On the Other Side of Hedge Fund Equity Trades

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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 is pronounced for short- and long-term holding periods, as well as if trading is conditional on return predictability associated with well-known market anomalies. It seems to be driven by the preferences of quasi-indexers for liquid, high-market-beta stocks, which tend to exhibit low future abnormal returns. Trading against other institutional investors or non-institutions does not result in abnormal performance for hedge funds.

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), recent studies find comprehensive evidence on the link between HF trading, future stock returns, and mispricing.[1] For example, Cao et al. (2018b) show that HFs tend to hold undervalued stocks and their trading predicts future stock returns and delivers a positive alpha. Cao et al. (2018a) find that HF equity holdings improve efficiency of stock prices. Calluzzo et al. (2019) further show that HFs trade on the well-documented market anomalies and these arbitrage activities generate positive risk-adjusted returns. We join this strand of literature, but instead of looking at the identity of arbitrageurs and quantifying their gains, we focus on the flip side of HF equity trades. We set out to find who the counterparties of these professional arbitrageurs are and what the economic reasons behind their trading decisions might be.

Given that institutional investors hold around 80% (\$18 trillion) of the S&P 500 stocks[2] and account for about 70% of daily trading volume[3], in this paper we mainly focus on potential in-

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

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

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

stitutional counterparties of HFs.[4] To understand the economics of the other side of HF equity trades, we need to recognize the heterogeneous objective functions and trading behaviour of HFs and non-HF investors. One possibility would be that other investors make random errors in their judgements of stock profitability, and HFs exploit these errors. If this is the case, there should not be any specific type of institutions which as a group consistently exhibit "negative skill" when trading in the opposite direction of HFs. Alternatively, there may be groups of investors that do not have an alpha-maximizing objective functions (see, e.g., Baker et al., 2011; Christoffersen and Simutin, 2017). For such investors, forgoing an alpha may be a natural consequence of their optimal trades. Such investors may constitute systematic counterparties of HFs, facilitating their abnormal gains. In this paper, we set out to establish if any type of institutional investors consistently provides HFs with profitable trading opportunities, and if yes, what the economic reasons behind such behaviour might be.

The group of institutional investors is heterogeneous. Passive and active mutual funds, index funds and exchange-traded funds, pension funds and insurance companies all have different objective functions, investment horizons, compensation schemes, and trading strategies. Their trading has been extensively studied in the literature,[5] and all of them can be potential direct or indirect counterparties of HF equity trades. However, even within the same nominal type, the investment behaviour of institutions can be substantially different (Bushee, 2001). In his influential work Bushee (2001) suggests classifying institutions according to their actual trading behaviour, and not according to nominal labelling. Such a "revealed" classification scheme provides more insights into preferences and investment goals of the institutions. In particular, Bushee (2001) subdivides institutions into three big categories, (1) quasi-indexers (QIXs), (2) transient institutions (TRAs), and (3) dedicated holders (DEDs). A quasi-indexer is defined as an institutional investor exhibiting

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

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

high portfolio diversification and low turnover, and also pursuing index-based buy-and-hold strategies. A transient institution also holds a highly-diversified portfolio but has a high turnover, and follows predominantly short-term trading strategies. A dedicated holder invests in concentrated portfolios and has low turnover, focusing on long-term trading strategies with low sensitivity to current firm earnings.[6] For example, Vanguard group is classified as QIX, Fidelity International is TRA, while Apollo Investment Management is classified as DED.

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

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

The beta-over-alpha preferences explain the negative abnormal returns on stock bought by QIXs and simultaneously sold by HFs. When we control for the betting against beta factor of Frazzini and Pedersen (2014), the negative alpha of this portfolio loses significance, as its underperformance

[6] This classification has been also used in, for example, Boone and White (2015); Ke and Ramalingegowda (2005); Cella et al. (2013); Fang et al. (2014); Appel et al. (2016).

in now absorbed by the negative factor loading. The positive abnormal return of stocks bought by HFs and sold by QIXs remains significant even after controlling for the beta preferences of QIXs and stock illiquidity, suggesting some extra stock-picking skills of HFs.

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

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

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

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

2. Research Design

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

Key "suspects" in our investigation of the other side of HF equity trades are QIXs. These institutions may constitute a systematic counterparty of HFs, as they are less likely to have alpha-maximizing objective functions. Instead, they may be more concerned with minimizing the tracking error with respect to their benchmark index, while still trying to beat it. Harris and Gurel (1986) show that when indices adjust their company lists, large index funds frequently buy stocks that are newly added to indices and sell stocks deleted from the indices, leading to substantial demand shifts. Even in the absence of any index adjustment, an important feature of the trading of institutions that face benchmarking is that they tilt their portfolios to high-beta stocks, in order to beat the benchmark. Buffa et al. (2019) develop an equilibrium framework in which choosing higher-beta investments is optimal for a benchmarking manager. Christoffersen and Simutin (2017) empirically show that those mutual funds that have a large share of investment from pension funds and, thus, are more likely to be benchmarked, invest disproportionally into high-beta stocks, and stocks with high market betas tend to have low alphas (Frazzini and Pedersen, 2014). Additionally, QIXs do not seem to closely monitor firms they invest into. They do not have any effect on innovation in firms they hold, while other types of institutional investors have positive association with innovation (Aghion et al., 2013). Another important feature of QIXs is that they tend to prefer more liquid stocks (Gompers and Metrick, 2001), whereas HFs are known for earning high returns by trading

[9] More details are provided in Section 3.

less liquid assets and providing market liquidity (Teo, 2011; Jylhä et al., 2014). These leads to our "swap" hypotheses as follows:

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

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

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

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

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

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

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

and $\mathrm{TSO}_{\mathrm{i,q\text{-}1}}$ is the total number of outstanding shares of firm i at the end of quarter $\mathrm{q}-1$.

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

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

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

Last but not least, we evaluate the performance of these portfolios. We compute monthly average excess returns over the risk-free rate (measured as the 3-month T-bill rate) as well as the abnormal returns (α-s) and market factor loadings (β-s) relative to CAPM model.[12] We then compute the average Amihud (2002) illiquidity measure to check if HFs swap liquid to illiquid stocks with QIXs. Our swap hypotheses imply that the alpha of stocks bought by HFs and simultaneously sold by QIXs should be larger than that of stocks sold by HFs and bought by QIXs, while the relation of their market betas is the opposite. Stocks bought by HFs and sold by QIXs are also expected to be less liquid than stocks sold by HFs and bought by QIXs.

To take into account other stock characteristics that may impact performance in potentially

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

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

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

If the superior HF performance on swapped stocks is indeed driven by the β- and liquidity-swap, one should observe that the abnormal returns of HFs on swap portfolios to disappear after the differences in stock betas and liquidity are accounted for. In doing so, we use the betting against beta factor (hereafter BAB) of Frazzini and Pedersen (2014),[13] who find that high-beta assets earn low alphas due to funding constraints, and the traded liquidity factor (hereafter LIQ) of Pástor and Stambaugh (2003), who show that liquidity risk is an important determinant of HF returns.[14] We evaluate the alphas from the regressions of the DGTW-adjusted excess returns of the swapped portfolios on these two factors.

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

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

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

3. Data Sources and Sample Construction

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

Our data on institutional holding are from the Thomson Reuters Institutional (13f) Holding database (CDA/Spectrum s34). The 13f mandatory reports of institutional holding are filed with the Securities and Exchange Commission (SEC) and are compiled by Thomson Reuters. According to the 1978 amendment to the Securities and Exchange Act of 1934, institutions with aggregate fair market values over $100 million must file their forms within 45 days after the end of a calendar quarter. The managers are allowed to omit their "small" holding (if they hold fewer than 10,000 shares and less than $200,000 in terms of their market values). Thus, most of the disclosed holding data come from relatively large positions of large firms.

To identify HFs, we use a union of three major HF databases – EurekaHedge, TASS Lipper, and Morningstar – for the period from 1994 to 2017.[16] We merge the databases following the procedure described in Joenväärä et al. (2016). We then create a list of HFs' 13f identifiers, i.e. manager numbers (hereafter MGRNOs), by matching the HF company name and the names of the institution reporting to the 13f database. We manually check that the identified companies

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

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

do not have any other business (e.g., a mutual fund, insurance, banking etc.), ensuring that we obtain a list of pure HF companies. Altogether, we identify 734 HF companies that report to the 13f databases. Next, we use Brian Bushee's database[17] to identify 2,906 QIXs, 1,448 TRAs and 161 DEDs for our sample. We consider only those institutions which have a unique identifier of permanent classification provided in the Bushee's database. We remove institutions without a permanent classification or those with several permanent classifications. Overall, the 5,278 institutions in our final sample cover 74.92% of all institutions from the database existing between 1994 and 2017. As of the end of 2017, the overall portfolio size of QIXs was $9.72 trillion, whereas it was $2.83 trillion for TRAs, $0.29 trillion for DEDs, and $1.59 trillion for HFs.

[Place Table 1 about here]

Panel B of Table 1 reports the descriptive statistics of the institutional portfolios. The largest group of institutions are QIXs, with on overage 1,352 institutions reporting holding per quarter compared to 319 HFs. The smallest group is DEDs with only 69 institutions reporting per quarter, on average. QIXs are also the most diversified institutions, holding on average 170 different stocks in a quarter, followed by TRAs with 166 stocks per quarter, compared to 118 of HFs and only 52 of DEDs. QIXs have the smallest turnover, on average 6.57% per quarter, compared to over 22.04% per quarter for HFs and 23.73% for TRAs. Turnover for quarter q is calculated as the minimum of purchases and sales during quarter q, divided by the average market value of the portfolio at the end of quarter q and the previous quarter.

Table 2 reports the descriptive statistics of the holding and the change in holding of all types of investors in our sample across three periods: the pre-crisis period 1994q2 to 2007q2, the crisis period 2007q3-2009q1, and the post-crisis period 2009q2-2017q4. The changes in holdings are winsorized at the 1% and 99% quantiles.[18] The descriptive statistics of the holdings are broadly similar to those reported in Jiao et al. (2016). QIXs hold a substantial share of the market. Their average holdings of shares in listed non-financial and non-utility companies have increased from

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

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

29% in the pre-crisis period to around 40% in the later periods. The average holdings of HFs and TRAs in these firms also have increased from 6% and almost 10% pre-crises to 10% and nearly 14% in the later sample, respectively. DEDs hold below 2% of the stocks in all the sub-samples. Before the crisis, QIXs had the largest average changes in the position of 0.87% per quarter, compared to 0.30% for HFs, 0.28% for TRAs, and 0.04% for DEDs. During the crisis period, QIXs kept purchasing stocks on average, although at a slower pace (the average change of 0.40%), while HFs as a group kept their holdings largely unchanged (the average change of 0.02%), and TRAs and DEDs have been selling stocks on average (the corresponding change are -0.30% and -0.20% respectively). Post-crisis, TRAs, QIXs, and HFs are net buyers in the stock market, with the average changes of 0.33%, 0.30%, and 0.15%, while DEDs are net sellers (the average change in holdings of -0.11%). Given how few DEDs exist per quarter, the small share of their holding, and a particular investment style of long-term holding of concentrated portfolios, we exclude these institutions from the further analysis.

[Place Table 2 about here]

4. Empirical Results

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

Panel A of Table 3 reports the excess returns over the risk-free rate, the CAPM alphas and betas[19], and Amihud illiquidity measures for stocks swapped between HFs and other types of investors.

Consistent with our expectations, the stocks sold by HFs and simultaneously bought by QIXs exhibit negative future alphas of -0.35% per month, have high beta of 1.34, and are more liquid (Amihud illiquidity of 0.70×10^{-6}), compared to stocks bought by HFs and sold by QIXs. The latter exhibit a positive alpha of 0.57% per month, have smaller beta of 1.10, and higher illiquidity (1.10×10^{-6}), with all the differences being highly statistically significant. In contrast, stocks swapped

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

between HFs and TRAs do not exhibit any statistically significant alphas in either direction. The differences between betas and illiquidity measures are not significant, either. Stocks sold by HFs and purchased by OTHs exhibit significantly negative alpha with respect to the CAPM, but no difference in beta or illiquidity can be seen for stocks swapped in different directions between HFs and OTHs.

Even after controlling for other factors via DGTW-adjusted returns (Panel B of Table 3), the excess return of stocks sold by HFs and purchased by QIXs remains negative of -0.19% per month and significant at the 10% level, whereas the DGTW-adjusted excess return of stocks bought by HFs and sold by QIXs is 0.50% per month, significant at the 1% level. The swaps between HFs and TRAs or OTHs do not generate any significant adjusted returns.

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

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

[Place Table 3 around here]

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

The beta-over-alpha preferences discussed above can be seen for all three types of QIXs (Table 4). The worst performance in terms of the abnormal returns seems to be generated by BNKs. The CAPM alpha spread between the portfolio of stocks bought by HFs and sold by BNKs, and sold by HFs while purchased by BNKs is 1.15% per month. The corresponding difference in the DGTW-adjusted excess returns is 0.88% per month. It is 0.59% for IIAs and 0.58% for OTQIXs. All the differences are significant at the 1% level. The difference in CAPM betas is the strongest for IIAs of -0.36, significant at the 1% level. It is substantially larger than -0.24 reported in Table 3 for all QIXs.

[Place Table 4 around here]

An alternative explanation for the significant ex-post alphas associated with HF/QIX swaps may be position reversals by QIXs and/or herding by investors after HF trades. If various investors sell a substantial amount of the stocks that have been bought by QIXs but sold by HFs during the previous quarter, the selling pressure would reduce the abnormal returns. The abnormal returns would increase if investors follow previous HF purchases. To check if such a mechanism is supported by the data, we compute the average change in holdings of HF/QIX swapped stocks during each quarter and the average quarterly change in holdings of HFs and non-HF investors of these stocks during the subsequent quarter (Table 5). During trading quarters, the change in holding of HFs is smaller in absolute value than the corresponding change in holdings of QIXs. HFs do not seem to fully exploit potential arbitrage opportunities, which may be due to the relatively small total size of the HF industry as compared to the overall market value. We find no evidence of substantial trade reversals or herding, however. QIXs, moreover, tend to keep buying during quarter q+1 stocks they purchased during the previous quarter and that were sold by HFs. On the HF buying side, HFs and TRAs increase their holdings in stocks swapped between HFs and QIXs, but these changes are small (0.33% and 0.35% respectively) as compared to the initial HF purchase size of 3.43%. Thus, we cannot find empirical support for trade reversals of QIXs or institutional herding into swapped stocks, which can lead to the observed abnormal return patterns.

[Place Table 5 about here]

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

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

The difference in CAPM alpha between stocks sold by HFs/bought by QIXs, and those bought by HFs/sold by QIXs is persistent across all three periods (Table 6). In the pre-crisis and crisis periods, HFs were gaining significantly by buying future winners. The effect is especially strong during the crisis period, where the ex-post alpha of stocks bought by HFs and sold by QIXs relative to the CAPM reaches 1.92% per month. During the post-crisis period, the performance differences are generated predominantly by HFs selling future losers. As for market betas, QIXs have been buying especially high-beta stocks during the pre-crisis periods, but not during the crisis, when the difference in betas between stock sold by HFs/bought by QIXs, and those bought by HFs/sold by QIXs is not statistically significant. This result is consistent with the intuition that QIXs tilt their portfolios towards high-beta stocks when trying to beat the benchmark. This strategy works, however, only as long as the benchmark has a positive expected return. During the crisis period the market returns were negative, and retreating from high-beta stocks was optimal for benchmarked institutions.

Similar pattern is observed when DGTW-adjusted returns are used (Table 7). The largest spread between two swapped portfolios (in terms of the DGTW-adjusted returns and their alphas relative to LIQ and BAB factors) is generated during the crisis period. In the post-crisis period, although stocks bought by HFs and simultaneously sold by QIXs still significantly outperform those sold by HFs/bought by QIXs, the magnitude of the difference is only about one third of that during the crisis period.

[Place Tables 6 and 7 around here]

Figure 1 further plots the time series of alphas and market betas relative to the CAPM for stocks swapped between HFs and other investors estimated using three-year rolling windows. The alphas of stocks bought by HFs/sold by QIXs are almost always positive and above those sold by HFs/bought by QIXs, which are in most cases negative. The betas of the stocks purchased by HFs, on the other hand, are almost always smaller than those of sold stocks, apart from the crisis period, consistent with the previous discussion. As for the swaps between HFs and other investors, no persistent difference can be seen for either alphas or market betas over time.

[Place Figure 1 about here]

Long-term performance of the swapped stocks (Table 8) reveals that the alpha losses of QIXs that buy stocks which are sold by HFs are predominantly associated with the short-term performance over the first quarter, and the losses are not statistically significant over the annual horizon. It turns almost zero when LIQ and BAB are taken into account with DGTW-adjusted returns. At the same time, the gains which HFs make by purchasing stocks sold by QIXs remain positive and statistically significant even on the annual horizon, although their magnitude decreases. This findings is consistent with HFs being shorter-term investors with high turnover, capitalising predominantly on their skills to predict short-term returns (see Agarwal and Naik, 2000; Edwards and Caglayan, 2001; Jagannathan et al., 2010, among others). The difference in market betas and in loadings on the BAB factor remains statistically significant, with HFs selling/QIXs buying high-beta stocks, and this swap portfolio having a significantly negative exposure to the BAB factor. No statistical difference can be found for other counterparties of HFs.

[Place Table 8 around here]

4.3. Implications for market anomalies

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

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

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

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

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

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

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

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

Panel A of Table 9 reports the descriptive statistics of the firm performance measures, related to the nine market anomalies in our sample. All of the anomaly measures are winsorized at the 1% and 99% levels. Panel B of Table 9 reports the CAPM alphas for portfolios sorted on each of the nine anomalies under study and the equal-weighted portfolio of nine anomaly portfolios (EW-Avg); Panel C reports the corresponding DGTW-adjusted excess returns. The results substantiate the existence of these anomalies in our sample, with the GP and NOA anomalies being the most pronounced. By investing in the corresponding long-short portfolios investors can obtain up to 0.65% per month in terms of abnormal returns relative to the CAPM, and 0.56% per month in terms of DGTW-adjusted returns, both signifiant at the 1% level (the NOA anomaly).

[Place Table 9 about here]

Table 10 reports CAPM alphas, betas, and liquidity for swapped stocks related to the equal-weighted combination of the market anomalies under consideration during the entire holding period, and Table 11 reports the DGTW-adjusted excess returns (Daniel et al., 1997), corresponding ex-post 2-factor alphas, and factor loadings. Swaps in which HFs sell/QIXs buy overpriced stocks deliver a significantly negative alpha of -0.46% per month, while swaps in which HFs buy/QIXs sell underpriced stocks exhibit a positive alpha of 0.51% per month. The differences in alphas of stocks bought by HFs/sold by QIXs and sold by HFs/bought by QIXs are positive and highly statistically significant for both short leg and long leg of market anomalies. In terms of market betas in each sub-group of stocks (overpriced/underpriced relative to market anomalies), QIXs buy stocks with significantly higher market betas than those of stocks they sell. Swaps between HFs and other types of investors do not exhibit such patterns in either alpha or beta.

Similar to our main results, the negative abnormal returns of swapped stock in the short leg

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

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

[Place Tables 10 and 11 about here]

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

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

5. Conclusion

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

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

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

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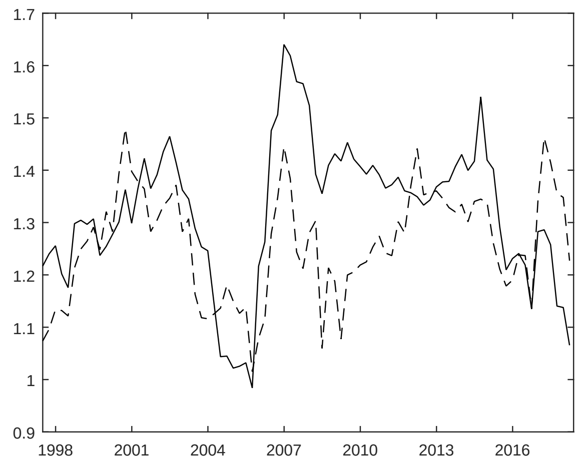
Figure 1: Time series of alphas and market betas for trading swaps

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

(i) HF/QIX Swap: α

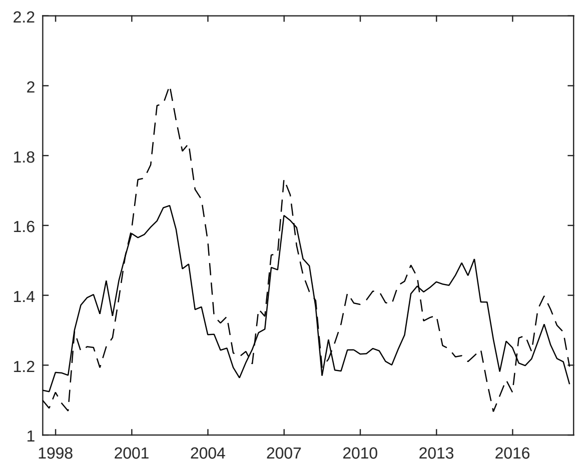
(ii) HF/QIX Swap: β

(iii) HF/TRA Swap: α



(iv) HF/TRA Swap: β

(v) HF/OTH Swap: α



(vi) HF/OTH Swap: β

Table 1: Descriptive statistics: stocks traded and portfolios

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

Panel A: Characteristics of Stocks Traded

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

Panel B: Portfolio Charactistics of Different Groups of Institutional Investors

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

Table 2: Descriptive statistics: ownership and trading of different groups of investors

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

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

	Mean	Std.Dev	P5	P25	Median	P75	P95
StockHold^{HF} (% per quarter)	6.04	6.50	0.00	0.61	4.17	9.36	18.61
StockHold^{QIX} (% per quarter)	29.18	17.78	2.76	13.99	28.55	42.85	58.92
StockHold^{TRA} (% per quarter)	9.89	8.96	0.00	2.87	7.71	14.55	27.45
StockHold^{DED} (% per quarter)	1.94	4.68	0.00	0.00	0.03	1.61	10.25
StockHold^{OTH} (% per quarter)	52.29	26.09	11.35	30.95	51.57	74.16	94.03
$\Delta\text{StockHold}^{HF}$ (% per quarter)	0.30	2.36	-3.30	-0.61	0.10	1.09	4.40
$\Delta\text{StockHold}^{QIX}$ (% per quarter)	0.87	4.28	-5.73	-1.15	0.44	2.70	8.45
$\Delta\text{StockHold}^{TRA}$ (% per quarter)	0.28	3.61	-5.43	-1.12	0.06	1.49	6.65
$\Delta\text{StockHold}^{DED}$ (% per quarter)	0.04	1.35	-1.72	-0.07	0.00	0.10	2.02
$\Delta\text{StockHold}^{OTH}$ (% per quarter)	-0.07	6.51	-10.10	-2.92	-0.26	2.18	10.84

Panel B: Crisis (2007q3-2009q1)

	Mean	Std.Dev	P5	P25	Median	P75	P95
StockHold^{HF} (% per quarter)	10.89	7.85	0.54	5.25	9.45	15.11	25.60
StockHold^{QIX} (% per quarter)	40.49	19.77	5.28	25.41	43.13	55.77	69.79
StockHold^{TRA} (% per quarter)	12.63	8.50	0.82	6.30	11.49	17.65	28.15
StockHold^{DED} (% per quarter)	1.72	5.06	0.00	0.00	0.00	0.22	10.54
StockHold^{OTH} (% per quarter)	33.08	25.84	1.22	12.18	25.93	50.15	85.01
$\Delta\text{StockHold}^{HF}$ (% per quarter)	0.02	2.55	-4.16	-1.14	-0.02	1.06	4.36
$\Delta\text{StockHold}^{QIX}$ (% per quarter)	0.40	4.36	-6.66	-1.69	0.21	2.36	8.12
$\Delta\text{StockHold}^{TRA}$ (% per quarter)	-0.30	3.54	-6.27	-1.87	-0.18	1.19	5.56
$\Delta\text{StockHold}^{DED}$ (% per quarter)	-0.20	1.81	-3.80	-0.21	-0.01	0.04	2.34
$\Delta\text{StockHold}^{OTH}$ (% per quarter)	0.59	5.54	-7.88	-1.91	0.27	2.87	9.53

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

	Mean	Std.Dev	P5	P25	Median	P75	P95
StockHold^{HF} (% per quarter)	10.51	7.56	0.42	5.17	9.26	14.47	24.45
StockHold^{QIX} (% per quarter)	40.08	19.52	2.25	26.03	44.13	55.03	67.04
StockHold^{TRA} (% per quarter)	13.79	8.20	0.11	7.92	13.81	19.28	27.36
StockHold^{DED} (% per quarter)	1.33	5.25	0.00	0.00	0.00	0.01	8.27
StockHold^{OTH} (% per quarter)	33.26	27.33	2.87	12.18	24.24	48.59	94.07
$\Delta\text{StockHold}^{HF}$ (% per quarter)	0.15	2.24	-3.17	-0.78	0.01	0.89	3.99
$\Delta\text{StockHold}^{QIX}$ (% per quarter)	0.30	3.55	-5.03	-1.21	0.10	1.67	6.06
$\Delta\text{StockHold}^{TRA}$ (% per quarter)	0.33	2.99	-4.18	-0.91	0.07	1.39	5.67
$\Delta\text{StockHold}^{DED}$ (% per quarter)	-0.11	1.45	-2.34	-0.10	0.00	0.04	1.52
$\Delta\text{StockHold}^{OTH}$ (% per quarter)	-0.05	4.64	-6.74	-1.77	-0.07	1.49	6.37

Table 3: Trading swaps and possible counterparties of hedge fund trades

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

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

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

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

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

Table 4: Trading swaps: QIXs sub-groups

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

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

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX
S/B	0.60	0.42	0.67	-0.37**	-0.52**	-0.29	1.39***	1.35***	1.37***	0.74***	0.43***	0.51***
	(1.47)	(0.97)	(1.58)	(-2.12)	(-2.40)	(-1.46)	(23.09)	(20.68)	(21.62)	(6.48)	(5.29)	(5.29)
B/S	1.38***	1.38***	1.30***	0.66***	0.63***	0.47**	1.03***	1.08***	1.18***	1.10***	0.70***	0.78***
	(4.80)	(4.53)	(3.76)	(2.85)	(2.71)	(2.24)	(24.33)	(25.13)	(28.05)	(5.49)	(5.43)	(5.35)
B/ S− S/B	0.78***	0.96***	0.62**	1.04***	1.15***	0.76***	-0.36***	-0.26***	-0.19***	0.36**	0.27***	0.26*
	(3.26)	(3.41)	(2.47)	(5.04)	(4.37)	(3.11)	(-5.05)	(-3.04)	(-2.75)	(2.55)	(3.01)	(1.92)

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

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX	HF/IIA	HF/BNK	HF/OTQIX
S/B	-0.17	-0.34*	-0.10	-0.06	-0.23	0.00	0.09	0.12*	0.12	-0.20***	-0.22**	-0.19**
	(-1.07)	(-1.86)	(-0.66)	(-0.33)	(-1.10)	(-0.00)	(1.58)	(1.69)	(1.55)	(-2.82)	(-2.28)	(-2.43)
B/S	0.41***	0.54***	0.48***	0.39***	0.52***	0.49***	0.08***	0.09**	0.12**	-0.02	-0.03	-0.07
	(2.71)	(3.65)	(2.95)	(2.62)	(3.74)	(2.75)	(2.89)	(2.27)	(2.22)	(-0.28)	(-0.64)	(-1.49)
B/S − S/B	0.59***	0.88***	0.58***	0.45**	0.74***	0.49**	-0.01	-0.03	0.00	0.18***	0.19*	0.12**
	(2.90)	(3.73)	(2.87)	(2.04)	(2.89)	(2.45)	(-0.12)	(-0.42)	(0.04)	(2.95)	(1.80)	(1.99)

Table 5: Average change in holdings of trading-swap stocks

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

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

Table 6: Impact of financial crisis on trading swaps: risk-free excess return, alpha, market beta, and Amihud illiquidity

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

	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
Panel A: Pre-Crisis (1994q2-2007q2)												
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	0.64	0.92**	0.48	-0.33	0.06	-0.55**	1.43***	1.25***	1.50***	0.83***	0.67***	1.20***
	(1.34)	(2.11)	(1.02)	(-1.41)	(0.23)	(-2.51)	(17.02)	(18.10)	(15.81)	(5.87)	(6.52)	(7.95)
B/S	1.43***	0.92**	0.98*	0.68**	0.03	0.03	1.10***	1.29***	1.38***	1.39***	0.86***	1.14***
	(3.75)	(2.17)	(1.90)	(2.14)	(0.12)	(0.11)	(18.03)	(19.79)	(20.93)	(5.69)	(5.50)	(6.81)
B/S − S/B	0.79**	0.00	0.50*	1.01***	-0.03	0.58*	-0.33***	0.04	-0.12*	0.56***	0.19**	-0.06
	(2.49)	(-0.01)	(1.69)	(3.47)	(-0.14)	(1.97)	(-3.39)	(0.68)	(-1.80)	(4.06)	(2.19)	(-0.64)
Panel B: Crisis (2007q3-2009q1)												
	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-2.52	-1.68	-0.68	-0.06	0.71*	1.95**	1.24***	1.21***	1.33***	0.38***	0.33***	1.03***
	(-1.08)	(-0.80)	(-0.28)	(-0.15)	(1.90)	(2.37)	(29.77)	(24.08)	(24.31)	(5.42)	(3.38)	(3.11)
B/S	-0.40	-1.25	-1.01	1.92***	1.54***	1.41***	1.17***	1.41***	1.22***	0.48***	0.78***	1.13***
	(-0.21)	(-0.51)	(-0.49)	(6.35)	(4.02)	(3.78)	(41.40)	(31.24)	(45.77)	(4.85)	(3.92)	(3.24)
B/S − S/B	2.12***	0.43	-0.33	1.98***	0.83**	-0.54	-0.07	0.20***	-0.11*	0.10	0.45*	0.10
	(3.55)	(1.01)	(-0.50)	(4.25)	(2.85)	(-0.86)	(-1.31)	(2.89)	(-2.05)	(0.69)	(2.07)	(0.24)
Panel C: Post-Crisis (2009q2-2017q4)												
	Risk-Free Excess Returns (%)			CAPM Alphas (%)			CAPM Betas			Amihud Illiquidity ($\times 10^{-6}$)		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	1.11**	1.36***	1.09***	-0.44**	-0.24	-0.45***	1.24***	1.27***	1.22***	0.58***	0.53***	0.94***
	(2.49)	(3.18)	(2.63)	(-2.05)	(-1.39)	(-3.02)	(20.36)	(23.11)	(23.10)	(3.72)	(4.41)	(4.76)
B/S	1.54***	1.49***	1.54***	0.14	-0.08	-0.03	1.12***	1.26***	1.25***	0.79***	0.56***	1.12***
	(4.04)	(3.62)	(3.58)	(0.83)	(-0.38)	(-0.15)	(19.67)	(19.21)	(15.99)	(3.41)	(3.06)	(5.87)
B/S − S/B	0.43***	0.14	0.45***	0.58***	0.16	0.41**	-0.13**	-0.02	0.03	0.21	0.04	0.18
	(3.03)	(0.84)	(2.71)	(3.62)	(0.92)	(2.03)	(-2.47)	(-0.34)	(0.45)	(0.80)	(0.16)	(0.65)

Table 7: Impact of financial crisis on trading swaps: DGTW-adjusted excess return, 2-factor alpha, and factor loading

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

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

Table 8: Trading swaps: long-term

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

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

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

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

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

Table 9: Market anomalies: descriptive statistics and portfolio performance

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

Panel A: Descriptive Statistics of Market Anomalies

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

Panel B: CAPM Alphas of Anomaly Portfolios

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

Panel C: DGTW-Adjusted Excess Returns of Anomaly Portfolios

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

Table 10: Trading swaps for market anomalies: risk-free excess return, alpha, market beta, and Amihud illiquidity

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

Panel A: HF/QIX Swap

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

Panel B: HF/TRA Swap

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

Panel C: HF/OTH Swap

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

Table 11: Trading swaps for market anomalies: DGTW-adjusted excess return, 2-factor alpha, and factor loading

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

Panel A: HF/QIX Swap

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	-0.24	0.39	0.63*	-0.21	0.37	0.58*	0.03	0.29***	0.26***	-0.06	-0.13	-0.07
	(-1.51)	(1.47)	(1.95)	(-1.20)	(1.24)	(1.82)	(0.41)	(2.81)	(2.93)	(-0.86)	(-0.79)	(-0.62)
Long Leg	0.11	0.39***	0.28*	0.14	0.34***	0.20	0.06	0.00	-0.06*	-0.08	0.07	0.15**
	(0.68)	(3.45)	(1.69)	(0.83)	(2.97)	(1.17)	(1.35)	(-0.02)	(-1.69)	(-1.19)	(0.83)	(2.39)
Long − Short	0.35*	0.00	-0.35	0.35*	-0.03	-0.38	0.03	-0.29***	-0.32***	-0.02	0.20*	0.22*
	(1.89)	(-0.00)	(-1.04)	(1.93)	(-0.13)	(-1.14)	(0.64)	(-3.26)	(-3.61)	(-0.53)	(1.76)	(1.88)

Panel B: HF/TRA Swap

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	0.07	-0.01	-0.08	0.02	0.17	0.16	0.05	0.13	0.08	0.05	-0.34*	-0.39***
	(0.37)	(-0.03)	(-0.40)	(0.07)	(0.63)	(0.82)	(0.60)	(1.24)	(1.01)	(0.37)	(-1.71)	(-2.83)
Long Leg	0.12	0.39**	0.27	0.07	0.50***	0.43**	0.05	0.06	0.02	0.05	-0.19**	-0.24*
	(0.67)	(2.30)	(1.31)	(0.41)	(2.68)	(2.18)	(0.92)	(1.26)	(0.27)	(0.44)	(-2.17)	(-1.77)
Long − Short	0.05	0.40**	0.35	0.05	0.32	0.27	-0.01	-0.07	-0.06	0.00	0.15	0.15
	(0.25)	(2.08)	(1.57)	(0.26)	(1.47)	(1.26)	(-0.09)	(-0.70)	(-0.78)	(-0.03)	(1.10)	(1.52)

Panel C: HF/OTH Swap

	DGTW-Adjusted Excess Returns (%)			2-Factor Alphas (%)			Factor Loadings on LIQ			Factor Loadings on BAB		
	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B	S/B	B/S	B/S − S/B
Short Leg	-0.27	0.16	0.43	-0.15	0.24	0.39	0.03	0.15*	0.12	-0.20***	-0.21	-0.01
	(-1.22)	(0.75)	(1.58)	(-0.73)	(1.00)	(1.24)	(0.56)	(1.68)	(1.11)	(-2.95)	(-1.31)	(-0.05)
Long Leg	-0.01	0.31**	0.32	0.11	0.34*	0.23	0.01	0.08	0.08	-0.18***	-0.08	0.10
	(-0.08)	(2.12)	(1.55)	(0.81)	(1.83)	(0.96)	(0.21)	(1.28)	(0.91)	(-3.34)	(-0.57)	(0.79)
Long − Short	0.26	0.16	-0.11	0.26	0.09	-0.16	-0.03	-0.07	-0.04	0.02	0.13	0.11
	(1.60)	(0.87)	(-0.58)	(1.65)	(0.58)	(-0.78)	(-0.55)	(-1.32)	(-0.74)	(0.38)	(1.46)	(1.21)

On the Other Side of Hedge Fund Equity Trades

SUPPLEMENTARY RESULTS

August 5, 2020

Table A1: Trading swaps and possible counterparties of hedge fund trades: different models

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

Panel A: Fama-French 3-Factor Alphas and Market Betas

	3-Factor Alphas			3-Factor Market Betas		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.32***	0.04	-0.30**	1.20***	1.12***	1.27***
	(-3.15)	(0.31)	(-2.00)	(37.01)	(37.02)	(26.60)
B/S	0.53***	0.05	0.17	1.04***	1.21***	1.15***
	(3.46)	(0.38)	(1.38)	(30.80)	(33.95)	(33.60)
B/S − S/B	0.86***	0.01	0.47**	-0.17***	0.09**	-0.11**
	(4.94)	(0.10)	(2.46)	(-3.88)	(2.29)	(-2.18)

Panel B: Carhart 4-Factor Alphas and Market Betas

	4-Factor Alphas			4-Factor Market Betas		
	HF/QIX	HF/TRA	HF/OTH	HF/QIX	HF/TRA	HF/OTH
S/B	-0.26**	0.01	-0.13	1.17***	1.14***	1.18***
	(-2.29)	(0.08)	(-0.92)	(39.33)	(38.55)	(23.57)
B/S	0.64***	0.19	0.13	0.98***	1.14***	1.18***
	(4.27)	(1.40)	(1.01)	(28.38)	(31.04)	(31.10)
B/S − S/B	0.91***	0.18	0.26	-0.19***	0.01	-0.01
	(5.02)	(1.23)	(1.38)	(-4.53)	(0.18)	(-0.13)

Table A2: Trading swaps and possible counterparties of hedge fund trades: 10% cutoff

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

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

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

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

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

Table A3: Trading swaps and possible counterparties of hedge fund trades: 30% cutoff

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

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

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

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

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

Table A4: Market anomalies: description

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

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

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