016

Table 3.7: Fund-level blip and future fund flows

This table reports the estimation results of regressions for the net fund flow in q+1 on the fund-level blip, a time dummy for the after-publication period, fund return, and the interaction terms among them. Fund-level blip is measured using the positive volatility-adjusted blip. The quadratic term of fund-level blip ($(\text{Adj blip}^{+}/\text{vol})^2$) captures potential non-linearities. We control for other known characteristics impacting fund future capital flows. Standard error are corrected for heteroskedasticity and fund-level clustering with t-statistics reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

	Dependent variable: Net fund flow (q+1)			
	(1)	(2)	(3)	(4)
Avg net fund flow of all HFC in TASS (q+1)	0.084	0.076	0.067	0.068
	(1.227)	(1.134)	(0.977)	(0.988)
Net fund flow	0.076**	0.076**	0.073**	0.072**
	(2.506)	(2.508)	(2.447)	(2.429)
After publication dummy			0.420	0.531
			(0.974)	(1.224)
Fund return	0.148**	0.130*	0.402***	0.546***
	(2.062)	(1.932)	(6.539)	(6.024)
× After publication dummy			-0.332***	-0.489***
			(-5.058)	(-5.283)
Adj blip^{+}/vol	0.016***	0.014**	0.018***	0.020***
	(2.888)	(2.527)	(2.846)	(3.170)
× Fund return		0.004*		-0.005**
		(1.841)		(-2.080)
× After publication dummy			-0.004	-0.010
			(-0.378)	(-0.858)
× Fund return × After publication dummy				0.015***
				(3.240)
(Adj blip^{+}/vol)^2	-0.000***	-0.000**	-0.000***	-0.000***
	(-3.003)	(-2.590)	(-3.043)	(-3.169)
× Fund return		-0.000*		0.000
		(-1.920)		(1.210)
× After publication dummy			0.000	0.000
			(0.683)	(1.023)
× Fund return × After publication dummy				-0.000**
				(-2.089)
Constant	6.166**	6.331**	6.344**	6.189**
	(2.485)	(2.555)	(2.569)	(2.511)
Controls of HF characteristics	Yes	Yes	Yes	Yes
Observations	5,813	5,813	5,813	5,813
R-squared	0.031	0.032	0.037	0.040

Table 3.8: Fund-level “blip” dummies and future fund flow

This table reports the estimation results of regressions for the net fund flow in q+1 on the fund-level blip, a time dummy for the after-publication period, fund return, and the interaction terms among them. Fund-level blip is measured as a dummy variables taking the value of one if the positive volatility-adjusted blip is above 25th percentile and zero otherwise, and a dummy variables taking the value of one if the positive volatility-adjusted blip is above 75th percentile and zero otherwise. We control for other known characteristics impacting fund future capital flows. Standard error are corrected for heteroskedasticity and fund-level clustering with t-statistics reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

	Dependent variable: Net fund flow (q+1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg net fund flow of all HFC in TASS (q+1)	0.086	0.076	0.071	0.075	0.086	0.086	0.071	0.076
	(1.262)	(1.143)	(1.041)	(1.084)	(1.266)	(1.263)	(1.035)	(1.106)
Net fund flow	0.075**	0.075**	0.073**	0.073**	0.075**	0.075**	0.073**	0.072**
	(2.489)	(2.478)	(2.433)	(2.428)	(2.493)	(2.495)	(2.436)	(2.401)
After publication dummy			0.254	0.377			0.275	0.382
			(0.571)	(0.845)			(0.651)	(0.904)
Fund return	0.147**	0.115**	0.395***	0.548***	0.147**	0.145*	0.395***	0.530***
	(2.072)	(2.004)	(6.468)	(5.303)	(2.065)	(1.896)	(6.476)	(6.557)
× After publication dummy			-0.325***	-0.493***			-0.325***	-0.469***
			(-4.979)	(-4.707)			(-4.991)	(-5.643)
Adj blip^{+}/vol > 25th percentile	0.488**	0.390*	0.423	0.597**				
	(2.194)	(1.716)	(1.589)	(2.155)				
× Fund return		0.195**		-0.265**				
		(2.472)		(-2.404)				
× After publication dummy			0.302	0.043				
			(0.621)	(0.089)				
× Fund return × After publication dummy				0.667***				
				(4.104)				
Adj blip^{+}/vol > 75th percentile					0.378	0.369	0.247	0.490
					(1.286)	(1.215)	(0.764)	(1.429)
× Fund return						0.022		-0.425***
						(0.190)		(-3.235)
× After publication dummy							0.585	0.245
							(1.027)	(0.433)
× Fund return × After publication dummy								0.899***
								(4.234)
Constant	6.068**	6.219**	6.264**	6.180**	6.278**	6.294**	6.458***	6.222**
	(2.429)	(2.502)	(2.525)	(2.505)	(2.515)	(2.527)	(2.598)	(2.503)
Controls of HF characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,813	5,813	5,813	5,813	5,813	5,813	5,813	5,813
R-squared	0.031	0.032	0.036	0.038	0.030	0.030	0.036	0.039

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