On the Other Side of Hedge Fund Equity Trades

Abstract

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 seems to be driven by the preferences of quasi-indexers for high-market-beta stocks together with the ability of hedge funds to identify subsets of especially profitable trades. It remains pronounced when accounting for other determinants of hedge fund trades, such as stock liquidity, market anomalies, and major corporate events. Trading against other institutional investors or non-institutions does not result in abnormal performance for hedge funds.

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

JEL Classification: G12, G14, G23.

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), previous studies find comprehensive evidence on the link between HF trading, future stock returns, and mispricing.[1] 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.

Institutional investors hold around 80% ($18 trillion) of the S&P 500 stocks[2] and account for about 70% of daily trading volume[3], hence, 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

[1]Brunnermeier and Nagel (2004), among the first ones to examine fund holdings, find that HFs possess stock-picking and market timing abilities. HFs front-run distressed mutual funds, and seem to sell short stocks in anticipation of sales by mutual funds (Chen et al., 2008). Similarly, they profitably trade in the direction of the expected future aggregate mutual fund flow (Shive and Yun, 2013). HF option holdings predict stock returns and their volatilities (Aragon and Martin, 2012). HF demand shocks also predict stock returns over the next quarters (Sias et al., 2016), while their informed demand predicts not only stock returns but firms' fundamentals such as returns on assets (Jiao et al., 2016). HFs tend to hold undervalued stocks and trade on known market anomalies and deliver positive risk-adjusted returns (Cao et al., 2018b; Calluzzo et al., 2019). 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; Cao et al., 2018a; Ha and Hu, 2018).

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

[3]Institutional Investor, 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

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.[5] 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 be groups of investors that do not have 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 some groups of institutional investors consistently provide 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,[6] 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 (the level of their portfolio diversification and turnover), and not according to nominal labelling. This classification has been also used in, for example, Ke and Ramalingegowda (2005); Ramalingegowda and Yu (2012); Cella et al. (2013); Fang et al. (2014); Boone and White (2015); Appel et al. (2016). Such a "revealed" classification scheme provides more insights into preferences and investment goals of the institutions. Following Bushee (2001), we identify two

the detailed analysis of the economics of individual decision making for future research.

[5]Indeed, HFs have been shown to possess market timing and stock-picking skills and often outperform the market (Kosowski et al., 2007; Agarwal et al., 2013b; Bali et al., 2013, 2020).

[6]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).

large groups of institutional investors: quasi-indexers (QIXs) and transient institutions (TRAs). 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.[7] A transient institution also holds a highly-diversified portfolio but has a high turnover, and follows predominantly short-term trading strategies. For example, Vanguard group is classified as QIX, while Fidelity International is TRA.[8] We also confirm that in our sample, compared to other groups of institutions considered, QIXs have the lowest turnover and the smallest active share, computed following Cremers and Petajisto (2009).

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 −0.33% per month relative to the CAPM, whereas stocks purchased by HFs and sold by QIXs earn a significantly positive alpha of +0.49% 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. Stocks purchased by HFs while being sold by QIXs correspond to around 8% of the total dollar value of HF stock holdings. However, they contribute almost 30% of the overall HF stock portfolio alpha.

QIXs usually have limited potential to lock in alpha. 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. 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

[7] Our results remain robust if we directly use CRSP index fund classification instead. The classification system of Bushee (2001) may still fit best the purpose of our study because it is based on the actual trading patterns of investors, instead of on what the investors claim they do.

[8] Bushee (2001) identifies a third group of institutional investors – dedicated holders – institutions with concentrated portfolios and low turnover, focusing on long-term trading strategies with low sensitivity to current firm earnings. In our sample, on average, only 69 such institutions report per quarter, with their aggregate holdings being less than 2%. We do not use them as a separate sub-group, but we integrate them into the group of other investors.

tracking errors around the benchmark. We find that the average market beta of stocks sold by HFs and purchased by QIXs is 1.33, whereas the average beta of stocks purchased by HFs and sold by QIXs is 1.13, with the difference being highly statistically significant and persistent over time as well as for longer holding periods. These results are robust when we consider different sub-groups of QIXs (such as independent investment advisors or banks), as well as when we directly use index mutual funds from CRSP.

Preference for high-beta stocks on its own, however, does not explain negative ex-post alphas for stocks purchased by QIXs. Stocks that are intensively traded by QIXs but not traded in the opposite direction by HFs do not have significant alphas, while still exhibiting significant differences in betas. This suggests that HFs are skilled in identifying subsets of low- and high-beta stocks with especially good and bad future performance, respectively, and act as counterparties of QIXs on such trades. In particular, within the set of stocks purchased by QIXs, HFs seem to be able to identify those that also exhibit lottery-type features and, hence, negative future alphas. When we control for the FMAX factor of Bali et al. (2017), the negative alpha of the portfolio of stocks sold by HFs and purchased by QIXs loses significance, as the underperformance is absorbed by the positive loading on FMAX.[9] The positive abnormal return of stocks bought by HFs and sold by QIXs remains significant even after controlling for the FMAX factor, suggesting some extra stock-picking skills of HFs. Consistent with prior literature,[10] other factors, such as stock illiquidity, market anomalies, price reversals, stock idiosyncratic volatility, and major corporate events contribute to the good performance of stocks bought by HFs. These factors, however, do not fully explain the differences in performance of swapped stocks between HFs and QIXs.

Our paper extends the recent studies on trading of HFs with mutual funds. Jame (2018) documents that HFs tend to earn abnormal returns when trading against distressed mutual funds that are suffering extreme outflows (Coval and Stafford, 2007). We show that while HFs indeed

[9] We also consider the betting against beta (BAB) factor of Frazzini and Pedersen (2014) as an alternative explanation for the underperformance of high-beta stocks. Consistent with Bali et al. (2017), we find that FMAX dominates BAB in explaining the return pattern.

[10] Teo (2011); Jylhä et al. (2014); Cao et al. (2018b); Calluzzo et al. (2019); Fich et al. (2020); Bali and Weigert (2021); Jame (2018); Grinblatt et al. (2020).

provide liquidity to distressed mutual funds, the alpha-beta swap is not driven by those stocks. The alpha-beta swap is likely to be associated with those QIXs (including mutual funds) that are not in distress. Furthermore, Grinblatt et al. (2020) find that HFs following contrarian strategies tend to earn abnormal returns from trading with momentum-oriented mutual funds. We concur that HFs are likely to engage in contrarian trades when trading against QIXs. However, these contrarian trades do not explain the documented alpha-beta swap, suggesting a different, non-contrarian nature of the trades contributing to the alpha-beta swap.

Our approach allows us also to contribute to the extensive literature on the relation between institutional ownership and market anomalies.[11] 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 stocks 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

[11] 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.

alpha to their investors by 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.[12]

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.[13] Following Bushee (2001), we first identify two distinct large groups of institutional investors, namely, QIXs and TRAs.[14] We also consider other investors, institutional or not, (OTHs) as potential counterparts for HF equity trades.

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.[15] 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. In addition, benchmarked funds tend to invest at least part of their portfolios in

[12]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.

[13]Another potential way to classify institutional investors would be through direct textual processing of their prospectus as, for example, in Abis (2020).

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

[15]There are other factors that provide incentives/disincentives for funds to generate alpha. Among those are, for example, distribution channels of funds (Guercio and Reuter, 2014).

their benchmark index, purchasing stocks included in the index and selling stocks excluded from the index (Pavlova and Sikorskaya, 2022). It leads to comovement in the stock returns and an increase in the betas of these stocks with respect to their index (Barberis et al., 2005; Vijh, 1994).

Stocks with high market betas naturally bear higher market risk, but they also tend to have low alphas (Frazzini and Pedersen, 2014). At the same time, as shown by Bali et al. (2017) underperformance of high-beta stocks is likely to be driven by lottery-type stocks, hence low alpha may be related to a higher idiosyncratic risk of such stocks. This discussion leads to our "swap" hypothesis as follows:

α-β swap: *HFs earn positive abnormal returns when trading in the opposite direction of QIXs by selling high-risk stocks and buying low-risk stocks.*

To test our hypothesis, we first select institutional investors with a unique identifier of permanent classification provided by Bushee (2001), and we split them into HFs and non-HF investors. Then, we identify QIXs and TRAs among non-HFs. We obtain institutional holdings from the 13f filings, and compute the holdings of other investors (OTHs) in the spirit of Ben-David et al. (2012) as the difference between 100% and the total percentage holdings of HFs, QIXs, and TRAs.[16] We exclude from the sample those quarter-stock data points for which the total percentage holding of HFs, QIXs, and TRAs exceeds 100%, similar to Campbell et al. (2009) and Yan and Zhang (2009), among others.

Second, for each type of trader and quarter, we compute quarterly changes in the fractional holdings of each stock.[17] For example, the change in holding of stock i by HFs during quarter q

[16] Holdings of OTHs include holdings of institutional investors without a permanent classification or with several permanent classifications in the database of Bushee (2001), investors classified as dedicated, small US-based institutional investors and foreign institutions which do not need to comply with 13f filing requirements, as well as small holdings of large US-based institutional investors, which are below the reporting threshold or for which confidential treatment was requested by reporting institutions, and individual investors (French, 2008; Ince and Kadlec, 2020).

[17] This measure is widely used, see, for example, Gompers and Metrick (2001); Sias et al. (2006); Campbell et al. (2009); Edelen et al. (2016), among others.

($\Delta\text{StockHold}^{\text{HF}}_{\text{i,q}}$) is given by:

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

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.

$$\text{StockHold}^{\text{HF}}_{\text{i,q}} = \sum_{\text{j}} \text{StockHold}^{\text{HF}_\text{j}}_{\text{i,q}}, \tag{2}$$

and $\text{TSO}_{\text{i,q}}$ is the total number of outstanding shares of firm i at the end of quarter q. $\Delta\text{StockHold}^{\text{HF}}_{\text{i,q}}$ is considered to be a missing value if any of $\text{TSO}_{\text{i,q}}$ 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, or OTHs. We consider stocks with the change in holding below the 20^{th} percentile as those that investors intensively sell, and those above the 80^{th} percentile as those that investors intensively buy. The swapped stocks are those which belong to the intensively traded stocks for two types of investors, but in different directions.[18] We compute the returns of these portfolios following the procedure of Fama and French (1993) and Edelen et al. (2016). Stocks are assigned in two size groups – above or below the NYSE size median at the end of year $\text{t}-1$. We then compute the value-weighted average returns of the swapped stocks within each size group. In the last step, we compute the equal-weighted averages across the two size-group portfolios. The portfolios are held for one quarter until the end of the following quarter and then rebalanced. This procedure allows us to minimize the impact of micro-caps, and at the same time to prevent mega firms from dominating the resulting return series.[19]

[18] As a robustness check, we also used 10% and 30% cutoffs. The results remain qualitatively the same and are reported in the Online Appendix Table A1.

[19] As a robustness check, we consider a different weighting scheme which controls for the effect of small stocks only. Small stocks with the size in the lowest NYSE decile are excluded, and portfolio returns are computed as the value-weighted average returns of the remaining stocks. The results reported in the supplementary Online Appendix in Table A2 are qualitatively unchanged as compared to the main results discussed in the paper.

To capture the longer-term performance of swapped stocks, we 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) relative to the CAPM model.[20] Our swap hypothesis implies 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.

To take into account other stock characteristics that may impact performance in a potentially nonlinear manner, we follow the procedure of Daniel et al. (1997) (hereafter DGTW) and construct the DGTW-adjusted monthly 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 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 returns of stocks swapped by HFs and other types of investors. Similar to the CAPM abnormal returns, we expect the DGTW-adjusted returns to be higher of stocks bought by HFs and sold by QIXs, compared to the returns of the opposite swap.

To assess the link between the swap portfolio returns and their risk, we measure the overall

[20] As a robustness check, we also use the Carhart 4-factor model (Carhart, 1997), Fama-French 5-factor model (Fama and French, 2015) augmented by the momentum and the traded liquidity factor of Pástor and Stambaugh (2003), as well as the Stambaugh mispricing model (Stambaugh and Yuan, 2017) augmented by the liquidity factor. Results reported in the supplementary Online Appendix Tables A3, A4, and A5 show the same pattern in the estimated alphas and market betas after controlling for the additional factors for the HF/QIX swap. In terms of other factors, the most robust results are for RMW, CMA, and MGMT factors. Exposures to these factors are negative and significant for stocks sold by HFs and bought by QIXs, while stocks bought by HFs have virtually zero exposure, resulting in statistically significant differences in the exposures.

risk of these portfolios using the return standard deviation. We next decompose the total risk into its systematic and idiosyncratic components. The systematic risk is measured as the standard deviation of fitted returns from the CAPM, while the idiosyncratic risk is captured by the standard deviation of the residuals. We also compute the standard deviation of the DGTW-adjusted returns of the swapped portfolios. Our α-β swap hypothesis suggests that the total risk and at least the systematic risk of stocks sold by HFs and bought by QIXs could be expected to be higher than that of stocks swapped in the opposite direction.

If the superior HF performance on swapped stocks is indeed driven by the α-β swap, the abnormal returns of HFs on swap portfolios should disappear after the differences in stock betas are accounted for. One way to control for this is to use the betting against beta (hereafter BAB) factor of Frazzini and Pedersen (2014),[21] who find that high-beta assets earn low alphas due to differential funding constraints of institutions. At the same time, as Bali et al. (2017) show, the poor performance of high-beta stocks is predominantly driven by stocks that exhibit lottery-type features. HFs may be exploiting this feature of stocks in their trades, as opposed to directly relying on market beta. We use the FMAX factor to control for such a possibility.[22]

We evaluate the alphas from the regressions of the DGTW-adjusted returns of the swapped portfolios on these two factors (BAB and FMAX) separately, as well as jointly. When the joint analysis is conducted, following Bali et al. (2017), we first regress each of the factors on one another in turn, to obtain Resid_FMAX (orthogonal part of FMAX not explained by BAB) and Resid_BAB (orthogonal part of BAB not explained by FMAX), and then use FMAX in combination with Resid_BAB and Resid_FMAX in combination with BAB to assess the relative importance of these factors (if any) for the alphas of the swapped portfolios.

To assess the stability of the results during different market conditions, we control for the stringency of funding constraints over time, and we also run a rolling window regression using

[21] 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.

[22] The FMAX factor longs 10% of stocks with the highest MAX (the average of the largest 5 returns over the past month) and shorts 10% of stocks with the lowest MAX, and it can be downloaded from the web page of Tarun Bali at https://sites.google.com/a/georgetown.edu/turan-bali/data-working-papers.

a three-year window and quarterly steps. We further assess the long-term performance of the swapped stocks and use an annual holding period instead of a quarterly one.

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 use 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 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.[23]

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 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.

We identify HFs using a union of three major HF databases – EurekaHedge, TASS Lipper, and Morningstar – for the period from 1994 to 2017.[24] We merge the databases following the procedure described in Joenväärä et al. (2021). We then create a list of HFs' 13f identifiers,

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

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

i.e. manager numbers (hereafter MGRNOs), by matching HF company names 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 836 HF companies, 734 of which also have permanent classifications in the Bushee (2001) database and are included in the analysis.[25] Further, we identify 2,906 QIXs and 1,448 TRAs from the remaining institutions in the Bushee (2001) database. Overall, identified HFs, QIXs, and TRAs institutions in our final sample cover 63.84% of all institutions from the 13f database existing between 1994 and 2017.[26] As of the end of 2017, the overall portfolio size based on the holdings of our sample stocks of QIXs was $9.69 trillion, whereas it was $2.82 trillion for TRAs, and $1.58 trillion for HFs.[27]

Panel B of Table 1 reports the descriptive statistics of holdings and changes in holdings for all types of investors in our sample. 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 is 34.61%. The average holdings of HFs and TRAs are 8.31% and 11.79% respectively. Over the complete period QIXs, TRAs, and HFs have been net buyers (with the average quarterly changes in holdings being 0.12%, 0.41%, and 0.08%, respectively), while OTHs have been net sellers (the average change in holding is -0.62%).

Panel C of Table 1 reports the descriptive statistics of the institutional portfolios. The largest

[25]The number of HF companies we identify is generally consistent with the prior literature. This value depends on the number of HF databases used, time period, required length of HF reported history, and the stringency of classification criteria (e.g., more than 50% of company assets invested in HFs vs no other business apart from HFs). Agarwal et al. (2013a) use a larger set of databases (CISDM, EurekaHedge, HFR, MSCI, and TASS) from 1980 to 2008 to identify 1,199 HF companies. Griffin and Xu (2009) use Nelson's Directory, Altvest, TASS, and the MAR graveyard databases from 1980 to 2004, and identify 306 HF companies. Kokkonen and Suominen (2015) use TASS and identify 255 hedge fund companies from 1991 to 2010. Giannetti and Kahraman (2017) use TASS, CISDIM/Morningstar, and HFR databases from 1994 to 2014 and identify 355 HF companies. Bali and Weigert (2021) identify 679 HF companies using EurekaHedge, HFR, Morningstar, and TASS databases from 1997 to 2017, requiring HFs to have a minimum of 36 reported returns. Agarwal et al. (2017) also use a union of EurekaHedge, HFR, Morningstar, and TASS from 1994 to 2012 and identify 793 hedge fund companies reporting to 13f. Using the same set of databases but a longer period from 1994 to 2017 Agarwal et al. (2021) identify 915 hedge fund companies.

[26]The rest of the reporting institutions are included in OTHs.

[27]Similar to most of the papers in the literature, our sample of HFs is restricted to those HFs that voluntarily report to commercial databases. There may be a large proportion of HFs that do not report, which may have different properties to the reporting funds (Barth et al., 2020).

group of institutions are QIXs, with on average 1,352 institutions reporting holding per quarter compared to 319 HFs. 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. QIXs have the smallest turnover, on average 6.59% per quarter, while that of HFs is over 22.26% per quarter and it is 23.95% 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.

Another economically appealing and widely adopted method to classify institutional investors is the active share measure of Cremers and Petajisto (2009).[28] Active share is designed to measure to what extent a portfolio manager deviates from a passive benchmark index. In the spirit of Cremers and Petajisto (2009), we compute this measure for HFs, QIXs, and TRAs using CRSP all share value-weighted index. In Panel C of Table 1, we see clear correspondence between the active share and Bushee's classifications, with QIXs exhibiting on average the lowest active share of 72.75%, and HFs having the highest value of 88.70%. The average active share for QIXs is consistent with that for pure-ETF of 70.47% (Cremers et al., 2016). Therefore, we proceed with the following analysis based on Bushee's classification system.

[Place Table 1 about here]

4. Empirical Results

4.1. Institutional trading: α-β swap

Panel A of Table 2 reports the excess returns over the risk-free rate, the CAPM alphas and betas[29], and DGTW-adjusted returns of swapped portfolios. Consistent with our expectations, stocks sold by HFs and simultaneously bought by QIXs exhibit a negative future alpha of −0.33% per month, and they have a higher beta of 1.33, compared to stocks bought by HFs and sold by QIXs. The

[28] See Cremers et al. (2016) and Crane and Crotty (2018), among others.

[29] The results based on the alternative models are qualitatively the same and are reported in the Online Appendix Tables A3, A4 and A5 .

latter exhibit a positive alpha of 0.49% per month and a smaller beta of 1.13 with all the differences being highly statistically significant. In contrast, stocks swapped between HFs and TRAs or OTHs do not exhibit any statistically significant alphas in either direction. The differences between beta measures are not significant, either.[30] Even after controlling for other factors via DGTW-adjusted returns, the excess return of stocks sold by HFs and purchased by QIXs remains negative of −0.16% per month but not significant, whereas the DGTW-adjusted return of stocks bought by HFs and sold by QIXs is 0.45% per month, significant at the 1% level. The swaps between HFs and TRAs or OTHs do not generate any significant adjusted returns.[31]

As for the differences in risk, stocks bought by HFs while sold by QIXs exhibit significantly lower lower total risk (as measured by the return standard deviation) than stocks sold by HFs and bought by QIXs, consistent with our hypothesis. Remarkably, we find that both systematic and idiosyncratic risks contribute to the difference. HFs purchase lower systematic risk stocks from QIXs, which is also captured by the lower market beta; and they purchase lower idiosyncratic risk stocks, which can contribute to the documented alpha difference too. We cannot see any significant differences in the total risk or systematic risk for HF/TRA or HF/OTH swaps, while the idiosyncratic risk of stocks bought by HFs and sold by OTH is higher than that of stocks swapped in the opposite direction. Using the DGTW-adjusted returns, we can see that HFs purchase lower-risk stocks from both QIXs and TRAs, and higher-risk stocks from OTH.

[Place Table 2 around here]

As a robustness check, we evaluate the performance of swapped stocks across all other pairs of investors and report the results in the Online Appendix Table A6, Panel A. We find that swaps between TRAs and QIXs have similar properties to swaps between HFs and QIXs based on CAPM alpha. This is consistent with the findings of Ke and Petroni (2004) and Bushee and Goodman

[30] Remarkably, the CAPM betas of the swapped portfolios between all the institutions in all directions are higher than one, suggesting that high-beta stocks are generally more likely to change owners from quarter to quarter.

[31] We run a robustness check by subdividing OTHs into other institutions reporting to 13f (OTH_INSTs) and unreported holdings (OTH_OTHERs). The results reported in the Online Appendix Table A6 Panel B similarly indicate no significant differences in CAPM alphas, betas, or DGTW adjusted returns for these swaps. The only exception is the CAPM alpha for the stocks that are sold by HFs and bought by OTH_OTHER, which is negative and statistically significant. The differences in DGTW-adjusted returns are still not significant for this swap.

(2007), who show that TRAs are active and skilful investors.[32] The superior performance of TRAs is much smaller in magnitude than that of HFs, however.

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 several sub-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 pension plans, insurance companies, and university endowments. These sub-categories are based on the detailed classification of Bushee (2001). We further refine this classification and identify a group of QIXs, which explicitly report managing index funds (INDEX). We follow Crane and Crotty (2018) and use the CRSP index fund flag (denoted as "D") and manually match the names of companies that manage at least one index fund with the names of QIXs in our sample. In total, we identify 108 QIXs that have managed at least one CRSP index fund.[33]

The beta-over-alpha preferences discussed above can be seen for all three types of QIXs (Table 3). The lowest 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 0.92% per month. The corresponding difference in the DGTW-adjusted returns is 0.71% per month, significant at the 1% level. It is 0.35% (the 10% significance level) for IIAs, 0.54% for OTQIXs (the 1% significance level), and 0.55% for INDEX (the 1% significance level). The difference in CAPM betas is the strongest for IIAs of -0.29, significant at the 1% level. It is larger in absolute value than -0.20 reported in Table 2 for all QIXs.

[32] Remarkably, most of HFs in our sample are classified as TRAs in Bushee's database. Hence, they contribute to the good performance of the overall group of TRAs in these papers.

[33] The complete list of these funds, including 13f identifiers is available in Online Appendix Table A7.

[Place Table 3 around here]

As a further robustness check, we repeat the analysis using the CRSP mutual fund database from 2003q2-2017q4. The sample starts in 2003q2 since the database reports the index fund flag starting from this date.[34] Funds with the CRSP index fund flags are regarded as index mutual funds. We divide the index mutual funds into two sub-groups: (1) pure index funds with the flag "D", and (2) active index funds with the flags "B" or "E". The flag "D" indices pure index funds, which are expected to fully replicate some indices. The flag "B" indicates index-based funds, which track and invest in components of various indices, and may deviate from the indices. The flag "E" indicates index-enhanced funds that aim to outperform the indices by using different weighting schemes of the index components and/or trading derivatives.[35] We link index funds to the TFN/CDA S12 mutual fund holdings via MFLINK tool and repeat our analysis. For each type of index fund and quarter, we compute quarterly changes in the fractional holdings of each stock, and consider stocks intensively traded in different directions by the index funds and HFs.[36] The results reported in Online Appendix Table A8 are consistent with our main findings. Stocks bought by HFs and simultaneously sold by index funds exhibit a positive ex-post alpha, which is 1.11% per month higher than that of stocks sold by HFs and bought by index mutual funds. The difference in betas is -0.30, with stocks bought by HFs having lower beta. The beta swap is significant for all index funds, while the alpha swap is more pronounced for pure index funds. This further supports our main findings that the key alpha benefits for HFs are related to trading against QIXs and not TRAs, as some of the active index mutual funds are likely to be classified as TRAs based on their actual trading patterns.

Figure 1 further plots the time series of alphas and market betas relative to the CAPM for stocks swapped between HFs and QIXs 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

[34]See the database guide https://wrds-www.wharton.upenn.edu/documents/1303/MFDB_Guide.pdf.

[35]See https://wrds-www.wharton.upenn.edu/documents/1303/MFDB_Guide.pdf for more details.

[36]In the TFN/CDA S12 database, not all holdings are reported at quarter-end. Within-quarter reports amount to 22.23% of holdings in our sample. We aggregate such within-quarter reports to construct effective quarter-end holdings, to be matched with those of HFs for the analysis.

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. Remarkably, towards the end of the sample period, the alpha of stock bought by HFs and sold by QIXs turns negative, although still remaining higher than that of stocks swapped in the opposite direction. This is consistent with the overall deterioration of HF performance during recent years (Bollen et al., 2021).

[Place Figure 1 about here]

4.2. Swapped-stock contribution to hedge fund performance

To evaluate the contribution of such swap trades to the overall HF long-equity portfolio performance, we conduct a decomposition analysis of HF equity portfolios.[37] First, we use dollar-holding-weighted portfolios for each HF based on their 13f reports of the sample stocks and evaluate the total average performance of these portfolios. Each quarter we calculate the dollar-holding-weighted average monthly DGTW-adjusted returns of portfolios of each HF, and then calculate the equal-weighted average and the total-holdings-weighted average across all HFs reporting during this quarter. The equal-weighted scheme allows capturing HF skill in its purest form, while the holding-weighted scheme controls for scalability of the skill and accounts for the potentially weaker performance of larger HFs (Griffin and Xu, 2009). Next, we decompose the total performance of the HF equity portfolio. At the end of each quarter q, we split equity holdings of each HF into three categories based on trading in quarter q: (1) "HF.S/QIX.B" contains stocks that have been in the HF/QIX swap portfolio in q with HFs selling them and QIXs buying, (2) "Other Trades" contains stocks that have not been in the swap portfolio in q in either direction, and (3) "HF.B/QIX.S" contains stocks from the HF/QIX swap portfolio which HF have bought in q while QIXs sold. We calculate the partial performance for each category using the same weights as for the total portfolio performance.

The decomposition results are reported in Table 4. The equal-weighted HF equity portfolio,

[37] This decomposition captures only reported in 13f large long positions of HFs in the US equity. It does not account for the returns generated by short-selling positions of HFs, their options trading, fixed income investments, or investments in other assets not subject to reporting requirements in 13f, such as for example, foreign equity or real estate.

on average, earns a significant ex-post abnormal return of 0.11% per month, while the holdings-weighted HF equity portfolio has an overall abnormal return of 0.02, not statistically different from zero. This is consistent with prior studies on decreasing returns to scale in the HF industry (see Avramov et al., 2011; Joenväärä et al., 2021, among others). At the same time, the dollar holdings of stocks in HF.B/QIX.S swap during quarter q increase from 5.95% at the end of q-1 to almost 8% at the end of q, consistent with HFs buying these stocks. These stocks contribute a significant abnormal return of 0.03 percentage points per month for the equal-weighted portfolio, which amounts to about 27% of its total abnormal performance. In the holdings-weighted portfolio, these stocks similarly exhibit a positive and significant abnormal return of 0.02, being the only group that significantly positive contributes to the overall HF portfolio performance. The dollar holdings of stocks in HF.S/QIX.B swap decrease from 6.25% at the end of quarter q-1 to 5.40% at the end of quarter q, again consistent with HFs selling these stocks. The remaining unsold stocks (5.40% of the total value of HF equity portfolio) contribute negatively to the total portfolio abnormal return, reducing it by 0.01 percentage points (around 13.1% of the total portfolio abnormal performance of equal-weighted and 48% of holdings-weighted HF portfolios). Hence, by engaging in swap trades with QIXs, HFs improve the performance of their equity portfolio, especially through purchased stocks, while reducing the negative effects of poorly performing stocks by decreasing their holdings.

[Place Table 4 around here]

The decomposition results above capture only large long holdings of HFs in US equity. HFs, however, follow complex investment strategies involving leverage, derivatives trading, and investing in other asset classes. We check now if the overall performance of HFs is affected by their trading in swapped stocks. In doing so, for each HF company in our sample, we use the information on returns and assets under management of the constituent funds and compute HF company-level returns as the asset-weighted average returns of the individual funds within the company. Then at the end of each quarter q for each company i, we compute the average fractional values of the correctly held stocks ($VCH_{q,i}$) using the signed fractional values of those stocks held by the company, which belong to the swapped portfolios during this quarter. Holdings in swapped stocks where HFs buy and QIXs sell are assigned a positive sign, while holdings in stocks that HFs sell and QIXs buy are assigned a negative sign:

$$(3) \qquad VCH_{q,i} = \frac{1}{N} \frac{\sum_k N\_Stocks_{k,i,q} \cdot Price_{k,q} - \sum_l N\_Stocks_{l,i,q} \cdot Price_{l,q}}{\sum_j N\_Stocks_{j,i,q} \cdot Price_{j,q}},$$

where stocks k belong to HF.B/QIX.S swap and stocks l belongs to HF.S/QIX.B swap, $N\_Stocks_{j,i,q}$ denotes the number of stocks j held by HF company i at the end of quarter q, $Price_{j,q}$ denotes the price per share of stock k at the end of quarter q, and N is the total number of distinct firms in a HF portfolio. Hence, positive values of $VCH_{q,i}$ indicate that, on average, HFs hold "correct" stocks according to swapped stocks trades, while negative values indicate that HFs hold "incorrect" stocks.

We then run a panel regression of monthly returns of HF companies on their $VCH_{q,i}$ as of the end of the previous quarter, Fung and Hsieh (2004) seven factors, and HF-company and quarter fixed effects. If trading in the correct direction associated with swapped stocks adds value, we should observe a positive and significant loading on $VCH_{q,i}$ in the regression. At the same time, if stock trading constitutes only a small proportion of HF trades, then the positive effect of swap-based trading may be minor and undetectable within the overall HF return. Hence, we repeat the regression using sub-samples of HF companies, for which stock trading constitutes a substantial proportion of the business. We use only those HF companies for which the total value of the equity portfolio as reported to 13f is at least 30%, 50%, 70%, or 90% of the total assets under management of the company, as reported to the databases. The potential issue with such classification is the reliability of the reported assets under management as well as the generally absent detailed information on HF leverage. Hence, we further identify a "cleaner" subset of HF companies that are more likely to be engaged in the US equity trades. In particular, we use those HF companies that manage a single US equity-focused fund. If a fund originates from the EurekaHedge database, we include it in the sample if it states "Long Short Equities" as its main investment strategy and "North America" as its geographical mandate. If a fund originates from TASS, we include it if its primary category is "Long/Short Equity Hedge" and the dummy for geographical focus North America equals one. If a fund originates from the Morningstar database, we include it if its category is "HF U.S. Long/Short Equity".

The results reported in Table 5 show that while we cannot detect any significant change in risk-adjusted returns of all HF companies with respect to VCH, the effect turns positive and marginally significant for those companies that substantially engage in stock trading. For example, for funds with over 50% of assets invested in reported stocks, the estimated coefficient on VCH is 0.17, and it further increases in magnitude to 0.20 for HF companies with at least 70% of assets invested in stocks. The largest effect can be seen for US-equity focused funds, with the estimated coefficient on VCH being 0.35. Economically, it implies that if the VCH increases by one standard deviation (0.0036), the risk-adjusted return of such HF companies increases by around 13 basis points per month over the following three months. This is equivalent to 15% of an average monthly return of those funds. These results further highlight a substantial contribution of swap-based trading to the overall HF performance.

[Place Table 5 around here]

4.3. Counterfactual

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 6). 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. TRAs and OTHs, on average, take the same side of HF/QIX swap trades as HFs, and accommodate the remaining portion of QIXs's demand. 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, during subsequent quarter q+1 HFs and TRAs increase their holdings in stocks swapped between HFs and QIXs, while OTHs sell these stocks. All these changes are small in absolute values (0.22%, 0.27%, and -0.44% respectively) as compared to the initial HF purchase size of 3.40%. 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 6 about here]

Another potential explanation is related to the trading of QIXs themselves. As Jylhä et al. (2018) show, mutual funds (that constitute a large proportion of QIXs in our sample) trade and hold high-beta stocks, and such trading, in turn, affects stock betas, leading to their increase. In order to check to what extent the α-β swap we document is related to price pressure by QIXs as opposed to HF stock picking, we construct a counterfactual experiment. Similar to the main analysis, we create portfolios of stocks that are intensively traded by QIXs but not intensively traded by HFs in the opposite direction, and assess the ex-post performance of these portfolios. The results in Table 7 show that indeed ex-post betas of stocks intensively bought by QIXs are significantly higher than those sold by QIXs. Similarly, stocks bought QIXs exhibit higher systematic and idiosyncratic risks as compared to stocks sold by QIXs. However, there is no significant difference in either excess returns, alphas, or DGTW-adjusted returns between these portfolios. This result is consistent with Christoffersen and Simutin (2017) who do not find negative alphas for benchmarked mutual funds, despite these funds investing heavily in high-beta stocks.

[Place Table 7 about here]

Differential performance of stocks swapped between HFs and QIXs in opposite directions does not seem to be driven by the "negative skill" of QIXs or their mechanical price pressure. Instead, given the beta preference of QIXs, HFs seem to be able to pick up the most profitable trades when acting as counterparties for QIXs. This result echoes the findings of Bali and Weigert (2021) on wise trading of HFs in a different setting. The authors show that, even though on average stocks with high idiosyncratic volatility underperform, HFs are able to wisely pick a subsample of such stocks that outperform.

4.4. BAB and FMAX factors

So far we have established that when trading against QIXs, which tend to buy higher-beta stocks and sell lower-beta stocks, HFs are able to pick particularly profitable trades out of the pool of stocks intensively traded by QIXs. We now check if such stock-picking skills are related to the factors capturing the underperformance of high-beta stocks. As described in Section 2, we regress DGTW-adjusted returns of portfolios of swapped stocks between HFs and QIXs on the BAB and FMAX factors separately, as well as on the combinations of each of the factors and the orthogonal component of the other factor in turn.

Results in Table 8 reveal that stocks swapped between HFs and QIXs in opposite directions exhibit significant differences in their exposures to the BAB and FMAX factors. The negative abnormal return of stocks sold by HFs and simultaneously bought by QIXs decreases in absolute value after controlling for these factors, as it is now captured by the negative exposure to the BAB factor or positive exposure to the FMAX factor. Consistent with Bali et al. (2017), however, we find that the key driver of these results is the FMAX factor. When including the BAB factor in the regression, Resid_FMAX remains highly statistically significant, while when controlling for FMAX, the loading on Resid_BAB is virtually zero and not statistically significant. Combined together, the results suggest that, in trying to beat the benchmark while remaining within admissible tracking-error bounds, QIXs tilt their portfolios to high-beta stocks. HFs appear to exploit this opportunity and sell high-beta stocks that also exhibit lottery-type features when trading against QIXs, thus avoiding future negative returns of their equity portfolios.[38]

Remarkably, abnormal return on stocks purchased by HFs and simultaneously sold by QIXs

[38]Even though institutional investors trade relatively less in lottery stocks compared to retail investors (Bali et al., 2017), some mutual funds are incentivised to hold such stocks by the preferences of their own investors (Agarwal et al., 2022), providing an opportunity for HFs to trade these stocks in an alpha-maximizing way.

remains large positive (0.46% per month) and statistically significant at the 1% level, even after BAB and FMAX factors are controlled for, suggesting a different source of superior HF performance in this case.

[Place Table 8 about here]

4.4.1. Funding constraints

Our previous results suggest that the differential performance of stocks swapped between HFs and QIXs in different directions can be partly attributed to their loadings on the FMAX factor. The returns on this factor are related to funding constraints of institutional investors, and they become smaller in absolute values during periods of tighter constraints (Bali et al., 2017), with similar dynamics of the BAB factor (Frazzini and Pedersen, 2014).

We follow Frazzini and Pedersen (2014) and Bali et al. (2017) and use several proxies for funding liquidity constraints. We use (1) the monthly average of daily TED spreads,[39] (2) intra-month volatility of daily TED spreads, VOLTED, (3) the economic uncertainty index,[40] and (4) the financial leverage, FLEV. Monthly values of FLEV are computed following Chen and Lu (2019) as ratios of the total assets of financial firms (SIC codes 6000-6999) from Compustat at the end of a previous quarter over the total market value of these firms at the end of the current month. Figure 2 illustrates that although all these measures spike up during the financial crisis of 2007-2009, their dynamics are somewhat different during more stable periods. Hence, we construct an aggregate measure of funding constraints AggFC as the first principal component of the original four measures.

[Place Figure 2 about here]

In order to access if and how funding constraints impact the performance of the swapped portfolios as well as their link to the FMAX factor, we regress the DGTW-adjusted portfolio returns of HF/QIX swapped stocks on FMAX, AggFC, and their interaction. The effect of funding

[39] https://fred.stlouisfed.org/series/TEDRATE

[40] The data can be obtained from Tarun Bali's web page at https://sites.google.com/a/georgetown.edu/turan-bali/data-working-papers?authuser=0.

constraints may be non-linear. For instance, it may be substantially amplified during severe crisis periods. To account for such possibility, we replace AggFC with indicator variables taking a value of 1 if the measure is above 50th, 85th, or 90th percentiles ($D_{AggFC>P50}$, $D_{AggFC>P85}$, or $D_{AggFC>P90}$, respectively) to capture the most extreme periods.

The results reported in Table 9 show that, in general, funding constraints environment has little to no effect on the returns of the swapped stocks or their exposure to FMAX. The loadings on FMAX for portfolios of stocks sold by HFs and bought by QIXs remain positive and highly significant (0.16 to 0.18), while the interaction term $FMAX \times AggFC$ is not statistically significant.

During periods of severe constraints, the exposure to FMAX is reduced, with $FMAX \times D_{AggFC>P90}$ being -0.22, significant at the 5% level (column (4)), rendering the overall exposure to FMAX to almost zero. The exposure to FMAX of stocks bought by HFs and sold by QIXs turns negative during such periods, with the corresponding interaction term in column (8) being -0.16, significant at the 5% level. Hence, during periods of high economic uncertainty and tight funding constraints, institutional investors, HFs and QIXs alike, shy away from trading lottery-type stocks.

Remarkably, the level of DGTW-adjusted returns for stocks sold by HFs and bought by QIXs further decreases during the most extreme conditions (as captured by the negative coefficient of -0.82 on $D_{AggFC>P90}$ in column (4)), while the average levels of adjusted returns remain positive and highly significant for stocks bought by HFs and sold by QIXs (columns (5) to (8)). These results confirm the existence of α-β swap between HFs and QIXs, which is persistent across different market regimes.

[Place Table 9 about here]

4.5. Alternative factors

So far we have shown that the negative abnormal performance of stocks sold by HFs while bought by QIXs can be explained by their positive loading on the FMAX factor, while the positive abnormal performance for stocks swapped in the other direction is not captured by this factor. Now we check if the difference in the ex-post performance of the swapped portfolios is related to alternative factors, which have been found in the previous literature to drive HF stock-picking decisions.

We start by identifying stock characteristics that may be expected to be different between stocks bought and sold by HFs. We then compute and compare the average characteristics of the stocks in the two swapped portfolios (HF.B/QIX.S vs HF.S/QIX.B) before trading. We further report the fractions of stocks in each of the portfolios with the extreme levels of the characteristics of interest (below the 10th or above the 90th percentiles). Finally, we check if α-β swap remains pronounced if the stocks with extreme characteristics are excluded from the portfolios. In what follows, we describe each factor in detail and then discuss the results.

ILLIQ

The first factor to consider is stock liquidity (ILLIQ). QIXs 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 (Pástor and Stambaugh, 2003; Teo, 2011; Jylhä et al., 2014). Hence, stocks bought by HFs and sold by QIXs can be expected to be less liquid than stocks sold by HFs and bought by QIXs, and thus, delivering higher returns. We measure individual stock illiquidity in each of the portfolios using the Amihud (2002) illiquidity measure, computed using one quarter of daily return data. We use only those stocks that have a minimum of 20 return observations in a quarter of interest.

SIZE

Similarly, HFs tend to purchase smaller stocks (Fung and Hsieh, 2011; Cao et al., 2018a). We measure stock size as the market cap in million USD (SIZE), at the end of quarter q-1 – the last quarter before the trading quarter.

MAX

As we have shown, the portfolio of stocks sold by HFs to QIXs has a positive FMAX loading, hence these stocks tend to exhibit lottery-type features. Institutional investors, however, on average shy away from such stocks (Bali et al., 2017), while the sensation-seeking HF managers tend to load on such stocks, leading to lower risk-adjusted performance (Brown et al., 2018). We follow

Bali et al. (2011) and compute the average values of the five highest daily returns over the last month in a quarter for each stock to measure their resemblance to a lottery as of a quarter-end (MAX). Stocks in the HF.S/QIX.B swap portfolio would have higher average values of MAX than stocks in the HF.B/QIX.S portfolio, provided that the majority of HF managers are not sensation-seeking and such managers are able to identify subsets of lottery stocks for which QIXs exhibit demand.

AlphaPast

Mutual fund strategies are often trend-following, while HFs tend to follow contrarian strategies and earn positive abnormal returns on such trades (Jylhä et al., 2018; Grinblatt et al., 2020). Additionally, mutual funds often bear the costs of immediacy by demanding liquidity and, hence, entering the "wrong" side of contrarian trades (Ignashkina et al., 2022). To capture this effect, we follow Agarwal et al. (2013a) and estimate past alphas of stocks in the swapped portfolios using the past 48 months before portfolios' formation, requiring a minimum of 12 available data points for stocks to be included (AlphaPast). If the proportion of contrarian trades is higher in the HF.B/QIX.S swap portfolio, we should observe a smaller past alpha of this portfolio.

BetaPast

When QIXs purchase stocks (from HFs), they are likely to affect future betas (Jylhä et al., 2018). Hence, it may be possible that the difference in betas of swapped portfolios is "mechanical", and actually caused by the trades. If QIXs, however, do prefer to purchase high-beta stocks as suggested by Christoffersen and Simutin (2017), we can expect to see the beta difference not only in the future betas, but also in the past, pre-trade betas. We compute CAPM betas of swapped stocks using 48 monthly returns, preceding the trading quarter (BetaPast).

IDVOL

Stocks with high idiosyncratic volatility tend to underperform in the future. However, HFs seem to be wise and pick a subsample of such stocks that outperform (Bali and Weigert, 2021). If HFs use QIXs as trading partners for such wise trades on idiosyncratic volatility, we could expect to see higher idiosyncratic volatiles of stocks bought by HFs and sold by QIXs. If, however, volatility-related stock picking is not a basis of such trades, then the average idiosyncratic volatility of stocks bought by HFs and sold by QIXs would be expected to be lower. We compute idiosyncratic volatilities of stocks using past 48 monthly returns and the CAPM as a benchmark model (IDVOL).

SIR

A unique feature of HFs compared to most of QIXs is that they are able to use short sales. By selling future losing stocks to QIXs, HFs avoid value destruction. But such trades can lead directly to value creation for HFs, if they sell these stocks short. We do not observe individual fund-level short selling, but can use stock-level short selling information, bearing in mind that the majority of such trades are likely conducted by HFs. For each stock, we obtain the adjusted number of shares held short from the Supplemental Short Interest File of Compustat as of the last month of each quarter.[41] We then scale this by the total (adjusted) number of shares outstanding as of the end of the previous month to calculate our Short Interest Ratio (SIR) measure. We expect the SIR of stocks sold by HFs and bought by QIXs to be higher than for stocks swapped in the opposite direction.

Trading by distressed mutual funds

Using stock transaction data, Jame (2018) shows that HFs tend to profit from providing liquidity to mutual funds, when the latter experience strong inflow or outflow pressure. We identify mutual funds using the CRSP mutual fund database, and classify mutual funds as distressed ones if their average monthly flow during a quarter is below the 20th percentile. Next, stocks intensively sold (bought) by distressed mutual funds are defined as those with the change in the aggregate holdings by distressed mutual funds of these stocks being below the 10th (above the 90th) percentile. If HFs provide liquidity to distressed mutual funds, the faction of stocks sold by distressed mutual funds is expected to be higher in the swap portfolio where HFs buy and QIXs sell stocks.

FracM&A

Another related factor that can drive trading decisions of HFs is corporate events. For example, HFs increase holdings in target firms prior to merger announcements, while mutual funds tend

[41] If there are several reports of the number of stocks held short in a month, we use the first report.

to reduce such holdings (Fich et al., 2020). Since target firms tend to experience positive abnormal returns on the announcement date, this could contribute to positive excess returns of stocks purchased by HFs and sold by QIXs. To control for such a possibility, we collect information on all M&A announcements from Refinitive SDC (Securities Data Company), where the type of an event is either "merger" or "acquisition of major interest". We compute the fraction of firms in the swapped portfolios that are M&A targets (FracM&A) with announcement dates during the trading quarter or the subsequent quarter. If HFs indeed disproportionally overweight target stocks, we should see the proportions of target stocks to be higher in swapped portfolios when HFs buy and QIXs sell stocks.

The results reported in Table 10 are generally consistent with the intuition above. Compared to stocks sold by HFs and bought by QIXs (HF.S/QIX.B), stocks bought by HFs and sold by QIXs (HF.B/QIX.S) tend to be significantly less liquid, with the fraction of extremely illiquid stocks in this swapped portfolios also being significantly higher. Interestingly, firms in the HF.B/QIX.S swapped portfolio are, on average, about USD203 million larger. This seems to be related to a larger dispersion of market capitalizations of firms in this portfolio. HF.B/QIX.S portfolio contains significantly higher proportions of extremely small and extremely large firms. The fraction of very small firms in HF.B/QIX.S portfolio is about 5 percentage points higher than that of HF.S/QIX.B, while the fraction of extremely large firms is about 0.5 percentage points higher in the former portfolio.

As for MAX, stocks sold by HFs and bought by QIXs have on average a significantly higher value of MAX compared to stocks bought by HFs and sold by QIXs. Similarly, the fraction of stocks with extremely large MAX is higher for HF.S/QIX.B portfolio, while the fraction of stocks with extremely small MAX is higher for HF.B/QIX.S swap portfolio.

HFs do seem to engage in contrarian trades when trading against QIXs. The average past alpha of stocks bought by HFs and sold by QIXs is around 50 basis points per month smaller than that of stocks traded in the opposite direction. As for stock market beta, stocks bought by QIXs and sold by HFs have a significantly higher average pre-trade beta, which further supports our argument of the higher-beta preferences of QIXs.

The difference in the SIR between stocks in HF.S/QIX.B vs HF.B/QIX.S portfolios is not statistically significant, although the direction of the effect is consistent with the expectations: stocks sold by HFs to QIXs are also more likely to be sold short.

Consistent with the previous literature, HFs tend to provide liquidity to distressed mutual funds. The fraction of stocks sold by distressed mutual funds is significantly higher in the HF.B/QIX.S portfolio than in the HF.S/QIX.B portfolio, while the fraction of stocks bought by distressed mutual funds is significantly lower in the HF.B/QIX.S swap portfolio.

Looking at HF/QIX swaps and the contribution of M&A events, a remarkable picture emerges. The fraction of target stocks in HF.B/QIX.S portfolio is significantly larger than that in HF.S/QIX.B portfolio. The difference is especially pronounced for the M&A announcements made during the quarter of trades. On average, 5.33% of firms purchased by HFs and sold by QIXs experience an M&A announcement during the trading quarter, compared to just 0.68% for the swapped stocks in the opposite direction. As for the M&A announcements during the quarter following the trades, we still obverse a significantly higher fraction of future target firms in the HF.B/QIX.S portfolio, but the difference is smaller. The fraction of future target firms in HF.B/QIX.S is 2.34% while it is 1.60% in HF.S/QIX.B portfolio. This suggests that trading on corporate events is indeed an important factor for HFs. HFs seem to be able to predict future M&As, but such skills are stronger for immediate announcements. This would be also consistent with HFs trading on insider information related to upcoming M&A deals (Dai et al., 2017).

[Place Table 10 around here]

We now test if these factors explain the differences in alphas and betas between HF.B/QIX.S and HF.S/QIX.B portfolios. Table 11 reports the differences in CAPM alphas, betas, and DGTW-adjusted returns between swapped portfolios from which stocks with extreme values of characteristics (the largest 10%, or the smallest 10%, or both the largest and the smallest 10%) are excluded. Compared to our main results of the alpha difference of 0.82, beta difference of -0.20, and DGTW-adjusted return difference of 0.60 (Table 2), none of these exclusions lead to qualitative changes of the results. The strongest statistical support in Table 10 is associated with Alpha Past (that is, contrarian trading by HFs) and the percentage of M&A announcements (that is, trading on corporate events). Excluding the event stocks as well as stocks with the high and low Alpha Past, similarly to other factors considered, does not qualitatively change the results. All the differences remain highly statistically significant, with the alpha difference of at least 0.77, beta difference of at least -0.16 and DGTW-adjusted return differences of at least 0.54. Hence, although all the factors discussed above do impact trading decisions of HFs, they are not decisive to the documented α-β swap between HFs and QIXs.

[Place Table 11 around here]

5. Extensions and robustness

5.1. 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.[42] Calluzzo et al. (2019) show that HFs and other high turnover institutions do trade on market anomalies and exploit return predictability, especially over the 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. These equilibrium results suggest that HFs may be profiting by trading in the opposite direction of QIXs based on the stock mispricing signals related to known features of return predictability.

We consider nine well-known accounting 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

[42] Fama and French (See 2008); Campbell et al. (See 2009); Israel and Moskowitz (See 2013); Hou et al. (See 2015); Edelen et al. (See 2016, among others).

issues (NSI), accrual (ACR), and asset growth (AG) anomalies.[43] The anomalies are described in detail in Online Appendix, Table A9.

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 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 portfolios from the intersection of two size groups (above or below the NYSE size median at the end of calendar year $t - 1$) and each of the 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% of 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. 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

[43] We do not consider trading-based anomalies here, such as lottery-type features of stocks or momentum, since they are either used separately or controlled for by using DGTW-adjusted returns.

year t using the 20th and 80th 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 swap. Altogether, we end up with four swap portfolios between HFs and QIXs. 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.[44] We only use firms with a minimum of two years of data available, starting from their second reporting year. Panel A of Table A10 in the Online Appendix 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 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 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 0.67% per month in terms of abnormal returns relative to the CAPM, and 0.56% per month in terms of DGTW-adjusted returns, both significant at the 1% level (the NOA anomaly).

Table 12 reports CAPM alphas, betas, and DGTW-adjusted returns for swapped stocks related to the equal-weighted combination of the market anomalies under consideration. HF.S/QIX.B swaps of overpriced stocks (short-leg) deliver a significantly negative alpha of −0.53% per month, while HF.B/QIX.S swaps of underpriced stocks (long-leg) exhibit a positive alpha of 0.32% per month. However, the differences in alphas of stocks in HF.B/QIX.S over HF.S/QIX.B portfolios are positive and highly statistically significant only for short leg of market anomalies. Similarly, the difference in DGTW-adjusted returns is significant for the short leg of market anomalies trades.

[44] The accounting information we used in 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.

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. Consistently, the systematic risk of stocks in HF.S/QIX.B swap portfolio is higher than that of HF.B/QIX.S portfolio, with the difference being statistically significant for the short-leg anomaly stocks. Interestingly, the relation is reversed for the idiosyncratic risk of shot-leg stocks. If HFs intensively purchase stocks that should be sold according to the predictions based on market anomalies, they buy higher idiosyncratic risk stocks.

[Place Table 12 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 pronounced nowadays, despite the availability of theoretical research explaining their nature and accounting information underlying the corresponding portfolio choice.

5.2. Long-term performance

To assess the long-term performance of the swapped stocks, we repeat the main analysis but increase the stock holding period from one quarter to four quarters. The results in Table 13 show that the alpha losses of QIXs that buy stocks from HFs are predominantly associated with the short-term performance over the first quarter, and the losses are not statistically significant over the annual horizon. The abnormal losses turns almost zero when the performance is assessed via DGTW-adjusted returns. At the same time, the gains that HFs make by purchasing stocks sold by QIXs remain positive and statistically significant even on the annual horizon, although their magnitude decreases. These findings are consistent with HFs being short-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 remains statistically significant, with HFs selling/QIXs buying high-beta stocks. The same holds for the risk measures: QIXs tend to buy higher-risk stocks from and sell-lower risk stocks to HFs.

[Place Table 13 around here]

6. 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. On aggregate, such a strategy of quasi-indexers is not value-destroying. However, hedge funds are able to identify the most profitable trades out of those of quasi-indexers. By providing liquidity for such trades, hedge funds earn abnormal returns for their own investors. One of the factors contributing to the stock-picking decisions of hedge funds is the FMAX factor of Bali et al. (2017). Hedge funds tend to sell lottery-type stocks to quasi-indexes. 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 in 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 returns, various profit-making opportunities (including but not limited to market anomalies) are likely to persist in the market, and they could be potentially exploited by more active types of investors.

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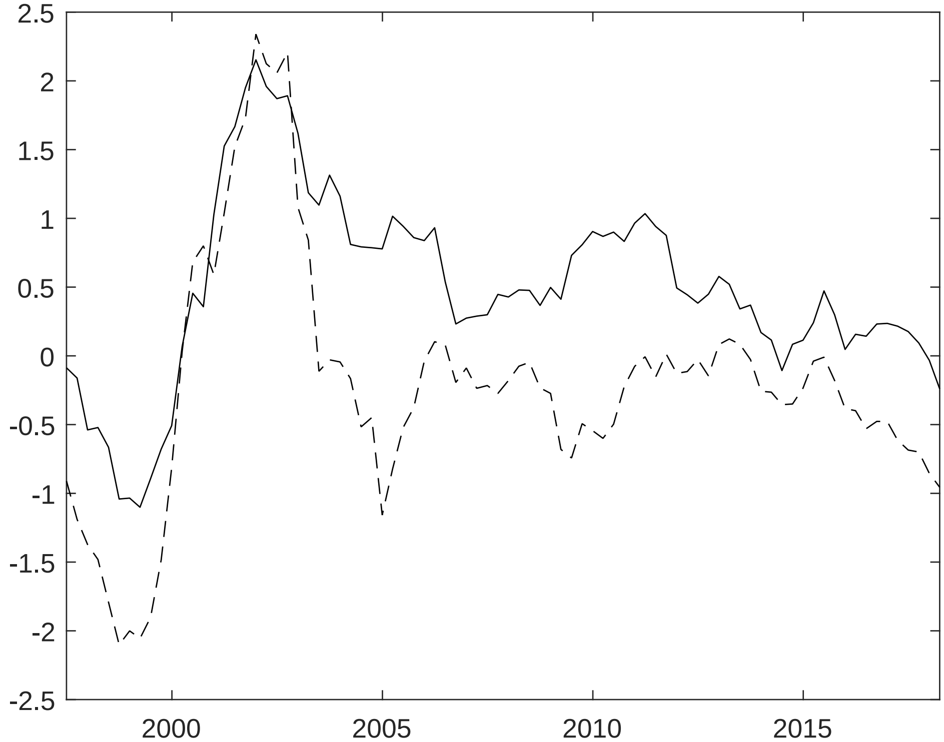
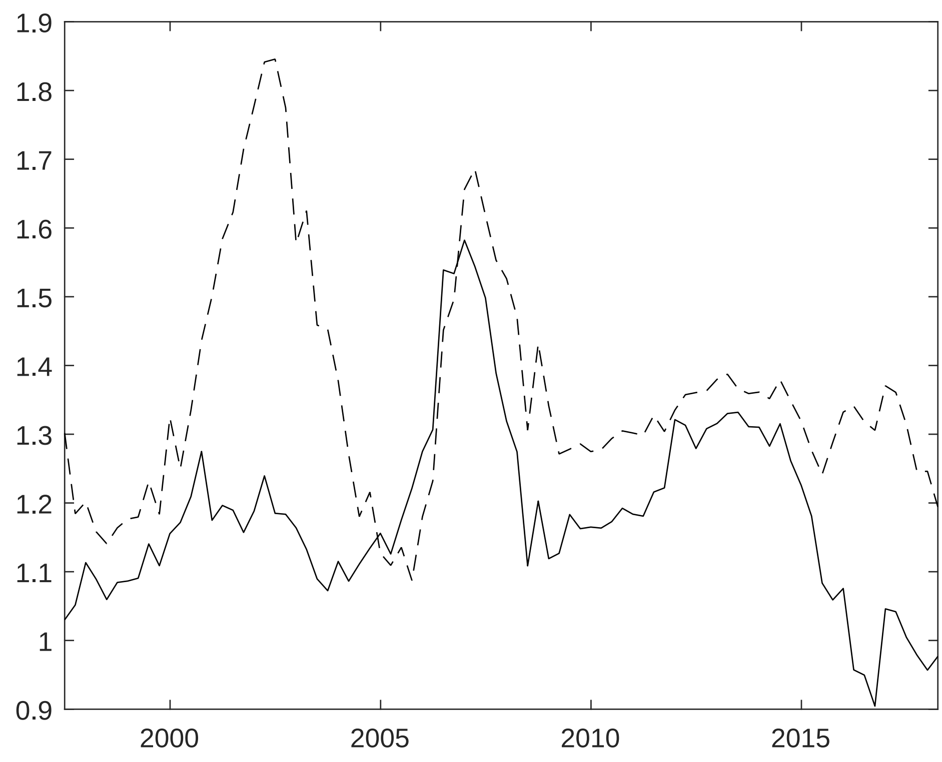
Figure 1: Time series of alphas and market betas for HF/QIX trading swaps

The figure plots the time series of alphas and market betas from the CAPM model of stocks bought by HFs from QIXs (HF.B/QIX.S, solid line) and sold by HFs to QIXs (HF.S/QIX.B, dashed line) from 1994q2 to 2017q4. The estimation is performed over three-year rolling windows.



(i) HF/QIX Swap: α



(ii) HF/QIX Swap: β

Figure 2: Time series of funding constraints measures

The figure plots the time series of funding constraints measures, including the TED spread (TED), intra-month volatility of TED spread (VOLTED), the macroeconomic uncertainty index (MACUNC), and the financial leverage (FINLEV) from 1994q2 to 2017q4.

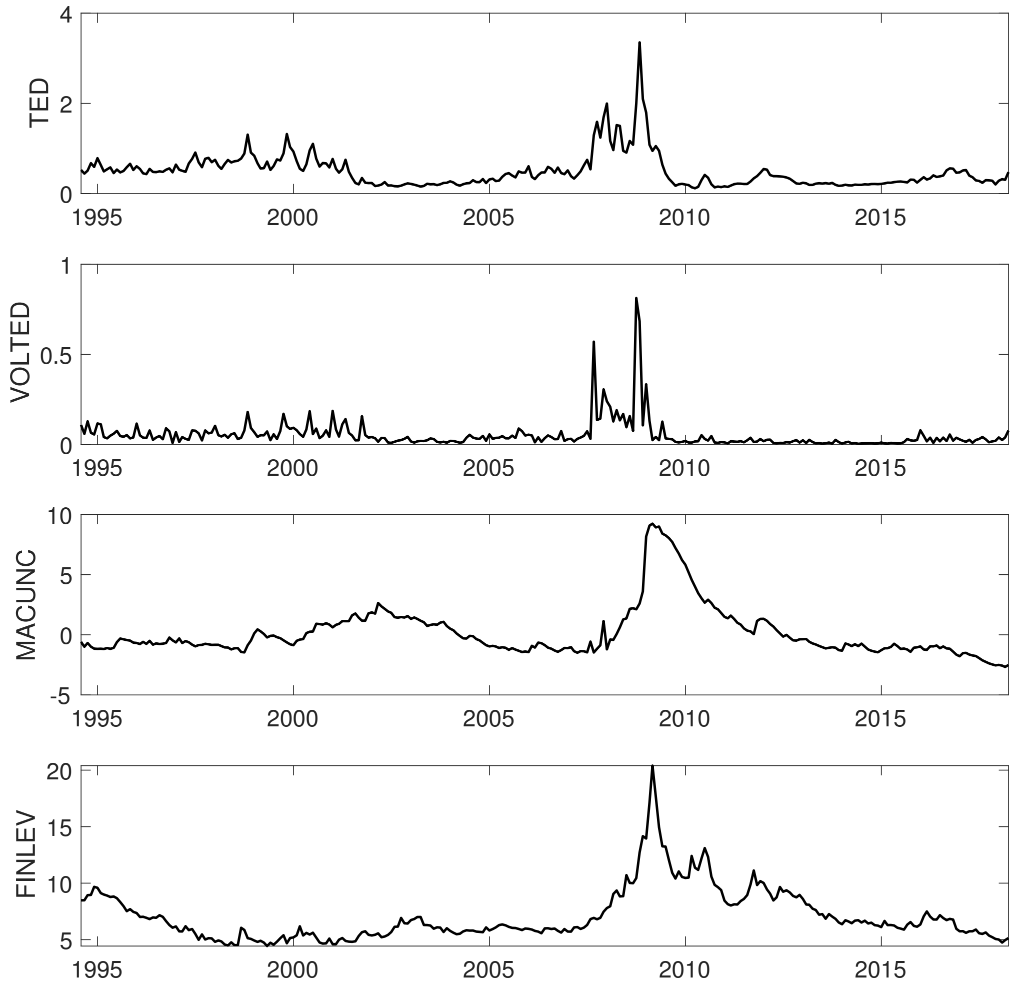


Table 1: Descriptive statistics: stocks, ownership and institutional portfolios

This table reports the descriptive statistics of individual stocks in our sample, as well as holdings and portfolio characteristics for different groups of investors from 1994q2 to 2018q4. Panel A reports stocks' monthly returns, market caps, and Amihud illiquidity measures (Amihud, 2002). We use common stocks (those with CRSP share codes of 10 or 11) traded on the NYSE, AMEX or NASDAQ (CRSP exchange codes of 1, 2 or 3) with monthly prices above $5 at the end of previous quarter, excluding utility firms (standard industrial classification (SIC) codes from 4900 to 4999) and financial firms (SIC codes from 6000 to 6999). Panel B reports summary statistics of the quarterly stock holding (StockHold, in %) and changes in holding (ΔStockHold, in % per quarter) of HFs, quasi-indexers (QIXs), transient institutions (TRAs), and other investors (OTHs). Holding of OTHs is calculated in the spirit of Ben-David et al. (2012) as the difference between 100% and the total percentage holding of HFs, QIXs, and TRAs. QIXs and TRAs are classified using the permanent classification provided in Brian Bushee's database (Bushee, 2001). Panel C reports the portfolio characteristics of HFs, QIXs, and TRAs, including portfolio assets (PortAssets, in $million), numbers of stock held per quarter (No.StockHold), turnover (Turnover, in % per quarter), and the active share (Cremers and Petajisto, 2009).

Panel A: Stock								
	Mean	Std.Dev	P5	P25	Median	P75	P95	
Adjusted Return (% per month)	0.95	15.27	-21.48	-6.30	0.58	7.57	23.88	
Market Capitalization (USD million)	4782	21300	51	196	582	2094	17800	
Amihud Illiquidity ($\times 10^{-6}$)	2.69	15.16	0.00	0.03	0.13	0.61	9.57	
Panel B: Ownership								
	Mean	Std.Dev	P5	P25	Median	P75	P95	
StockHold^{HF}	8.31	7.13	0.18	2.82	6.76	12.01	21.81	
StockHold^{QIX}	34.61	18.49	4.34	19.60	35.60	49.04	63.57	
StockHold^{TRA}	11.79	8.74	0.40	4.84	10.53	17.14	27.71	
StockHold^{OTH}	45.29	25.95	7.66	23.48	42.82	65.66	90.63	
$\Delta\text{StockHold}^{HF}$	0.12	2.54	-3.38	-0.70	0.01	0.90	3.89	
$\Delta\text{StockHold}^{QIX}$	0.41	4.66	-5.97	-1.37	0.25	2.23	7.13	
$\Delta\text{StockHold}^{TRA}$	0.08	3.71	-5.41	-1.17	0.00	1.32	5.71	
$\Delta\text{StockHold}^{OTH}$	-0.62	6.61	-9.73	-2.76	-0.33	1.66	7.61	
Panel C: Institutional Portfolio								
	Mean	Std.Dev	P5	P25	Median	P75	P95	No. Investors (per quarter)
PortAssets^{HF}	2345	11080	12	91	310	1229	8286	319
PortAssets^{QIX}	3388	23847	20	90	217	799	10537	1352
PortAssets^{TRA}	2543	23723	7	72	236	944	7671	489
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
Turnover^{HF}	22.26	18.04	0.21	8.47	17.51	32.63	57.96	306
Turnover^{QIX}	6.59	7.01	0.11	2.07	4.68	8.88	18.84	1293
Turnover^{TRA}	23.95	17.82	0.46	10.84	19.98	33.83	59.16	462
Active Share^{HF}	88.70	14.80	54.92	84.69	94.65	98.70	99.94	316
$\text{Active Share}^{QIX}$	72.75	19.08	34.97	61.91	73.86	87.70	99.39	1342
$\text{Active Share}^{TRA}$	83.23	17.60	46.42	74.14	89.57	97.29	99.85	485

Table 2: Trading swaps and possible counterparties of hedge fund trades

Panel A of 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 (in % per month) and market betas, and DGTW-adjusted returns (Daniel et al., 1997) for the portfolios of quarterly trading swaps between HFs and non-HF investors from 1994q2 to 2017q4. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in parentheses. Panel B reports standard deviations of raw returns, CAPM fitted returns, residuals, and DGTW-adjusted returns. F-statistics for the differences in variances are in parentheses. Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs). QIXs and TRAs are classified using the permanent classification provided in Brian Bushee's database (Bushee, 2001). Holding of OTHs is calculated in the spirit of Ben-David et al. (2012) as the difference between 100% and the total percentage holding of HFs, QIXs, and TRAs. 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 intensively sell (buy); they are denoted by S (B) respectively. Portfolios S/B and B/S contain stocks intensively traded by corresponding investors (HF/QIX, HF/TRA or HF/OTH) in different directions. Portfolio returns are computed following Edelen et al. (2016). Within each portfolio, stocks are assigned in two size groups – above or below the NYSE size median at the end of the previous year. Then the value-weighted average returns of the swapped stocks within each size group are computed. In the last step, the equal-weighted averages across the two size groups are calculated. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: Performance

	Risk-Free Excess Ret.			CAPM Alpha			CAPM Beta			DGTW-Adjusted Ret.		
	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	0.60	0.93**	0.70*	-0.33*	0.06	-0.24	1.33***	1.25***	1.35***	-0.16	0.12	0.00
	(1.49)	(2.57)	(1.91)	(-1.97)	(0.36)	(-1.58)	(28.88)	(34.16)	(26.84)	(-1.23)	(0.96)	(0.02)
B/S	1.28***	0.95**	0.98**	0.49***	0.04	0.06	1.13***	1.30***	1.32***	0.45***	0.18	0.19
	(4.11)	(2.56)	(2.50)	(2.67)	(0.23)	(0.30)	(31.11)	(32.04)	(22.26)	(4.00)	(1.60)	(1.29)
B/S − S/B	0.68***	0.02	0.28	0.82***	-0.02	0.30	-0.20***	0.06	-0.03	0.60***	0.06	0.19
	(3.70)	(0.11)	(1.43)	(5.04)	(-0.13)	(1.59)	(-3.55)	(1.34)	(-0.80)	(4.00)	(0.33)	(1.14)

Panel B: Risk

	Standard Deviation of											
	Raw Ret.			Fitted Ret. (CAPM)			Residual (CAPM)			DGTW-Adjusted Ret.		
	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	6.58	6.11	6.47	5.74	5.37	5.81	3.21	2.91	2.86	2.08	2.29	2.01
B/S	5.53	6.25	6.63	4.88	5.62	5.67	2.61	2.75	3.44	1.70	1.82	2.65
B/S − S/B	-1.05***	0.14	0.16	-0.86***	0.24	-0.14	-0.61***	-0.16	0.58**	-0.38***	-0.47***	0.64***
F-stat	(1.42)	(1.05)	(1.05)	(1.38)	(1.09)	(1.05)	(1.52)	(1.12)	(1.45)	(1.49)	(1.58)	(1.74)

Table 3: Trading swaps: QIXs sub-groups

Panel A of 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 (in % per month) and market betas, and DGTW-adjusted returns (Daniel et al., 1997) for the portfolios of quarterly trading swaps between HFs and different groups of QIXs from 1994q2 to 2017q4. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in parentheses. Panel B reports standard deviations of raw returns, CAPM fitted returns, residuals, and DGTW-adjusted returns. F-statistics for the differences in variances are in parentheses. QIXs include independent investment advisors (IIA), banks (BNK), and other QIXs like insurance companies, pension funds and endowments (OTQIX) following Bushee (2001). INDEX stands for those QIX companies that manage at least one CRSP index fund. 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 intensively sell (buy); they are denoted by S (B) respectively. Portfolios S/B and B/S contain stocks intensively traded by corresponding investors in different directions. Portfolio returns are computed following Edelen et al. (2016). Within each portfolio, stocks are assigned in two size groups – above or below the NYSE size median at the end of the previous year. Then the value-weighted average returns of the swapped stocks within each size group are computed. In the last step, the equal-weighted averages across the two size groups are calculated. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: Performance

	Risk-Free Excess Ret.				CAPM Alpha				CAPM Beta				DGTW-Adjusted Ret.			
	HF/IIA	HF/BNK	HF/OTQIX	HF/INDEX	HF/IIA	HF/BNK	HF/OTQIX	HF/INDEX	HF/IIA	HF/BNK	HF/OTQIX	HF/INDEX	HF/IIA	HF/BNK	HF/OTQIX	HF/INDEX
S/B	0.78*	0.52	0.66	0.69	-0.17	-0.43**	-0.31	-0.28	1.36***	1.36***	1.38***	1.39***	0.04	-0.23	-0.09	-0.08
	(1.91)	(1.21)	(1.51)	(1.62)	(-0.85)	(-2.11)	(-1.53)	(-1.34)	(27.78)	(25.53)	(20.04)	(22.55)	(0.23)	(-1.20)	(-0.60)	(-0.53)
B/S	1.31***	1.30***	1.31***	1.31***	0.57***	0.49**	0.47**	0.48***	1.07***	1.15***	1.21***	1.19***	0.39***	0.49***	0.45***	0.47***
	(4.49)	(4.03)	(3.83)	(4.07)	(2.67)	(2.26)	(2.39)	(2.73)	(27.99)	(25.22)	(30.13)	(31.73)	(2.81)	(4.05)	(3.10)	(4.23)
B/S − S/B	0.53**	0.78***	0.65***	0.62***	0.73***	0.92***	0.77***	0.76***	-0.29***	-0.20**	-0.17**	-0.20***	0.35*	0.71***	0.54***	0.55***
	(2.49)	(3.13)	(2.85)	(2.92)	(4.01)	(4.11)	(3.66)	(4.06)	(-5.28)	(-2.45)	(-2.38)	(-3.53)	(1.77)	(3.43)	(2.97)	(3.28)

Panel B: Risk

	Standard Deviation of															
	Raw Ret.				Fitted Ret. (CAPM)				Residual (CAPM)				DGTW-Adjusted Ret.			
	HF/IIA	HF/BNK	HF/OTQIX	HF/INDEX	HF/IIA	HF/BNK	HF/OTQIX	HF/INDEX	HF/IIA	HF/BNK	HF/OTQIX	HF/INDEX	HF/IIA	HF/BNK	HF/OTQIX	HF/INDEX
S/B	6.70	6.86	7.12	7.17	5.84	5.84	5.94	5.98	3.28	3.62	3.92	3.95	2.40	2.92	2.66	2.73
B/S	5.53	5.89	6.02	5.93	4.59	4.96	5.19	5.14	3.09	3.19	3.05	2.96	2.29	2.20	2.23	2.13
B/S − S/B	-1.17***	-0.97**	-1.10***	-1.24***	-1.25***	-0.88***	-0.75**	-0.84**	-0.19	-0.43**	-0.88***	-0.99***	-0.12	-0.72***	-0.43***	-0.60***
F-stat	(1.47)	(1.36)	(1.40)	(1.46)	(1.62)	(1.38)	(1.31)	(1.36)	(1.13)	(1.29)	(1.66)	(1.78)	(1.11)	(1.72)	(1.42)	(1.64)

Table 4: DGTW-adjusted returns: Hedge fund portfolio decomposition

This table reports the decomposition of the total performance of the HF equity portfolio. Portfolios are constructed at the end of each quarter q and held for the following quarter. For each HF, we compute the dollar-holding-weighted DGTW-adjusted return (in % per month) in q+1. Total portfolio performance is measured as the equal-weighted and total-holdings-weighted average across HFs. To decompose the total performance of the HF equity portfolio, at the end of each quarter q, the equity holdings of each HF are divided into three categories based on the trading swap in q, (1) stocks that have been sold by HFs and bought by QIXs – HF.S/QIX.B, (2) Other Trades, and (3) stocks that have been bought by HFs and sold by QIXs – HF.B/QIX.S. Partial performance is calculated using the same weights as for total portfolio performance.

	Partial DGTW-Adj. Ret.	Contribution to Total Port. Performance	Partial DGTW-Adj. Ret.	Contribution to Total Port. Performance	Average Port. Dollar Holding End of q-1	Average Port. Dollar Holding End of q
	Equal-Weighted		Value-Weighted			
HF.S/QIX.B	-0.01**	-13.09%	-0.01*	-47.96%	6.25%	5.40%
	(-2.22)		(-1.91)			
Other Trades	0.09***	86.09%	0.01	56.12%	87.80%	86.61%
	(2.85)		(0.32)			
HF.B/QIX.S	0.03***	27.00%	0.02***	91.84%	5.95%	7.99%
	(3.35)		(3.32)			
		Sum		Sum	Sum	Sum
Total	0.11***	100.00%	0.02	100.00%	100.00%	100.00%
	(2.81)		(0.52)			

Table 5: Swap trading and overall hedge fund performance

This table reports the panel regression results of HF companies' returns on the fractional value of correctly traded stocks at the end of the preceding quarter (VCH), Fung and Hsieh (2004) 7 factors, and HF-company and quarter fixed effects. Column (1) uses all HF companies, while columns (2) to (5) use subsets of companies with the total value of equity portfolio as reported to 13f being at least 30%, 50%, 70%, or 90% of the reported total assets under management of the HF company, respectively. Column (6) uses only those HF companies that manage a single fund that focuses on trading US stocks. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively. Standard errors are clustered by quarter and fund. t-statistics are reported in parentheses.

	All	%Equity>30%	%Equity>50%	%Equity>70%	%Equity>90%	#Equity Fund = 1
	(1)	(2)	(3)	(4)	(5)	(6)
VCH	-0.01	0.08	0.17*	0.20*	0.12	0.35*
	(-0.73)	(1.08)	(1.68)	(1.82)	(1.01)	(1.86)
MKTRF	0.12***	0.17***	0.17***	0.17***	0.16***	0.29***
	(4.67)	(5.10)	(4.80)	(4.52)	(4.10)	(4.28)
SMB	0.05**	0.07***	0.08***	0.07**	0.07**	0.03
	(2.36)	(2.73)	(2.83)	(2.58)	(2.33)	(0.48)
BD10RET	0.00	0.00	0.00	0.00	0.00	0.01
	(0.99)	(0.89)	(0.49)	(0.55)	(0.41)	(1.66)
BAAMTSY	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.60)	(-0.22)	(-0.27)	(-0.11)	(-0.02)	(-0.17)
PTFSBD	-0.00	-0.01	-0.01	-0.00	-0.00	-0.01
	(-0.69)	(-0.74)	(-0.64)	(-0.36)	(-0.19)	(-0.76)
PTFSFX	-0.00	-0.00	0.00	-0.00	-0.00	0.00
	(-0.24)	(-0.13)	(0.05)	(-0.05)	(-0.05)	(0.02)
PTFSCOM	0.02***	0.02***	0.02***	0.02***	0.02***	0.01**
	(3.35)	(2.88)	(2.79)	(2.71)	(2.75)	(2.07)
Constant	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(26.00)	(19.81)	(18.78)	(18.56)	(18.16)	(17.23)
HFC FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,576	20,390	17,884	15,885	14,262	6,706
R-squared	0.096	0.119	0.117	0.115	0.114	0.151

Table 6: Average change in holdings of trading-swap stocks

This table reports the average quarterly change in holding (ΔStockHold, in % per quarter) of swapped stocks between HFs and quasi-indexers (QIXs) in trading quarters (q) and the 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 the trading quarter, stocks with the change in holding below (above) the bottom (top) 20^{th} percentile are considered as those that investors intensively sell (buy); they are denoted by S (B) respectively. Portfolios S/B and B/S contain stocks intensively traded by corresponding investors in different directions. Non-HF investors include (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) other investors (OTHs). QIXs and TRAs are classified using the permanent classification provided in Brian Bushee's database (Bushee, 2001). Holding of OTHs is calculated in the spirit of Ben-David et al. (2012) as the difference between 100% and the total percentage holding of HFs, QIXs, and TRAs.

	ΔStockHold in q				ΔStockHold in q+1			
	HF/QIX		TRA	OTH	HF	QIX	TRA	OTH
S/B	-3.02***	5.60***	-0.59***	-2.00***	-0.06	0.36***	-0.25***	-0.05
	(-53.12)	(34.11)	(-6.39)	(-12.87)	(-1.04)	(3.07)	(-2.89)	(-0.29)
B/S	3.40***	-5.07***	0.59***	1.08***	0.22***	-0.05	0.27***	-0.44***
	(53.33)	(-41.80)	(5.87)	(6.88)	(4.63)	(-0.39)	(3.17)	(-2.80)

Table 7: Trading swaps: Counterfactual

Panel A of 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 (in % per month) and market betas, and DGTW-adjusted returns (Daniel et al., 1997) for the portfolios of quarterly trading in stocks intensively traded by QIXs but not traded in the opposite direction by HFs from 1994q2 to 2017q4. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in parentheses. Panel B reports standard deviations of raw returns, CAPM fitted returns, residuals, and DGTW-adjusted returns. F-statistics for the differences in variances are in parentheses. 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 intensively sell (buy); they are denoted by S (B) respectively. NS (NB) are stocks that do not belong to S (B) groups. Portfolios NS/B (NB/S) contain stocks not intensively sold (bought) by HFs but intensively bought (sold) by QIXs. Portfolio returns are computed following Edelen et al. (2016). Within each portfolio, stocks are assigned in two size groups – above or below the NYSE size median at the end of the previous year. Then the value-weighted average returns of the swapped stocks within each size group are computed. In the last step, the equal-weighted averages across the two size groups are calculated. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: Performance				
HF/QIX	Risk-Free Excess Ret.	CAPM Alpha	CAPM Beta	DGTW-Adjusted Ret.
NS/B	0.71**	-0.16	1.25***	-0.09
	(1.98)	(-1.23)	(32.63)	(-1.15)
NB/S	0.75**	-0.04	1.13***	0.02
	(2.45)	(-0.33)	(38.98)	(0.25)
NB/S − NS/B	0.04	0.13	-0.13***	0.10
	(0.33)	(1.20)	(-4.46)	(1.09)

Panel B: Risk				
	Standard Deviation of			
	Raw Ret.	Fitted Ret. (CAPM)	Residual (CAPM)	DGTW-Adjusted Ret.
NS/B	5.97	5.40	2.55	1.60
NB/S	5.21	4.85	1.94	1.30
NB/S − NS/B	-0.75**	-0.56*	-0.61***	-0.31***
F-stat	(1.31)	(1.24)	(1.73)	(1.52)

Table 8: DGTW-Adjusted returns: BAB and FMAX effect

This table reports the regression results of monthly DGTW-adjusted returns Daniel et al. (1997) of portfolios of quarterly trading swaps between HFs and QIXs from 1994q2 to 2017q4 on the BAB factor of (Frazzini and Pedersen, 2014) and FMAX factor of Bali et al. (2017). 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 intensively sell (buy); they are denoted by S (B) respectively. Portfolios S/B and B/S contain stocks intensively traded by corresponding investors (HF/QIX) in different directions. Portfolio returns are computed following Edelen et al. (2016). Within each portfolio, stocks are assigned in two size groups – above or below the NYSE size median at the end of the previous year. Then the value-weighted average returns of the swapped stocks within each size group are computed. In the last step, the equal-weighted averages across the two size groups are calculated. Resid_BAB is the residual component from the regression of BAB on FMAX, and Resid_FMAX is the residual component from the regression of FMAX on BAB. *, **, *** 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 parentheses.

HF/QIX	Alpha	BAB	Alpha	FMAX	Alpha	BAB	Resid_FMAX	Alpha	FMAX	Resid_BAB
S/B	-0.03	-0.15**	-0.06	0.16***	-0.03	-0.15**	0.16***	-0.06	0.16***	0.01
	(-0.21)	(-2.11)	(-0.50)	(3.90)	(-0.23)	(-2.59)	(4.59)	(-0.49)	(3.91)	(0.23)
B/S	0.46***	-0.02	0.46***	0.03	0.46***	-0.02	0.05	0.46***	0.03	0.03
	(3.90)	(-0.37)	(3.96)	(0.99)	(3.83)	(-0.38)	(1.64)	(3.88)	(1.00)	(0.60)
B/S − S/B	0.49***	0.13**	0.52***	-0.12***	0.49***	0.13***	-0.11***	0.52***	-0.12***	0.01
	(2.97)	(2.44)	(3.79)	(-4.52)	(3.28)	(2.83)	(-4.74)	(3.77)	(-4.54)	(0.32)

Table 9: DGTW-adjusted returns and FMAX: Funding constraints effect

This table reports the regression results of monthly DGTW-adjusted returns (Daniel et al., 1997) of portfolios of quarterly trading swaps between HFs and QIXs from 1994q2 to 2017q4 on the FMAX factor of Bali et al. (2017) and the aggregate funding constraints measure (AggFC), and indicators variables for months with AggFC above the 50$^{\text{th}}$ percentile ($D_{AggFC>p50}$), the 85$^{\text{th}}$ percentile ($D_{AggFC>p85}$), and the 90$^{\text{th}}$ percentile ($D_{AggFC>p90}$). 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 parentheses.

	HF.S/QIX.B				HF.B/QIX.S			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FMAX	0.16***	0.18***	0.18***	0.18***	0.04	0.05	0.06	0.05
	(4.37)	(5.36)	(4.57)	(4.74)	(1.22)	(1.11)	(1.50)	(1.41)
AggFC	-0.18				-0.07			
	(-1.46)				(-0.70)			
FMAX × AggFC	-0.03				-0.03			
	(-0.93)				(-1.35)			
$\mathrm{D_{AggFC>P50}}$		0.21				0.15		
		(0.84)				(0.65)		
FMAX × $\mathrm{D_{AggFC>P50}}$		-0.03				-0.02		
		(-0.51)				(-0.26)		
$\mathrm{D_{AggFC>P85}}$			-0.52				-0.16	
			(-1.55)				(-0.40)	
FMAX × $\mathrm{D_{AggFC>P85}}$			-0.20**				-0.16**	
			(-2.11)				(-2.33)	
$\mathrm{D_{AggFC>P90}}$				-0.82**				-0.06
				(-2.01)				(-0.12)
FMAX × $\mathrm{D_{AggFC>P90}}$				-0.22**				-0.16**
				(-2.03)				(-2.11)
Constant	-0.07	-0.16	0.00	0.00	0.46***	0.39**	0.47***	0.46***
	(-0.56)	(-1.21)	(0.00)	(0.02)	(3.99)	(2.55)	(3.95)	(4.07)
Observations	285	285	285	285	285	285	285	285
R-squared	0.23	0.22	0.25	0.25	0.03	0.02	0.05	0.05

Table 10: Alternative factors and swapped stocks

This table reports the average characteristics of stocks in the swapped portfolios between HFs and QIXs in different directions from 1994q2 to 2017q4. 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. B/S denotes stocks bought by HFs and sold by QIXs. S/B denotes stocks sold by HFs and bought by QIXs. Stocks are said to have a high characteristic if it is above the 90th percentile, and low if it is below the 10th percentile. All the characteristics are computed based on pre-trade information as of the end of quarter q-1. ILLIQ is the Amihud (2002) illiquidity calculated using one-quarter of daily stock returns; SIZE is the market capitalisation in million USD; MAX is the lottery demand (Bali et al., 2011) calculated as the average values of the five highest daily returns over the previous month for each stock; AlphaPast and BetaPast are the monthly CAPM alpha and beta for each stock estimated using past 48 monthly returns, and IDVOL is the corresponding volatility of residuals; SIR is the short interest ratio over the previous month for each stock; %Firms sold (bought) by distress mutual funds is the fraction of stocks that are intensively sold (bought) by CRSP mutual funds that experience substantial outflow; FracM&A is the fraction of target firms held in the portfolio with the M&A announcements during the trading quarter (q-1 to q) or during the holding quarter (q to q+1). *, **, *** 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 parentheses.

	HF/QIX			
	S/B	B/S	B/S − S/B	t-stat
ILLIQ	0.90	1.24	0.34***	(2.77)
%Firms with high ILLIQ	3.48	4.86	1.38***	(3.68)
%Firms with low ILLIQ	6.71	7.07	0.36	(1.11)
SIZE	1966.75	2169.65	202.89**	(2.54)
%Firms with large SIZE	1.26	1.74	0.47***	(2.70)
%Firms with small SIZE	21.70	26.81	5.11***	(6.45)
MAX	3.73	3.55	-0.18***	(-3.55)
%Firms with high MAX	10.81	9.96	-0.84**	(-2.10)
%Firms with low MAX	7.38	8.59	1.21***	(2.96)
AlphaPast	1.24	0.74	-0.50***	(-10.19)
BetaPast	1.37	1.32	-0.05***	(-3.84)
IDVOL	13.43	12.71	-0.72***	(-5.14)
SIR	9.66	6.82	-2.84	(-1.33)
%Firms with high SIR	13.9	13.66	-0.24	(-0.36)
%Firms with low SIR	5.52	5.87	0.35	(0.69)
%Firms sold by distressed mutual funds	9.12	11.68	2.56***	(4.58)
%Firms bought by distressed mutual funds	10.08	8.52	-1.56***	(-3.94)
%PctM&A (announcement between q-1 to q)	0.68	5.33	4.66***	(12.63)
%PctM&A (announcement between q to q+1)	1.60	2.34	0.75***	(4.80)

Table 11: Swapped portfolio performance controlling for alternative factors

This table reports the differences (Δ) in monthly ex-post CAPM alphas (in % per month) and market betas, and DGTW-adjusted returns (Daniel et al., 1997) between portfolios of stocks intensively bought by HFs and sold by QIXs (HF.B/QIX.S), and those stocks swapped in the opposite direction (FH.S/QIX.B) from 1994q2 to 2017q4. 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). From these portfolios we exclude stocks with various characteristics: (1) if they are high (above 90th percentile), (2) if they are low (below the 10th percentile), and (3) stocks with either high or low value of the characteristic. All the characteristics are computed based on pre-trade information as of the end of quarter q-1. ILLIQ is the Amihud (2002) illiquidity calculated using one-quarter of daily stock returns; SIZE is the market capitalisation in million USD; MAX is the lottery demand (Bali et al., 2011) calculated as the average values of the five highest daily returns over the previous month for each stock; AlphaPast and BetaPast are the monthly CAPM alpha and beta for each stock estimated using past 48 monthly returns, and IDVOL is the corresponding volatility of residuals; SIR is the short interest ratio over the previous month for each stock. "Sold (bought) by distressed mutual funds" are stocks that are intensively sold (bought) by CRSP mutual funds that experience substantial outflow. All target firms involved in M&A with the announcements during quarters q-1, q, or q+1 are excluded ("M&A involved firms"). *, **, *** 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 parentheses.

	HF.B/QIX.S − HF.S/QIX.B		
Excluding Stocks With:	ΔCAPM Alpha	ΔCAPM Beta	ΔDGTW-Adjusted Ret.
High ILLIQ	0.84***	-0.20***	0.60***
	(5.11)	(-3.55)	(4.08)
Low ILLIQ	0.74***	-0.16***	0.52***
	(6.01)	(-4.43)	(4.35)
High or Low ILLIQ	0.75***	-0.16***	0.52***
	(6.07)	(-4.44)	(4.39)
Large SIZE	0.70***	-0.17***	0.48***
	(5.43)	(-4.40)	(3.78)
Small SIZE	0.83***	-0.21***	0.59***
	(5.02)	(-3.57)	(3.93)
Large or Small SIZE	0.70***	-0.18***	0.48***
	(5.29)	(-4.44)	(3.64)
High MAX	0.83***	-0.19***	0.62***
	(5.29)	(-3.33)	(4.58)
Low MAX	0.83***	-0.17***	0.60***
	(4.98)	(-3.01)	(3.89)
High or Low MAX	0.84***	-0.17***	0.63***
	(5.24)	(-2.82)	(4.40)
High AlphaPast	0.77***	-0.18***	0.59***
	(4.39)	(-3.68)	(3.55)
Low AlphaPast	0.81***	-0.21***	0.57***
	(4.94)	(-3.87)	(3.81)
High or Low AlphaPast	0.76***	-0.19***	0.57***
	(4.22)	(-3.93)	(3.35)
High BetaPast	0.74***	-0.18***	0.56***
	(4.33)	(3.27)	(3.77)
Low BetaPast	0.78***	-0.19***	0.53***
	(5.18)	(3.58)	(4.11)
High or Low BetaPast	0.68***	-0.17***	0.49***
	(4.29)	(-3.39)	(3.76)
High IVOL	0.79***	-0.19***	0.57***
	(4.35)	(3.47)	(3.59)
Low IVOL	0.88***	-0.19***	0.65***
	(5.04)	(3.43)	(4.34)
High or Low IVOL	0.83***	-0.18***	0.62***
	(4.19)	(-3.36)	(3.77)
High SIR	0.87***	-0.20***	0.64***
	(5.33)	(-3.62)	(4.41)
Low SIR	0.83***	-0.20***	0.59***
	(5.10)	(-3.54)	(4.04)
High or Low SIR	0.87***	-0.20***	0.64***
	(5.40)	(-3.62)	(4.44)
Sold by distressed mutual funds	0.87***	-0.18***	0.66***
	(4.97)	(-2.93)	(4.14)
Bought by distressed mutual funds	0.87***	-0.21***	0.64***
	(4.83)	(-3.70)	(3.96)
Sold or bought by distressed mutual funds	0.94***	-0.19***	0.73***
	(4.71)	(-2.98)	(4.09)
M&A involved firms (q-1 to q+1)	0.77***	-0.16***	0.54***
	(4.41)	(-2.73)	(3.53)

Table 12: Trading swaps for market anomalies

Panel A of 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 (in % per month) and market betas, and DGTW-adjusted returns (Daniel et al., 1997) for trading-swap on market anomalies portfolios from 1994q3 to 2018q2. We use nine market 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 QIXs. For each market anomaly, we construct four portfolios including stocks swapped in two different directions within the long and the short legs of the anomaly. 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. The final returns are obtained as the averages of the corresponding portfolio returns across the nine anomalies. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 12 lags. t-statistics are reported in parentheses. Panel B reports standard deviations of raw returns, CAPM fitted returns, residuals, and DGTW-adjusted returns. F-statistics for the differences in variances are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: Performance

HF/QIX	Risk-Free Excess Ret.		CAPM Alpha		CAPM Beta		DGTW-Adjusted Ret.	
	Short-Leg	Long-Leg	Short-Leg	Long-Leg	Short-Leg	Long-Leg	Short-Leg	Long-Leg
S/B	0.62	1.12***	-0.53**	0.15	1.45***	1.22***	-0.21	0.21
	(1.31)	(3.20)	(-2.29)	(0.64)	(21.97)	(26.33)	(-1.34)	(1.46)
B/S	1.34***	1.19***	0.34	0.32*	1.26***	1.11***	0.33	0.19**
	(3.30)	(4.37)	(1.17)	(1.93)	(27.76)	(40.97)	(1.46)	(2.06)
B/S − S/B	0.72**	0.07	0.87***	0.16	-0.19***	-0.12**	0.55**	-0.02
	(2.24)	(0.43)	(2.89)	(0.94)	(-2.74)	(-2.54)	(1.99)	(-0.13)

Panel B: Risk

	Standard Deviation of							
	Raw Ret.		Fitted Ret. (CAPM)		Residual (CAPM)		DGTW-Adjusted Ret.	
	Short-Leg	Long-Leg	Short-Leg	Long-Leg	Short-Leg	Long-Leg	Short-Leg	Long-Leg
S/B	6.90	5.86	6.16	5.22	3.12	2.67	2.38	1.93
B/S	6.63	5.30	5.36	4.72	3.88	2.41	3.17	1.98
B/S − S/B	-0.27	-0.56	-0.80**	-0.50	0.76***	-0.26	0.79***	0.04
F-stat	(1.08)	(1.22)	(1.32)	(1.22)	(1.55)	(1.22)	(1.77)	(1.05)

Table 13: Trading swaps: long-term

Panel A of 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 (in % per month) and market betas, and DGTW-adjusted returns (Daniel et al., 1997) for the long-term portfolios of quarterly trading swaps between HFs and QIXs from 1994q2 to 2017q4. The standard errors are adjusted for heteroscedasticity and serial correlation using the Newey-West estimator with 6 lags. t-statistics are reported in parentheses. Panel B reports standard deviations of raw returns, CAPM fitted returns, residuals, and DGTW-adjusted returns. F-statistics for the differences in variances are in parentheses. 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^{th} percentile are considered as those that investors intensively sell (buy); they are denoted by S (B) respectively. Portfolios S/B and B/S contain stocks intensively traded by corresponding investors (HF/QIX) in different directions. Portfolio returns are computed following Edelen et al. (2016). Within each portfolio, stocks are assigned in two size groups – above or below the NYSE size median at the end of the previous year. Then the value-weighted average returns of the swapped stocks within each size group are computed. In the last step, the equal-weighted averages across the two size groups are calculated. *, **, *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: Performance				
HF/QIX	Risk-Free Excess Ret.	CAPM Alpha	CAPM Beta	DGTW-Adjusted Ret.
S/B	0.70*	-0.18	1.33***	-0.02
	(1.89)	(-1.35)	(36.06)	(-0.25)
B/S	1.05***	0.28**	1.17***	0.23***
	(3.29)	(1.99)	(36.73)	(3.08)
B/S − S/B	0.35***	0.45***	-0.16***	0.25***
	(3.87)	(5.09)	(-3.93)	(3.21)

Panel B: Risk				
	Standard Deviation of			
	Raw Ret.	Fitted Ret. (CAPM)	Residual (CAPM)	DGTW-Adjusted Ret.
S/B	6.22	5.72	2.46	1.59
B/S	5.51	5.05	2.21	1.41
B/S − S/B	-0.72**	-0.68**	-0.25*	-0.18**
F-stat	(1.28)	(1.29)	(1.24)	(1.28)