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How Skilled are Hedge Funds? Evidence from their Daily Trades

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Abstract

We examine the trading skill of hedge funds using transaction-level data. After accounting for trading commissions, we find no evidence that the trades of the average hedge fund outperform across holding periods ranging from one month to one year. However, bootstrap simulations indicate that the trading skill of the top 10% of hedge funds cannot be explained by luck. Similarly, we find that the performance of top hedge funds persists and much of this persistence stems from intra-quarter trading skill. Skilled hedge funds tend to be short-term contrarians and their profits are largely concentrated in smaller, more illiquid stocks. Our findings suggest that while the average hedge fund is unskilled, there are a small minority of skilled funds who persistently create value through liquidity provision.

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1. Introduction

The hedge fund industry has grown from $38 billion in 1990 to over $2 trillion in 2012.[1] Presumably, much of this growth is driven by investors' faith in hedge funds' ability to generate abnormal returns via informed trading. The belief that hedge fund trading is informed seems plausible, particularly when the structure of the hedge fund industry is compared to other institutional investors. Unlike most institutional investors, hedge funds have no restrictions on short-selling or the use of leverage, and are free to take highly concentrated positions. Moreover, in contrast to mutual funds who are required to provide daily liquidity and satisfy investor redemption requests within 7 days, hedge funds often have lock-up periods of several years. Lastly, it is commonly believed that the higher incentives and fewer investment restrictions have resulted in many top managers leaving the mutual fund industry for the hedge fund industry. For example, Mario Gabelli, a top mutual fund executive, admitted, "The brain drain to hedge funds from the traditional money management industry is real."[2]

Despite the above reasoning, empirical evidence of hedge fund skill is inconclusive. Most studies using commercial databases estimate hedge fund annual alphas in the range of 3-5%[3], although a few studies find no evidence of hedge fund skill.[4] Evidence on performance persistence, particularly over longer horizons, is also mixed.[5] The varied results are at least partially attributable to challenges inherent in estimating hedge fund performance from

[1] "Hedge-fund assets rise to record level", Juliet Chung (The Wall Street Journal), April 19, 2012. http://online.wsj.com/article/SB10001424052702304331204577354043852093400.html?mod=googlenews_wsj

[2] "Brain Drain to Hedge Funds for Real - Gabelli", Herbert Lash (Reuters), September 7, 2005. http://www.reuters.com/article/2005/09/07/specialeventiii-financial-summit-gabelli-idUSHAR76019620050907

[3] Such studies include Ibbotson, Chen, and Zhu (2011), Agarwal, Daniel, and Naik (2011), Kosowski, Naik, and Teo (2007), and Fung et al. (2008).

[4] See, for example, Asness, Krail and Liew (2001), Amin and Kat (2003) and Dichev and Yu (2011).

[5] Brown, Goetzmann, and Ibottson (1999) find little evidence of persistence and Agarwal and Naik and Liang (2000) find persistence is limited to quarterly horizons. Kosowski, Naik, and Teo (2007) and Jaganathan, Malakhov, and Novokov (2010) find performance persists for up to one year and three years, respectively.

commercial databases. First, reported returns for the same hedge fund may vary across different datasets (Liang 2000, 2003) or across different vintages of the same dataset (Patton, Ramadorai, and Streatfield, 2012). In addition, the databases suffer from a number of biases including self-selected reporting, survivorship bias, backfilling bias, and smoothing bias.[6] Lastly, hedge fund payoffs are option-like, and hence, traditional linear factor models may do a poor job measuring alpha (Fund and Hsieh, 2001).

To circumvent these challenges, Griffin and Xu (2009) use 13F filings to analyze the quarterly holdings of hedge funds. They find little evidence that the equity trades (or holdings) of hedge funds generate abnormal returns, either in absolute terms or relative to mutual funds. They also find no significant evidence of performance persistence. Their findings point to the possibility that the significant differences in incentives, flexibility, and possibly talent, do not translate into meaningful differences in the information content of equity trading. However, there are several limitations of 13F holdings which may significantly understate hedge fund skill. First, changes in quarterly holdings do not capture intra-quarter roundtrip trades. Second, quarterly holdings do not identify the exact timing or execution price of trades. Lastly, quarterly holdings do not report all of a fund's holdings, including short positions and confidential 13F filings.

The purpose of this paper is to obtain a better understanding of hedge fund skill by examining the daily equity trades of hedge funds and other institutional investors from 1999-2010. Our analysis relies on daily transaction data provided by ANcerno Ltd, an execution cost consulting firm. The data include the name of the institution, which allows us to distinguish hedge funds from other institutions. Although the data only contain a subset of institutions, it

[6] See e.g. Aiken, Clifford, and Ellis (2012), Ackerman, McEnally, and Ravenscraft (1999), Brown, Goetzman, and Ibbotson (1999), Fund and Hsieh (2000), Liang (2000), Getmansky, Lo, and Makarov (2004), and Bollen and Pool (2008).

contains all the trades for that subset. Unlike commercial databases, ANcerno does not suffer from survivorship bias or backfill bias. Moreover, since ANcerno is not a marketing tool aimed at attracting new investors, performance-related self-selection biases are likely less severe. Lastly, the data contain the exact date and execution price of each trade, which allows for more powerful tests of trading skill than quarterly holdings (e.g. Puckett and Yan (2011)).

We estimate hedge fund performance by computing calendar-time transaction portfolios (see e.g. Seasholes and Zhu (2010)) with holding periods ranging from 21 days to 252 days. We also estimate intra-quarter trading skill (as defined in Puckett and Yan (2011)). We find no evidence that the trades of hedge funds earn abnormal returns across horizons ranging from one quarter to one year. We find some evidence that hedge fund trading is profitable over a one month holding period and also find weak evidence of intra-quarter trading skill. However, these profits do not survive after taking into account trading commissions.

Although the average hedge fund does not outperform, it is still possible that some hedge funds are skilled. Using bootstrap simulations, we find that the one-year trading performance of the top 10% of hedge funds cannot be attributed to sample variability or luck alone. Moreover, these results are robust to the inclusion of commissions. In contrast, there is no evidence that any non hedge fund institutions are truly skilled.

We next explore performance persistence. We sort funds into quintiles based on their intra-quarter trading performance over the prior quarter and track their intra-quarter performance over the subsequent two years. Consistent with Puckett and Yan (2011), we find that all institutions exhibit significant persistence in intra-quarter trading skill. However, the magnitudes are substantially stronger for hedge funds. For example, the interim-trading performance of the top quintile of non hedge funds over the subsequent quarter is 0.61%, compared to 1.42% for hedge funds, and the difference between the two estimates is statistically significant. Persistence in interim performance is also long-lived. The top quintile of hedge funds (as well as non hedge funds) significantly outperform for at least two years after the formation period.

The significant persistence in intra-quarter trading skill suggests that studies relying on quarterly holdings may significantly understate hedge fund persistence. To explore this possibility, we estimate hedge fund persistence using a one-year holding period based on both actual transaction data as well as 'implied' quarterly trades. For each fund and stock, we obtain implied quarterly trades by aggregating all trades within the quarter and calculating net trading positions as of the quarter end. Using actual transaction data, we find that the top quintile of hedge funds outperform by a statistically significant 0.40% per month over the subsequent year. In contrast, when sorting on the implied quarterly trading, the magnitude of hedge fund persistence is reduced by 40% and is no longer statistically significant. This finding suggests that much of hedge fund persistence is driven by short-term trading. This finding also highlights the limitations of quarterly holdings data in estimating the performance persistence of hedge funds.

Our final set of tests explore the source of trading profits for the subset of skilled hedge funds. We find that relative to other hedge funds (or other non hedge fund institutions), skilled hedge funds are more likely to trade smaller stocks and more illiquid stocks, and are significantly more likely to be short-term contrarians with small implicit trading costs. We also find that the trading profits of skilled hedge funds are concentrated in small stocks and illiquid stocks. The results are consistent with smart hedge funds profiting from liquidity provision. Further, we find that the persistence of top hedge funds is substantially stronger for the subset of liquidity supplying funds (i.e. funds with low implicit trading costs or funds that follow short-term contrarian strategies), and is not at all present for liquidity demanding funds. These findings suggest that liquidity provision is a critical source of skilled hedge funds' persistent outperformance.

Our findings contribute to the debate over average hedge fund performance. Many papers including Kosowki, Naik and Teo (2007), Agarwal, Daniel, and Naik (2011), and Ibbotson, Chen, and Zhu (2011) find hedge funds deliver annual alphas of 3-5% after fees. However, other work by Amin and Kat (2003), Griffin and Xu (2009), and Aitken, Ellis, and Clifford (2012) find no evidence of hedge fund skill. Our results add to the literature that paints a more skeptical view of hedge fund performance. Specifically, we find little evidence that the average hedge fund engages in skilled trading, even prior to accounting for management fees and incentive fees. Thus, it seems unlikely that the average hedge fund earns significantly positive alpha net of expenses. Admittedly, it is possible that our estimates may understate hedge fund skill, particularly if hedge funds exhibit skilled trading in asset classes besides equity (e.g. Aragon and Martin (2011)). Nevertheless, 42% of hedge funds are simply invested in long/short equity strategies (see e.g. Fung and Hsieh (2006)), which suggests that many funds rely exclusively on equity trading to generate abnormal returns.

Our findings also add to the literature on whether *some* hedge funds are skilled and whether such skill is persistent. Griffin and Xu (2009) and Brown, Goetzmann, and Ibbotson (1999) find no evidence of performance persistence, Aggarwal and Naik (2000) and Liang (2000) conclude that performance persists only at the quarterly horizon, while Kosowski Naik and Teo (2007) and Jagannathan, Malakhov, and Novikov (2010) find evidence of longer-horizon persistence. Our results provide support for the latter group and also offer some explanations for why other studies fail to find persistence. For example, since transaction data allows for more accurately estimated alphas relatively to factor models, our findings are consistent with Jagannathan, Malakhov and Novikov (2010) who find that measurement error in estimated alphas results in a significant downward bias in estimates of persistence. Similarly, since intra-quarter trading skill explains a large fraction of annual performance persistence, studies relying on quarterly holdings will understate persistence.

The importance of intra-quarter trading skill in explaining persistence also highlights that short-term trading skill is a critical driver of the success of high performing funds. In this sense, our findings also relate to Kacperczyk, Sialm, and Zheng (2008) who show that unobserved actions of mutual funds within the quarter are important and persistently create (or destroy) value; as well as Puckett and Yan (2011), who find that institutional investors (as a whole) exhibit intra-quarter performance persistence. Our findings suggest that, relative to other institutions, short-term trading persistence is particularly pronounced for hedge funds. Moreover, we identify a specific channel, namely liquidity provisions, through which skill hedge funds are able to persistently create value via short-term trading.

The remainder of this paper is organized as follows. Section 2 discusses the data and presents descriptive statistics. Section 3 examines the magnitude of intra-quarter trading by hedge funds. Section 4 examines hedge fund performance and section 5 investigates performance persistence. Section 6 explores the source of skilled hedge funds' outperformance. Section 7 concludes.

2. Data

2.1 Data and Descriptive Statistics

We obtain data on institutional trading from January 1, 1999 to December 31, 2010 from ANcerno Ltd. (formerly the Abel Noser Corp).[7] ANcerno is a consulting firm that works with institutional investors to monitor their trading costs. The ANcerno data include the complete transaction history for all of its institutional clients. Each observation corresponds to an executed trade. For each execution, the database reports the date of the trade, the execution price of the trade, the stock traded, the number of shares traded, whether the trade was a buy or a sell, and identity codes for the institution making the trade. For each stock traded in the ANcerno dataset, we collect returns, share price, trading volume, and shares outstanding from *CRSP,* and we collect book value of equity from *Compustat.*

Each institution in the ANcerno dataset has three identifier variables: an institution type identifier, a client identifier, and a manager identifier. The institution type identifier distinguishes between clients that are plan sponsors (e.g. CalPERS and United Airlines) and clients that are money managers (e.g. Putnam Investments and Fidelity). The client identifier corresponds to the plan sponsor or money manager who is subscribing to ANcerno. The client identifier is a permanent numeric code, which allows us to track a given client both in the cross-section and throughout time. However, the names of the clients are not provided.

The manager code identifies a specific money management company.[8] The manager code, like the client code, is a permanent numeric identifier. However, ANcerno also provides a separate reference file that links manager codes to specific money management companies (e.g. manager 3 = 'Acadian Asset Management').[9] The identification is at the fund-family level,

[7] Other papers that use ANcerno data include Anand, Irvine, Puckett, and Venkataraman (2012), Jame (2012), Jegadeesh and Tang (2010), and Puckett and Yan (2011).

[8] In some cases, ANcerno cannot reliably identify the money management firm in which case ANcerno assigns a manager code value of either -1 or 0. These observations are excluded from the analysis.

[9] The reference file linking manager codes to manager names became available in 2011; prior to 2011 the dataset was completely anonymous.

and there is no way to distinguish between different products within a money management company. The manager code is constant across different clients. For example, if CalPERS and United Airlines both hire Putnam Investments, the manger code would be identical (although the client code would be different). Similarly, if Putnam Investments subscribed to ANcerno, it would be given the same manager code (although it would now be classified as a money manager, not a plan sponsor).

We begin by identifying hedge fund managers within the ANcerno sample. Our identification process closely follows the approach outlined in Brunnermeier and Nagel (2004) and Griffin and Xu (2009). Specifically, for every manager in the ANcerno dataset, we search for Form ADV Filings on the SEC website.[10] Starting in March 2012, the Dodd-Frank Act requires that nearly all investment advisors, including hedge funds, file form ADV.[11] In addition, a 2004 SEC Investment advisor rule required all hedge funds to file form ADV for a short period in 2006.[12] Thus, we are able to obtain form ADV for nearly all hedge fund families that had operations in 2006, or 2012 onwards, plus any funds that voluntarily filed form ADV. Ultimately, we obtain a form ADV for 566 of the 654 managers in the ANcerno sample.[13]

We classify a manager as a hedge fund if more than half of its clients are categorized as "high net worth individuals" or "other pooled investment vehicles" in item 5.D of Form ADV.

[10] All current advisor ADV filings are available on the SEC's investment advisor public disclosure website: http://www.adviserinfo.sec.gov.

[11] Some exceptions still apply. For example, advisors to private funds with less than $150 million in total net assets are not required to file form ADV. More details on the Dodd-Frank registration requirements can be found here: http://www.sec.gov/rules/final/2011/ia-3221.pdf

[12] More specifically, all domestic hedge funds with more than 14 clients, assets of at least $25 million, and a lockup period of less than two years were required to file form ADV (see Brown et al. (2008) for further details).

[13] There are two common reasons why we were unable to match some funds. First, there was no record of Form ADV for the ANcerno manager, perhaps because the fund is very small (less than $100 million in assets) or because the fund is exempt from reporting requirements (e.g. venture capital funds). Second, the manager name reported in ANcerno could be linked to a number of different money management companies. For example, it is unclear whether the manager name 'Delphi" in ANcerno corresponds to 'Delphi Management', 'Delphi Investments', 'Delphi Securities', etc.

In addition, we require that the manager charge a performance-based fee (item 5.E). We also manually verify that large investment banks and prime brokers (e.g. Goldman Sachs Asset Management, Bear Stearns Asset Management, etc.) are not included in the hedge fund sample.

We classify a manager as a non hedge fund if the manager does not charge performance based fees or if more than 75% of the manager's clients are individuals. Such managers are unlikely to have *any* hedge fund operations. This group includes pure mutual funds as well as many banks and insurance companies. We define all remaining institutions as mixed funds. These institutions charge performance based fees, but fewer than 50% of their clients are high net worth individuals or other pooled investment vehicles. In addition, the mixed sample includes the large investment banks that were initially classified as hedge funds based on the ADV criteria, but were later removed from the hedge fund sample. The mixed sample includes many large asset managers who primarily manage mutual funds, but also have some hedge fund operations.

Panel A of Table1 provides summary statistics on the sample size of each manager type. Our sample consists of 74 hedge fund management companies who manage money for 253 different clients. There are 364 different client/hedge fund manager pairs. Hereafter, we will loosely refer to a client/manager pair as a *fund.* Our sample of hedge funds is considerably smaller than our sample of mixed funds (2084) or non hedge funds (1655).

There are two ways a hedge fund can enter our database. First, the hedge fund can invest on behalf of a plan sponsor who subscribes to ANcerno. Second, the hedge fund company can subscribe directly to ANcerno. In the first case, we observe hedge fund trading for a specific plan sponsor, while in the later case we observe the aggregate trading of the hedge fund company. 64

of the 74 hedge fund managers in the sample manage money on behalf of a plan sponsor who subscribes to ANcerno, while 27 of the 74 hedge fund managers directly subscribe to ANcerno, with 17 managers entering as both. There are 335 different hedge funds trading on behalf of plan sponsors and 29 different hedge funds trading on behalf of their own account.[14] Many of our tests will use the fund as our unit of analysis. Thus, these tests are heavily tilted toward hedge fund trading on behalf of plan sponsor clients. Although this may not be representative of aggregate hedge fund trading, plan sponsors (i.e. public and private pension funds, endowments, and foundations) hold over 50% of all hedge fund assets.[15]

Panel B of Table 1 provides the average number of funds that appear in the sample each quarter across all the years in our sample. In the average quarter in 1999, there are roughly 116 hedge funds. This number is relatively stable until around 2005, at which point the sample of funds steadily decreases. In 2010, the average quarter contains only 32 hedge funds. We find a similar decay in the sample size for mixed funds and non hedge funds. In untabulated analysis, we find that the declining sample size is driven entirely by the plan sponsor portion of the sample; the sample of money managers slightly increases from 1999 to 2010.

We also examine how long the average funds stays in the ANcerno sample (unreported). We find that the average hedge fund remains in the sample for a little over 12 quarters, although there is significant cross-sectional variation. Funds at the 75th and 25th percentile stay in the sample for roughly 18 and 4 quarters, respectively. The distribution is similar for mixed funds and non hedge funds, and does not significantly vary depending on whether the client is a plan sponsor or money manager.

[14] Since money managers typically only make trades for their own behalf, there will typically only be 1 manager code for a given money management firm. Of the 206 different money manager clients in our sample, only 9 have multiple manager codes. These may correspond to sub-advised funds.

[15] http://www.aei-ideas.org/2011/10/who-invests-in-hedge-funds

Panel B also presents the average and median quarterly trading volume for hedge funds by year. We see that the average trading volume by hedge funds has increased dramatically over time. In fact, aggregate hedge fund trading is greater in 2010 (roughly $82 billion) than in any year prior to 2005, despite the significant reduction in sample size. Much of the increase in average trading volume is due to a larger fraction of the sample consisting of money managers, who are responsible for much more trading than plan sponsors. There is also an increase in trading volume for the median fund (which always reflects trading on behalf of plan sponsors), however this increase is less dramatic.

2.2 Database Integrity

As noted in the introduction, hedge fund commercial databases suffer from a number of biases including: backfill bias, survivorship bias, unreliable returns, and self-selected reporting. In this section, we discuss the extent to which the ANcerno data is likely to suffer from similar biases.

We are confident that ANcerno does not suffer from backfill bias or survivorship bias. ANcerno representatives have told us that they only collect trading data on a fund for the period *after* it has subscribed to ANcerno, which eliminates the possibility of backfill bias. ANcerno representatives have also confirmed that the data is free of survivorship bias. Moreover, ANcerno provides new trading data each quarter (with a three-quarter lag), but historical data is not updated. Thus, the trades of non-surviving funds remain in the historical data.

We also have no reason to doubt the reliability of the reported trades. First, there is a little incentive for institutions to lie about their transactions. Unlike commercial databases, these transactions are not disclosed to potential investors. Moreover, institutions incur a significant expense when hiring ANcerno, and the benefits of ANcerno's transaction cost analyses would be significantly reduced if the institution did not provide ANcerno with reliable data. A related concern is that hedge funds conceal their most informed trades. For example, Agarwal et al. (2012), find that hedge funds occasionally avoid public disclosure of their holdings via confidential fillings. They also find that these confidential filings earn superior returns. However, unlike 13F filings, trades reported to ANcerno are not made publically available; they are disclosed only to academics after a three quarter delay. Thus, compared to 13F filings, the incentives to conceal informed trading from ANcerno are much weaker.

A final concern is that the funds that subscribe to ANcerno are not representative of the population of funds. It is worth emphasizing that very few hedge funds self-select into the database. The overwhelming majority of hedge funds enter the dataset because they manage money for a plan sponsor who chooses to hire ANcerno. Of course, it is still possible that the plan sponsor's decision to subscribe to ANcerno is correlated with important hedge fund characteristics. In contemporaneous work, Franzoni and Plazzi (2012) match the subset of ANcerno hedge funds to hedge funds that report in TASS. They find that the distribution of assets under management and dollar flows line up almost exactly with TASS. They also find that ANcerno funds tend to have somewhat weaker performance compared to funds in TASS. However, it is unclear whether this reflects a bias in the ANcerno dataset or the TASS dataset (or both). We plan to address this question in future versions of the paper by comparing the performance of the trades (and holdings) of all 13F hedge funds, to the subset of 13F hedge funds that also appear in ANcerno.

3. The Magnitude of Intra-Quarter Trading

In this section, we investigate the significance of intra-quarter trading (i.e. buying and selling the same stock within the quarter) for hedge funds and other institutional investors. Our analysis allows us to examine whether a significant fraction of hedge fund trading is motivated by relatively short-term considerations. In addition, it provides insight into the reliability of studies that rely on changes in quarterly holdings to infer the trading strategies and performance of hedge funds (e.g. Griffin and Xu (2009)).

We begin by reporting the cross-sectional distribution of quarterly trading for hedge funds and other institutions. Our unit of analysis is the fund and we report the results for plan sponsors and money managers separately. Panel A reports the results for plan sponsors. The average hedge fund executes roughly $40 million in total trading in the average quarter. However, there is substantial cross-sectional dispersion, with the largest 1% of hedge funds trading over $400 million while the smallest 1% trades less than $40,000 per quarter.

We also report the cross-sectional distribution of the ratio of actual to implied quarterly trading volume. Implied quarterly trading volume is computed as the net dollar volume (buys - sells) for a stock over a quarter. For example, if a fund bought $50,000 of Microsoft in January 2008 and sold $20,000 in February 2008, the total trading volume for Microsoft in quarter 1 of 2008 would be $70,000, while the implied trading volume would be $30,000.[16] The implied trading volume more closely reflects the trading volume that would be reported in 13F filings.

[16] In computing the implied trading volume we use the actual transaction price. Studies using quarterly holdings would not know the transaction prices and would typically use the end-of-quarter price. Using end-of-quarter prices would more accurately reflect the extent to which quarterly holdings understate dollar trading volume; however it also makes it more difficult to get a sense of what fraction of funds engage in no intra-quarter trading since the ratio of actual to implied trading volume will generally not be equal to 1 for these funds. Using the end of quarter prices yield very similar average effects.

The ratio of actual to implied trading volume is a measure of the extent to which 13F filings would understate actual trading volume.[17]

We find that the actual quarterly trading of the average hedge fund is about 28% higher than the implied trading, indicating that there is some intra-quarter roundtrip trading. However, most of this measure if driven by a few funds in the far right-tail of the distribution. The corresponding measure for the median fund is only 3%, indicating that nearly half of hedge funds engage in virtually no intra-quarter trading when managing funds on behalf of plan sponsors. Moreover, the magnitude of intra-quarter trading does not appear to vary substantially across different types of institutional investors.

Panel B presents analogous results for the money manager sample. The money manager sample more closely corresponds to unit of analysis in Griffin and Xu's (2009) study of hedge fund performance. However, ‘intra-quarter' trading here may simply reflect two different funds within the same family taking opposing positions during a quarter. Using this broader definition of intra-quarter trading, we find that the actual quarterly trading of the average hedge fund is about 48% higher than the implied trading. This number is slightly larger than the corresponding measures for mixed funds (35%), and non hedge funds (41%). However, in untabulated analysis, we find that the different point estimates are not reliably different from each other. Moreover, the larger average values for hedge funds are again driven by a few very active traders in the right-tail of the distribution. The median values are nearly identical for the three groups of investors. Overall, there is little evidence that the typical hedge funds engages in significantly more intra-quarter trading than other institutional investors.

[17] Quarterly holdings also omit short-selling, confidential fillings, and very small trades. Thus, the ratio can be viewed as a lower bound.

4. Trading Performance

4.1 Measuring Trading Performance

We next investigate the performance of hedge fund trading. Following Seasholes and Zhu (2010), we compute performance using transaction-based calendar-time portfolios. Specifically, each time a fund buys a stock, we place the same number of shares in our calendar-time buy portfolio. Similarly, each a time a fund sells a stock, we place the same number of shares in our calendar-time sell portfolio. In contrast to Seasholes and Zhu (2010), we include day 0 (the transaction day) in our portfolios and compute day 0 returns based on the reported execution price. Shares are held in a portfolio for a pre-determined length of time. Our approach generates a time-series of daily buy and sell portfolios. Each day we compute the principal-weighted return on the buy and sell portfolio, as well as the difference between the buy and sell portfolio. We report the time-series average of daily returns, expressed as monthly returns in percent. We analyze holding periods of 21, 63, 126, and 252 trading days. We emphasize the 252 day holding since this is closest to the average holding period of a typical hedge fund. [18]

To further illustrate our methodology, consider the following example:

Ticker	Shares Purchased	Price at Purchase	Days since Purchase	Closing Price on Day -1	Day 0 Return
AAPL	100	$600	180	$620	3%
MSFT	200	$30	70	$36	-1%
GOOG	50	$650	0	$651	2%

In the above illustration, the total buy volume for a 252 day holding period is $101,700 (100 * $620 + 200 * $36 + 50 *650). The return is 2.45% (60.96% * 3% + 7.08% * -1% + 31.96% *

[18] Using quarterly holdings, Griffin and Xu (2009) and Reca Sias, and Turtle (2012) estimate that the median hedge fund has a turnover of 102% and 95%, respectively.

2.16%). Note that the weight and return of Google is based on the execution price. Computing the return for a 126 day holding period would be done analogously, but the weight on Apple would drop to zero since no shares of Apple have been purchased in the past 126 trading days.

We also estimate hedge fund intra-quarter (or *interim*) trading skill. This holding period is designed to capture skill that is ignored by studies that rely on quarterly holdings. In principal, we could estimate interim trading skill using a calendar-time transaction approach that holds all stocks until the end of the quarter. However, this approach has two shortcomings. First, trading days at the beginning of the quarter are estimated very imprecisely and are very sensitive to trading commissions, yet they are given equal weight relative to trading days at the end of the quarter. Second, the measure it not directly comparable to existing studies that explore interim trading skill (e.g. Puckett and Yan (2011) and Bernile et al. (2012)). Thus, we adopt the interim trading skill measure introduced by Puckett and Yan (2011). Specifically, we split all trades into buys and sells and then compute the principal-weighted return on the buy and sell portfolio, where returns are measured from execution price until the end of the quarter.

4.2 Aggregate Performance

Following Lewellen (2011) our initial performance tests focus on the aggregate trading of different institution types. In other words, we compute buy and sell portfolios based on the aggregate trading of hedge funds, mixed funds, and other institutional investors. Statistical inference is based on the time-series standard deviation. We adjust standard errors for serial correlation using the Newey-West (1987) approach with five lags.[19]

[19] Since our approach avoids overlapping holding periods, the Newey-West (1987) adjustment has a very small effect on standard errors.

Panel A of Table 3 present the average gross returns of the buy and sell portfolios for each groups across various holding periods. Across holdings periods ranging from one month (21 days) to one year (252 days) the returns earned on the buy portfolio of hedge funds is insignificantly different from the returns earned on the sell portfolio. For example, for a one year holding period, the stocks bought by hedge funds earn an average monthly return of 0.61%, while the stocks sold earn 0.61%. The difference between the buy and sell portfolio of -0.01% is small and statistically insignificant. Similarly, we find no evidence of interim trading skill. The stocks bought buy hedge fund outperform the stocks sold by hedge funds by a statistically insignificant 0.18% from execution price until the end of the quarter.

The table also reports the results for mixed funds and non hedge funds. Mixed funds appear to have some trading skill over the one-month horizon, but such skill dissipates over longer holding periods. There is no evidence that non hedge funds exhibit trading skill across any horizons.

Panel B presents a similar analysis using the characteristics adjustment proposed by Daniel, Griblatt, Titman and Wermers (1997) and Wermers (2004) (hereafter DGTW-adjusted returns). DGTW-benchmark portfolios are constructed by first sorting all stocks into quintiles based on market capitalization. Then within each size quintile, stocks are sorted into quintiles based on book-to-market ratio, resulting in 25 different portfolios. Within each portfolio, stocks are once again sorted into quintiles based on prior 12 month returns, resulting in 125 portfolios.[20] The benchmark for each stock is the portfolio to which it belongs. The DGTW-adjusted return

[20] For more details on the DGTW-benchmark construction procedure see DGTW (1997). The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

for each stock is the difference between the stock return and the value-weighted benchmark portfolio return over a particular holding period.

Using DGTW-adjusted returns yields similar conclusions. There is no evidence of hedge fund skill across holding periods ranging from one month to one year, although there is weak evidence of interim trading skill. Again, there is relatively little evidence that mixed funds or non hedge funds exhibit significant trading skill over longer horizons.

The results in Panels A and B are inclusive of implicit trading costs (e.g. price impact), but exclude trading commissions (as well as other expenses such as management fees and incentive fees). Panel C of Table 3 repeats the analysis after incorporating trading commissions. Intuitively, incorporating commissions has a pronounced effect on performance over shorter holding periods and a negligible effect over longer holding periods. After incorporating trading commissions there is no evidence of positive trading skill for any group of investors across any holding period, and mixed funds and non hedge funds typically generate significantly negative returns. The interim trading skill of hedge funds is not significantly different from zero. This suggests that studies that rely on quarterly holdings to estimate aggregate hedge fund performance are unlikely to result in a significant bias.

4.3 Average Fund Performance

The aggregate performance measure is likely more representative of the returns earned by the typical investor who is more likely to invest in large funds. However, the aggregate measure is very sensitive to the decisions of a few large hedge funds, and thus may do a poor job of characterizing the average funds' performance, particularly in light of the growing evidence of decreasing returns to scale in the hedge fund industry (see e.g. Fung et al. (2008) and Dichev and

Yu (2011)). In this section, we focus on performance earned by the average client-manager pair (hereafter *fund)*. For each fund, we compute the performance as described in section 4.1. For each holding period, we require that each fund-day have at least 10 stocks in both the buy and sell portfolio.

Panel A of Table 4 reports the average performance of hedge fund trading across all fund-days (or in the case of our interim skill measure, fund-quarters). We cluster standard errors by both fund and day (or quarter). There is evidence of short-term trading skill. Hedge fund trades outperform over the one-month holding period by 0.41%. However, there is no evidence that hedge funds exhibit skill over longer holding periods nor is there evidence of significant intra-quarter trading skill. Mixed funds and non hedge funds also perform well over shorter holding periods. Both outperform over the one month holding period and also exhibit significant intra-quarter skill. Neither perform well over longer holding periods.

Panel B of Table 4 presents the results using DGTW-adjusted returns and yields largely similar findings. Panel C adds back commissions. Accounting for commissions completely eliminates hedge funds short-term outperformance. In fact, there is no evidence of interim trading skill for hedge funds or other institutions after accounting for commissions.[21] Overall, our results are largely supportive of Griffin and Xu (2009). Specifically, there is little evidence that the average hedge fund is particularly skilled either in absolute terms or relative to other institutions. Our analysis also suggests that ignoring intra-quarter trading is unlikely to generate a significant bias is estimating the performance of the average fund, since trading costs are nearly equal to pre-commission interim trading profits.

[21] This finding appears at odds with Puckett and Yan (2011) who find significant interim trading skill even after accounting for commissions. However, more recent work by Bernile et al. (2012) finds no significant evidence of interim trading skill after commissions. This finding is also consistent with Kacperczyk, Sialm, and Zheng (2008) who find a statistically insignificant return gap.

4.4 The Cross-Section of Fund Performance

Although there is little evidence that the trades of average hedge fund outperform, it is still possible that some funds are skilled traders. To explore this possibility, we examine the cross-sectional distribution of $\hat{t}_{\hat{a}_i}$. $\hat{\alpha}_i$ is the average DGTW-adjusted return of the buy-sell portfolio of a fund across all days for which the fund is holdings at least 10 stocks in both the buy and sell portfolio, and $\hat{t}_{\hat{a}_i}$ is $\hat{\alpha}_i$ scaled by its standard error. To ensure a sufficient time-series of returns, we exclude funds that appear in the sample for less than one year. We focus specifically on the one year holding period (results for other holding periods are available upon request).[22]

Following Kosowski et al. (2006) and Fama and French (2010), we focus on $\hat{t}_{\hat{a}_i}$, rather than $\hat{\alpha}_i$. This helps control for disparity in the precision of $\hat{\alpha}_i$ due to both differences in the variance of $\hat{\alpha}_{it}$ across days, which is particularly pronounced given the substantial cross-fund variation in the number of stocks traded, as well as differences in the number of days the fund appears in the sample.[23] To examine whether the distribution of $\hat{t}_{\hat{a}_i}$ is consistent with the null hypothesis that α_i (i.e. true alpha) is zero for all funds, we use bootstrap simulations on returns that have the properties of fund returns, except that α_i is set to zero for every fund.

Our simulation approach follows Fama and French (2010). Specifically, for each fund, we subtract its average alpha ($\bar{\hat{\alpha}}_i$) from its daily estimate of alpha ($\hat{\alpha}_{it}$), yielding a time-series of

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[22] We do not report simulation results for our interim skill measure since this measure yields a time-series of quarterly returns (not daily returns). Since many funds appear in the sample for a relatively small number of quarters, bootstrap estimates are not reliable.

[23] Using $\hat{\alpha}_i$ yields very similar results.

daily residuals. A simulation run is a random sample of 3271 days (with replacement), drawn from all trading days between 1999 and 2011.[24] For each fund, we estimate the funds' average return based on its residual in the day of the random draw. By choosing the same random sample of days for all funds, our simulations capture the cross-correlation of fund returns. We do 10,000 simulation runs to produce the distribution of t-statistics for a world in which true α_i is 0 for all funds.

Panel A of Table 5 presents the simulation results for hedge funds and other institutions for the one year holding period excluding commissions. We find that the distribution of hedge fund performance is fat-tailed relative to the simulated distribution. For example, the bottom (top) 1% of hedge funds have an average t-statistic of -2.96 (3.43) compared to simulated t-statistics of -2.61 (2.61). More interestingly, we find the performance of funds in the right tail of the distribution cannot be attributed to luck alone. At a five percent significance level, the top 10% of hedge funds appear to exhibit true outperformance. In contrast, there is no evidence of skill in the right tail for either mixed funds or non hedge funds. Further, the distribution of non hedge fund performance is consistently worse than the simulated distribution, and often the difference is statistically significant.

Panel B of Table 5 repeats the simulation after incorporating trading commissions. Thus our simulations now imply a world where every manager has sufficient skill to generate performance that cover trading commissions. Even after accounting for commissions, we continue to find evidence of hedge fund skill in the right tail. Specifically, the top 10% of hedge funds exhibit outperformance at a 5% significance level (using one-sided p-values). The

[24] Although the transaction data ends in 2010, our annual calendar-time portfolio approach hold the stock for one year, resulting in a time-series of daily holdings that extends until the end of 2011.

performance of mixed funds and non hedge funds are never significantly positive, and are often significantly negative.

5. Performance Persistence

The results from the prior sections suggest that there is significant cross-sectional variation in performance across hedge funds. Moreover, there appears to be a small subset of funds that have some trading skill. This finding points to the possibility that past performance may be useful in identifying skilled funds. This section explores this question in greater detail.

5.1 Persistence in Interim Trading Skill

We begin by examining whether hedge funds exhibit persistent differences in interim trading skill. Our motivation for examining the interim persistence of hedge funds is twofold. First, prior work on mutual funds (e.g. Kacperczyk, Sialm, and Zheng (2008)) and institutional investors as a whole (e.g. Puckett and Yan (2011)) suggest that institutions exhibit persistent differences in interim trading skill, but there is no direct evidence on the persistence of interim trading skill for hedge funds. Given that hedge funds are less regulated than the typical institutional investor, it seems plausible that cross-sectional dispersion in interim trading skill may be particularly large for hedge funds. For example, the lack of transparency in the hedge fund industry can allow low-skilled hedge funds to conceal agency problems. Alternatively, the greater opacity may help highly-skilled managers hide the profitable investment ideas. Second, if hedge funds exhibit significant persistence in interim trading skill, then estimates of persistence using quarterly holdings may significantly understate true persistence.

To estimate persistence in interim trading skill, we form quintiles during a ranking period and then examine returns over a subsequent post-ranking period. We form quintiles based on

DGTW-adjusted interim returns over the prior quarter. We then compute the DGTW-adjusted return for each quintile over the subsequent quarter, two to four quarters, and five to eight quarters, as well as the cumulative two year return. To account for overlapping holding periods, standard errors are clustered by both fund and quarter.

We begin by sorting funds based on their pre-commission interim trading skill and explore subsequent pre-commission interim performance. Our performance measure reflects the average interim performance of each fund across each quarter in the post-ranking period. Panel A of Table 6 shows that hedge funds with the best interim performance in the prior quarter exhibit interim outperformance of 1.42% over the subsequent quarter. This estimate is highly significant and economically large. In contrast, the bottom quintile of funds generates negative, but statistically insignificant returns over the subsequent quarter.. We also see that persistence is long-lived. The top quintile outperforms by 1.07% per quarter in quarters 2 through 4 and 0.54% in quarters 5 through 8. Over a 2 year holding period, the top quintile outperforms by 0.91% per quarter.

We also sort funds based on the interim skill after commissions and investigate subsequent post-commissions performance. Intuitively, incorporating commissions reduces the performance of funds in both the top and bottom quintile, and the spread between the two remains nearly the same. For example, the performance of the top quintile of funds over the two-year holding period falls to 0.52%, while the performance of the bottom quintile of funds drops to -0.32%, and the difference between the two estimates is significant. Thus, ignoring interim trading may understate hedge fund persistence.

Panels B repeats the analysis for mixed funds. There is also evidence of interim persistence for mixed funds. For example, over a 2 year holding period, the top quintile of mixed funds outperform by 0.31% before accounting for commissions. This estimate is statistically significant but is roughly one-third the magnitude of the outperformance of top hedge funds. In untabulated analysis, we find that the top hedge funds outperform the top mixed funds by 0.60% per quarter over the subsequent two years (t=2.12). Incorporating trading commissions eliminates the outperformance of the top mixed funds, but the top quintile of mixed funds continue to outperform the bottom quintile of mixed funds.

Panel C reports the results for non hedge funds. We again find evidence of persistence. The top quintile of non hedge funds significantly outperform both in absolute terms and relative to the bottom quintile of non hedge funds. However, the magnitude of non hedge fund persistence is roughly half as large as hedge fund persistence. For example, the top hedge funds outperform the top non hedge funds by 0.80% over the first quarter (t = 2.33) and 0.47% over the subsequent two years (t = 1.73). Thus, the top hedge funds are particularly skilled at creating value via interim trading.

5.2 Annual Performance Persistence

Our findings suggest that the use of quarterly holdings significantly understates the persistence of hedge funds, both in absolute terms and relative to other institutions. To get a better sense for the magnitude of this bias, we estimate performance persistence using calendar-time transaction portfolios with one-year holding periods using two approaches. The first approach uses actual transaction data and thus adds the purchased (or sold) stock into the buy (sell) portfolio on the day of the trade (and computes day 0 returns based on the execution price of the trade). The second approach adds stocks to the portfolio at the end of every quarter based on net quarterly trading and assumes all trades occur at the end of quarter closing price.

Each year we sort stocks into quintiles based on the actual or implied average daily performance based on a 252 day holding period. The actual performance measure includes trading commissions. Using pre-commission performance results in very similar conclusions, although the performance of each quintile improves by 2 to 4 basis points per month.

Panel A of Table 7 reports the average actual (or implied) daily performance (expressed as monthly returns in %) over the subsequent one, two, or three years, as well as years one through three. Using actual transaction data, we find significant persistence over the one year horizon. Moreover, the persistence is driven entirely by winning funds. The top quintile of funds outperform by roughly 0.40% per month over the subsequent 12 months while the bottom quintile outperforms by a statistically insignificant 0.01%. In years 2 and 3, the spread between the top and bottom quintile is positive, but statistically insignificant. However, the spread between the top and bottom quintile over the cumulative three years after the formation period is a statistically significant 0.24% per month, or roughly 8.65% over the 3 year holding period. The fact that hedge fund persistence is long-lived is particularly relevant since hedge fund investors often have lock-up periods of 1 year or more. In addition, for plan sponsors, there are substantial costs associated with hiring and firing money managers (see e.g. Goyal and Wahal (2008)).

Panel A of Table 7 also reports the results based on implied quarterly trades. We find similar, but substantially muted patterns. For example, in the year after the formation period, the performance of the top quintile falls from 0.40% per month to 0.25% per month. This indicates that nearly 40% of the value created by the top quintile of funds is driven by their interim trading skill. This suggests that trading on short-lived information is a critical driver of the outperformance of top hedge funds. This also suggests that the use of quarterly holdings can generate a meaningful downward bias on estimates of hedge fund performance persistence.

Panels B and C report the results for mixed funds and non hedge funds. There is no evidence of persistence using either actual or implied performance for either group. The lack of persistence for mixed funds and non hedge funds is consistent with our simulation results in Table 5 which finds no evidence of any skill for either group.

6. The Source of Skilled Hedge Funds' Outperformance

6.1 Characteristics of Stocks Traded by Skilled Hedge Funds

The results in Tables 5 through 7 suggest that a subset of hedge funds are able to persistently create value through their trades. A natural question is what is the source of this trading skill? We consider three potential explanations. First, hedge funds may be skilled at collecting private information. Second, hedge funds may have a comparative advantage in interpreting public information. Lastly, hedge funds may earn abnormal profits as compensation for providing liquidity to other investors who demand immediacy.

To better understand the source of skilled hedge funds' trading profits, we begin by comparing the characteristics of stocks traded by smart hedge funds (i.e. funds in the top quintile of performance based on a 252 day holding period over the prior year), to the characteristics of stocks traded by other hedge funds and other non hedge fund institutions. If skilled hedge funds profit by collecting private information, we would expect their profits to be strongest in stocks with more limited publically available information and in stocks with greater information asymmetries. We expect that small firms are likely to have less publically available information (e.g. less analyst coverage and less media coverage) and growth firms and volatile firms are likely to have greater information asymmetries. Similarly, we expect that private information is likely to be particularly relevant prior to earnings announcements. In contrast, the ability to interpret public information is likely most relevant immediately after earnings announcements (e.g. Ivkovic and Jegadeesh (2004)). Finally, we expect liquidity provision to be most valuable in smaller and more illiquid stocks. In addition, we predict that liquidity providers will follow short-term contrarian strategies (i.e. buying recent losers and selling recent winners).

We assign a decile rank to each stock based on NYSE breakpoints for the following characteristics: *Size, Book-to-Market, Amihud Illiquidity, Volatility, Mom1,* and *Mom2_12.* The construction of these variables is presented in Appendix A. In addition, we include two dummy variables: *Pre Earnings* and *Post_Earnings. Pre-Earnings (Post Earnings)* is a dummy variable equal to 10 if the trade was made in the 10 trading days prior to (after) an earnings announcement and zero otherwise.

Figure 1A reports the average decile rank for the total trading (i.e. buys + sells) of skilled hedge funds, other hedge funds, mixed funds, and non hedge funds. We see that skilled hedge funds tend to trade smaller stocks. Specifically, the average size decile rank of the stocks traded for the average smart hedge fund is 6.59, as compared to 6.93 for other hedge funds and 8.03 for non hedge funds. All the differences are highly significant. Similarly, we find that smart hedge funds are more likely to trade illiquid stocks and volatile stocks. They also have a small tilt towards value stocks. They are not significantly more like to trade stocks in either the two weeks prior to or after an earnings announcement.

Figure 1B present the average decile rank for net trading (i.e. buys – sells) by institution type. There is some evidence that smart hedge funds tend to be net buyers of growth stocks. However, the most striking pattern is that skilled hedge funds are significant contrarians, both over a one-month and one-year horizon.

We next investigate the performance of hedge fund trades by each stock characteristic. Specifically, we divide all buy and sell trades into two portfolios based on the median NYSE stock characteristic breakpoint. To be included in the sample, we require that the fund trade at least 3 stocks during the quarter for each portfolio (e.g. for both small and large stocks). We compute the average principal-weighted interim trading across all funds in the sample for each stock characteristic. In the interest of brevity, we report only the DGTW-adjusted performance that incorporates trading commissions.

Table 8 presents the results. Smart hedge funds perform very well in small stocks. The small stocks bought by smart hedge funds outperform the small stocks sold by 2.01% until the end of the quarter. In contrast, there is no evidence that the any other institution exhibits significant outperformance in small stocks. In addition, there is no evidence that smart hedge funds outperform in larger stocks. A similar pattern emerges when we look at performance in illiquid stocks. Specifically, the performance of smart hedge funds in illiquid stocks is 3.42%. This is significantly stronger than the performance of other hedge funds or other non hedge funds in illiquid stocks. This is also significantly larger than the performance of smart hedge funds in liquid stocks.

There is no significant difference in the interim performance of smart hedge funds in growth vs. value stocks, nor is there a significant difference across high and low volatility stocks.

In untabulated analysis, we also found no significant differences in trading performance when sorting based on the stock's past return over the prior one or 12 months. Smart hedge funds do trade profitably prior to earnings announcements; however the magnitude of the outperformance is not significantly larger than their performance in the post earnings announcement period.

To explore whether hedge funds' trading advantage in smaller and more illiquid stocks is long-lived, we repeat the analysis of Panel A but now hold the stock for a 252 trading days (rather than until the end of the quarter).[25] We continue to find that hedge funds trade well in small stocks and illiquid stocks. However, the interim outperformance of hedge funds accounts for a relatively large fraction of hedge funds' annual outperformance. Specifically, interim performance accounts for 32% of smart hedge funds' annual outperformance (2.01/6.89) in small stocks, and 54% of their outperformance in illiquid stocks (3.42/6.31). In contrast, if outperformance were spread uniformly across each trading day, interim performance would account for only 11% of annual outperformance (30/252). Consistent with Table 7, the results suggest that much of smart hedge funds' trading advantage is short-lived.

6.2 Implicit Trading Costs of Skilled Hedge Funds

The fact that hedge funds are short-term contrarians whose trading profits are mostly short-lived and largely concentrated in smaller and more illiquid stocks raises the possibility that smart hedge funds profit primarily through liquidity provision. Following Puckett and Yan (2011), we investigate whether smart hedge funds are liquidity providers by examining their implicit trading costs. Intuitively, impatient liquidity demanding funds will have large implicit

[25] Using transaction-based calendar time portfolios leads to very similar conclusions.

trading costs as they are willing to pay a premium in exchange for immediacy. In contrast, patient liquidity supplying funds should exhibit very low (or negative) implicit trading costs.

We follow Anand et al. (2012) and measure implicit trading costs as the execution price of the trade less the price at the time the broker receives the trade, scaled by the price at the time the broker received the trade (hereafter: *execution shortfall*). The execution shortfall for sell trades is multiplied by negative one. For each fund, we calculate the principal-weighted average execution shortfall across all trades within the quarter. We find that there is a significant reduction in execution shortfall over time, presumably due to improved liquidity. To control for this trend, we subtract the average execution shortfall across all funds in a given quarter.

Table 9 reports the average execution shortfall for smart hedge funds, other hedge funds, mixed funds, and non hedge funds in both year zero (i.e. the year in which the smart hedge funds were in the top 20% of all hedge funds) and year 1. Using either year 0 or year 1 results, we find that non hedge funds tend to be relative liquidity suppliers while other hedge funds and mixed funds tend to be relative liquidity demanders. Smart hedge funds are also liquidity suppliers and they are significantly more likely to supply liquidity relative to other hedge funds.

Overall, the average results suggest that smart hedge funds are more likely to be liquidity suppliers. However, the average results may mask considerable cross-sectional variation across each institution type. As an alternative test, we create three dummy variables: *liquidity supplier*, *liquidity neutral, and liquidity demander.* Liquidity supplier equals one if the fund is in the bottom quintile of execution shortfall for a given quarter. Liquidity demander equals one if the funds is in the top quintile of execution shortfall in a given quarter, and liquidity neutral includes the remaining 60% of funds. We find that 36% of smart hedge funds are liquidity suppliers, nearly double the unconditional average of 20%. In contrast, only 23% of other hedge funds are liquidity suppliers. Roughly 22% of smart hedge funds are liquidity demanders and this estimate is not reliably different from the unconditional average of 20%.

6.3 Revisiting Performance Persistence by Trading Strategy

The results from the prior section suggest that an abnormally large fraction of smart hedge funds have relatively low execution shortfalls. This provides further evidence that many smart hedge funds are profiting via liquidity provision. As a final test, we revisit the performance persistence results documented in Table 7, but now report the results separately for the subset of smart hedge funds that are liquidity suppliers vs. liquidity demanders. If liquidity provision is one channel through which skilled hedge funds create value, then we would expect the superior performance of liquidity suppliers to persist. In contrast, our liquidity provision explanation of persistence offers no clear predictions for the subset of liquidity-demanding hedge funds. It is possible that there also exist smart liquidity-demanding hedge funds who persistently create value through strategies other than liquidity provision (e.g. short-term private information). However, it is also possible that top-performing liquidity demanders are just lucky, in which case their subsequent performance should revert.

Panel A of Table 10 presents the performance persistence results for the subset of smart hedge funds (i.e. quintile 5 in Table 7) further partitioned into 3 groups: liquidity suppliers, liquidity neutral, and liquidity demanders (as defined in Table 9). We find that the performance of smart liquidity supplying hedge funds is highly persistent. Specifically, smart liquidity supplying hedge funds outperform by 0.63% per month over the subsequent year and 0.43% per month over the subsequent 3 years. Liquidity neutral funds also exhibit persistence, although the magnitude of the persistence is small than that of liquidity suppliers. In contrast, the performance of 'smart' liquidity demanding hedge funds does not persistent. They outperform by a statistically insignificant 0.07% per month over the subsequent year, and underperform by a statistically insignificant 0.11% over the subsequent 3 years.

One concern is that our proxy for liquidity provision, execution shortfall, is proxying for trading desk skill, which may also be correlated with general stock-picking ability (e.g. Anand et al. (2012)). We consider an alternative proxy for liquidity provision which relies on the degree to which the fund follows short-term contrarian strategies. Specifically, for each fund we compute the principal-weighted prior one month return (in decile ranks) of the stocks bought less the stock sold. Funds in the bottom quintile (i.e. contrarians) are classified as liquidity suppliers while funds in the top quintile (i.e. momentum traders) are classified as liquidity demanders. The results using this alternative proxy lead to nearly identical results. Specifically, smart liquidity suppliers outperform by 0.40% per month over the subsequent 3 years while liquidity demanders underperform by 0.11% per month. The difference between the two is statistically significant.

The results from Panel A of Table 10 suggest that smart liquidity supplying hedge funds outperform ‘smart’ liquidity demanding hedge funds. A natural question is whether other hedge funds (i.e. funds outside of the top quintile of past performance) that supply liquidity consistently outperform other liquidity demanding funds. Panel B of Table 10 explores this issue. We find that other liquidity supplying funds tend to have slightly positive, but statistically insignificant performance. Similarly, liquidity supplying funds tend to do slightly better than liquidity demanding funds, but the difference is relatively small and statistically insignificant. Thus, not all liquidity providing hedge funds outperform. The persistence outperformance of smart liquidity suppliers, and the lack of persistence by ‘smart’ liquidity demanders or other liquidity supplying hedge funds, suggests that there is a relatively small subset of hedge funds who are truly skilled, and that liquidity provision is a critical channel through which these skilled hedge funds are able to persistently create value.

7. Conclusion

This paper offers a fresh look at hedge fund skill by examining transaction-level data. Transaction data avoids many of the biases associate with commercial databases (e.g. unreliable returns, backfill bias, survivorship bias, etc.) and provides a more powerful test of trading skill than quarterly holdings (e.g. transaction data captures intra-quarter trading and short-selling).

We find little evidence that the average hedge fund generates abnormal returns, particularly after accounting for trading commissions. Our analysis is gross of management fees and incentive fees and thus paints a pessimistic portrait of the average hedge fund. However, we do find some evidence of hedge fund skill in the right tail of the distribution. The top 10% of hedge funds significantly outperform even after accounting for trading commissions. In contrast, we find no evidence of skill for other institutions.

We also find strong evidence that hedge fund performance persists. The top quintile of hedge funds persistently creates value through intra-quarter trading skill. We find evidence of interim persistence for other institutions; however the magnitude of interim persistence for hedge funds is substantially larger than that of other institutions. We also find that hedge funds exhibit persistence at an annual horizon and much of this persistence is driven by persistence in interim trading skill. This suggests that a large fraction of the outperformance of skilled hedge funds stems from short-term informational advantages. Additional analysis suggests that liquidity provision is a critical driver of smart hedge funds persistent superior performance.

While our analysis does uncover a subset of skilled hedge funds; overall, our results cast doubt on the conventional view that most hedge funds are highly skilled. Our findings echo Griffin and Xu (2009) who, using quarterly holdings, find no evidence of average hedge fund outperformance. In addition, we verify that the average hedge fund does not generate significant value via interim-trading skill (after accounting for trading commissions). Our transaction data also includes short-selling, which suggests that short positions are unlikely to account for the differences in performance between commercial databases and quarterly holdings.

A natural question is why commercial databases appear to generate relatively large positive alphas for the average hedge fund even after accounting for management fees and incentive fees, while holdings and transaction data yield small, and statistically insignificant, alphas even prior to accounting for such fees. One possibility is that hedge funds generate significant value through non-equity trading. However, over 40% of hedge funds are dedicated to long-short equity strategies. These funds generate significant abnormal returns in commercial databases despite the fact that they invest primarily in equities. A second explanation is that database biases may be more severe than previously thought. For example, recent work by Aiken, Clifford, and Ellis (2012) argue that self-selection bias can account for nearly all of the abnormal performance of hedge funds in commercial databases. However, Fung and Hsieh (2000) and Agarwal, Fos, and Jiang (2012) argue that the magnitude of self-selection bias is not particularly severe. Alternatively, it is possible that factor models may do a poor job of properly measuring risk from reported monthly returns. As data quality improves, it will be interesting to distinguish between these and other explanations.

Appendix A: Description of Stock Characteristics

- *Size:* market capitalization computed as share price times total shares outstanding at the end of the year prior the year of the trade.
- *Book*-to-Market: book-to-market ratio computed as the book value of equity for the fiscal year ending before the most recent June 30th divded by the market capitalization on December 31st of the same fiscal year.
- *Mom1:* the return on the stock in the 21 trading days prior to the day of the trade.
- *Mom2_12:* the return on the stock in the 22 to 252 trading days prior to the day of the trade.
- *Volatility:* the standard deviation of monthly returns during the year prior to the year of the trade.
- *Illiquidity:* The Amihud (2002) measure computed using all daily data available for the year prior to the year of the trade.
- *Pre*-Earnings: a dummy variable equal to 1 if the trade occurred in the 10 days prior to the earnings announcement (i.e. -1 to -10).
- *Post*-Earnings: a dummy variable equal to 1 if the trade occurred in the 10 days after the earnings announcement (i.e. 1 to 10).

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Table 1: Summary Statistics

This table presents descriptive statistics for institutional trading data obtained from ANcerno. Panel A reports the total number of managers (i.e. management companies), clients (typically a plan sponsor) and manager-client pairs during the full sample period from 1999-2010. Panel B reports the number of manager-client pairs (funds), and the average and median dollar trading volume per fund averaged across the four quarters in each year. We report the results separately for hedge funds, mixed funds, and non hedge funds.

Panel A: Aggregate Sample Size

	Hedge Funds			Mixed Funds			Non Hedge Funds		
Manager Type	Managers	Clients	Man-Clients	Managers	Clients	Man-Clients	Managers	Clients	Man-Clients
All	74	253	364	217	566	2084	274	571	1655
Plan Sponsor	64	225	335	204	496	2002	254	488	1569
Money Manager	27	28	29	72	70	82	76	83	87

Panel B: Time-Series of Quarterly Averages

	Hedge Funds			Mixed Funds			Non Hedge Funds		
Year	Man-Clients	Ave Vol ($m)	Med Vol ($m)	Man-Clients	Ave Vol ($m)	Med Vol ($m)	Man-Clients	Ave Vol ($m)	Med Vol ($m)
1999	115.75	69.15	14.50	702.25	287.07	27.01	581.50	504.27	15.83
2000	115.75	57.62	17.99	669.75	308.99	28.96	540.00	961.37	21.59
2001	115.00	67.39	17.45	668.25	302.12	22.52	560.25	706.97	15.10
2002	126.50	119.50	10.84	686.50	359.90	18.97	571.75	656.20	13.63
2003	120.25	102.66	9.48	627.25	384.93	17.20	540.00	512.65	12.90
2004	111.50	148.11	11.13	594.50	362.34	19.14	506.75	797.55	14.90
2005	103.25	349.45	11.75	533.75	366.05	21.28	440.50	514.25	14.09
2006	91.25	473.64	17.59	461.50	576.56	23.13	372.00	800.21	16.57
2007	84.25	559.16	20.06	401.00	809.00	29.80	315.75	1099.85	19.95
2008	64.25	655.62	20.01	311.25	974.46	25.41	225.00	1261.81	17.60
2009	43.50	521.77	10.44	240.50	351.36	13.58	153.75	1026.34	12.27
2010	32.00	639.80	20.48	162.00	246.28	15.57	102.50	1219.03	14.88

Table 2: The Magnitude of Intra-Quarter Trading

This table reports the cross-sectional distribution of quarterly trading for hedge funds, mixed funds, and non hedge funds (Non HF). This measure is computed each quarter. The table presents the time-series average across the 48 quarters in the sample. We also report the ratio of actual to implied quarter trading. Actual trading is based on actual transaction data. Implied quarterly trading is computed as the net dollar volume (buys -sells) for a stock over a quarter. Panel A reports the results for pension plan sponsor clients and Panel B reports the results for money manager clients.

Panel A: Pension Plan Sponsors

	Quarterly Trading Volume per Client-Manager-Quarter ($ mil)								
	Mean	Std Dev	99	95	75	50	25	5	1
Hedge Funds	39.76	107.15	403.91	166.37	38.76	11.84	3.74	0.39	0.04
Mixed Funds	72.35	593.82	638.18	229.30	57.92	20.55	6.87	0.74	0.07
Non HF	51.81	338.67	433.77	161.48	39.29	13.99	4.47	0.58	0.10
	Ratio of Actual to Implied Quarterly Trading								
	Mean	Std Dev	99	95	75	50	25	5	1
Hedge Funds	1.28	7.01	2.52	1.59	1.16	1.03	1.00	1.00	1.00
Mixed Funds	1.40	23.06	2.41	1.51	1.19	1.08	1.00	1.00	1.00
Non HF	1.21	3.62	2.12	1.48	1.17	1.05	1.00	1.00	1.00

Panel B: Money Managers

	Quarterly Trading Volume per Client-Manager-Quarter ($ mil)								
	Mean	Std Dev	99	95	75	50	25	5	1
Hedge Funds	2,675.74	4,128.64	24,102.65	7,221.76	3,814.59	1,534.73	414.88	6.16	2.84
Mixed Funds	7,312.26	16,713.11	92,798.85	45,281.07	5,243.11	1,235.14	195.71	8.33	0.90
Non HF	11,225.47	30,303.51	165,384.86	53,625.52	7,311.40	1,727.11	392.86	31.76	4.35
	Ratio of Actual to Implied Quarterly Trading								
	Mean	Std Dev	99	95	75	50	25	5	1
Hedge Funds	1.48	0.62	3.96	2.90	1.53	1.26	1.16	1.01	1.00
Mixed Funds	1.35	0.32	2.43	1.91	1.47	1.29	1.12	1.00	1.00
Non HF	1.41	0.43	2.91	2.19	1.54	1.29	1.13	1.01	1.00

Table 3: Aggregate Performance by Investor Type

This table reports the results from analysis using transaction-based calendar-time portfolios with holding periods ranging from 21 days to 252 days. Transactions are aggregated across all funds within the same institution type (e.g. hedge funds, mixed funds, and non hedge funds). For each holding period, our approach generates a time-series of daily returns. Returns are inclusive of ‘Day 0' returns based on the reported execution price. This table reports the average return across all days in our sample period, expressed as monthly returns in percent. We also estimate 'interim skill' as defined in Puckett and Yan (2011). Specifically, we split all trades into buys and sells and compute the principal-weighted return on the buy and sell portfolio, where returns are measured from execution price until the end of the quarter. The interim skill measure reflects the average return across all 48 quarters in the sample, expressed in percent. Panel A reports the results using gross returns. Panel B reports DGTW-adjusted returns. Panel C reports DGTW-adjusted returns after incorporating trading commissions. T-statistics, based on Newey-West standard errors with five lags, are reported in parentheses.

Panel A: Gross Returns

	Holding Period				
	21	63	126	252	Interim Skill
Hedge Funds					
Buys	0.92	0.79	0.68	0.61	0.99
Sells	0.80	0.70	0.66	0.61	0.81
Buys - Sells	0.12	0.09	0.02	-0.01	0.18
	(0.68)	(0.65)	(0.18)	(-0.07)	(0.90)
Mixed Funds					
Buys	0.82	0.69	0.63	0.55	0.92
Sells	0.56	0.58	0.56	0.50	0.71
Buys - Sells	0.26	0.11	0.08	0.05	0.21
	(3.22)	(1.92)	(1.85)	(1.37)	(2.08)
Non Hedge Funds					
Buys	0.67	0.56	0.51	0.45	0.61
Sells	0.58	0.62	0.59	0.55	0.67
Buys - Sells	0.09	-0.06	-0.08	-0.09	-0.06
	(1.27)	(-1.07)	(-1.66)	(-2.11)	(-0.49)

Panel B: DGTW-Adjusted Returns

	Holding Period				
	21	63	126	252	Interim Skill
Hedge Funds					
Buys	0.27	0.08	-0.01	-0.05	0.39
Sells	0.14	-0.02	-0.05	-0.08	0.10
Buys - Sells	0.12	0.09	0.04	0.04	0.29
	(0.80)	(0.84)	(0.44)	(0.54)	(1.71)
Mixed Funds					
Buys	0.14	0.01	-0.03	-0.06	0.32
Sells	0.00	-0.04	-0.06	-0.08	0.17
Buys - Sells	0.14	0.05	0.03	0.03	0.15
	(2.29)	(1.07)	(0.80)	(1.02)	(2.19)
Non Hedge Funds					
Buys	0.05	-0.08	-0.10	-0.11	0.20
Sells	0.03	0.00	-0.02	-0.05	0.27
Buys - Sells	0.02	-0.08	-0.08	-0.06	-0.10
	(0.37)	(-1.95)	(-2.41)	(-2.25)	(-1.31)

Panel C: DGTW-Adjusted Returns Less Commissions (Table 3 Continued)

	Holding Period				
	21	63	126	252	Interim Skill
Hedge Funds					
Buys	0.12	0.03	-0.04	-0.06	0.26
Sells	0.29	0.04	-0.02	-0.07	0.24
Buys - Sells	-0.17	-0.01	-0.02	0.01	0.01
	(-1.10)	(-0.08)	(-0.23)	(0.03)	(0.05)
Mixed Funds					
Buys	0.04	-0.03	-0.05	-0.07	0.21
Sells	0.10	0.00	-0.04	-0.07	0.27
Buys - Sells	-0.06	-0.02	-0.01	0.01	-0.06
	(-0.91)	(-0.53)	(-0.33)	(0.22)	(-0.83)
Non Hedge Funds					
Buys	-0.04	-0.11	-0.12	-0.12	0.01
Sells	0.12	0.04	-0.01	-0.04	0.30
Buys - Sells	-0.16	-0.14	-0.11	-0.08	-0.29
	(-2.87)	(-3.56)	(-3.49)	(-2.93)	(-3.74)

Table 4: Fund-Level Performance by Investor Type

This table reports the results from analysis using transaction-based calendar-time portfolios with holding periods ranging from 21 days to 252 days. We estimate performance for each fund and report the equally weighted average across funds within the same institution type (e.g. hedge funds, mixed funds, and non hedge funds). For each holding period, we exclude fund-days in which there are fewer than 10 stocks in both the buy and sell portfolio. Returns are inclusive of 'Day 0' returns based on the reported execution price. This table reports the average return across all days in our sample period, expressed as monthly returns in percent. We also estimate 'interim skill' as defined in Puckett and Yan (2011). Specifically, we split all trades into buys and sells and compute the principal-weighted return on the buy and sell portfolio, where returns are measured from execution price until the end of the quarter. The interim skill measure reflects the average return across all 48 quarters in the sample, expressed in percent. Panel A reports the results using gross returns. Panel B reports DGTW-adjusted returns. Panel C reports DGTW-adjusted returns after incorporating trading commissions. T-statistics, based on standard errors clustered by fund and day (or quarter) are reported in parentheses.

Panel A: Gross Returns

	Holding Period				
	21	63	126	252	Interim Skill
Hedge Funds					
Buys	1.07	0.68	0.71	0.72	1.26
Sells	0.66	0.65	0.70	0.66	0.95
Buys - Sells	0.41	0.03	0.02	0.06	0.31
	(2.78)	(0.32)	(0.21)	(0.87)	(1.39)
Mixed Funds					
Buys	0.93	0.65	0.61	0.55	1.05
Sells	0.69	0.61	0.59	0.56	0.79
Buys - Sells	0.24	0.04	0.02	-0.01	0.25
	(3.89)	(0.91)	(0.69)	(-0.34)	(2.58)
Non Hedge Funds					
Buys	0.88	0.54	0.49	0.47	0.85
Sells	0.55	0.52	0.56	0.57	0.66
Buys - Sells	0.33	0.02	-0.07	-0.10	0.19
	(4.21)	(0.31)	(-1.53)	(-2.87)	(1.83)

Panel B: DGTW-Adjusted Returns

	Holding Period				
	21	63	126	252	Interim Skill
Hedge Funds					
Buys	0.28	0.01	0.02	0.01	0.43
Sells	-0.03	-0.02	-0.02	-0.06	0.09
Buys - Sells	0.30	0.03	0.04	0.07	0.33
	(2.28)	(0.34)	(0.50)	(1.36)	(1.61)
Mixed Funds					
Buys	0.22	0.02	-0.03	-0.08	0.44
Sells	0.12	0.03	-0.03	-0.06	0.26
Buys - Sells	0.10	-0.01	-0.01	-0.02	0.18
	(1.82)	(-0.31)	(-0.31)	(-0.88)	(2.36)
Non hedge Funds					
Buys	0.27	-0.02	-0.08	-0.09	0.40
Sells	0.03	-0.02	-0.03	-0.03	0.19
Buys - Sells	0.24	0.00	-0.05	-0.07	0.20
	(3.62)	(0.04)	(-1.33)	(-2.49)	(2.30)

Panel C: DGTW-Adjusted Returns less Commissions (Table 4 continued)					
	Holding Period				
	21	63	126	252	Interim Skill
Hedge Funds					
Buys	0.09	-0.05	-0.02	-0.01	0.24
Sells	0.16	0.04	0.01	-0.04	0.26
Buys - Sells	-0.07	-0.09	-0.03	0.04	-0.01
	(-0.49)	(-1.03)	(-0.35)	(0.68)	(-0.09)
Mixed Funds					
Buys	0.10	-0.02	-0.06	-0.09	0.32
Sells	0.24	0.07	0.00	-0.04	0.38
Buys - Sells	-0.13	-0.09	-0.05	-0.04	-0.06
	(-2.41)	(-2.62)	(-1.95)	(-2.10)	(-0.75)
Non Hedge Funds					
Buys	0.14	-0.06	-0.11	-0.11	0.27
Sells	0.16	0.02	-0.01	-0.01	0.32
Buys - Sells	-0.02	-0.09	-0.09	-0.09	-0.05
	(-0.26)	(-1.88)	(-2.60)	(-3.43)	(-0.58)

Table 5: The Cross-Section of Fund Performance

For each fund, we estimate performance using transaction-based calendar time portfolios with a 252 day holding period. We exclude fund-days in which there are fewer than 10 stocks in both the buy and sell portfolio. We also exclude funds that are in the sample for less than one year. Returns are inclusive of 'Day 0' returns based on the reported execution price. In Panel A, we estimate returns based on DGTW-adjusted returns but exclude trading commissions. In Panel B we estimate returns using DGTW-adjusted returns and include trading commissions. For each fund in the sample, we compute the actual t-statistic of alpha based on the entire time-series of the funds' returns. "Actual' reports the distribution of t-statistics across all funds by institution type. We compare the actual distribution of t-statistics to a simulated distribution of t-statistics under the null hypothesis that the true alpha is zero for all funds. Additional details of the simulation are described in the text. We also show the percentage of simulations draws that produce a t-statistic greater than the corresponding actual value.

Panel A : 252 Day Holding Period Without Commissions

	Hedge Funds			**Mixed Funds**			**Non Hedge Funds**		
Pct	Actual	Simulated	% > Act	Actual	Simulated	% > Act	Actual	Simulated	% > Act
1	-2.96	-2.61	86.6%	-2.73	-2.65	71.2%	-2.77	-2.65	77.0%
2	-1.93	-2.20	11.8%	-2.30	-2.17	84.8%	-2.32	-2.17	86.4%
3	-1.68	-1.99	5.5%	-2.05	-1.96	80.5%	-2.09	-1.96	86.0%
4	-1.57	-1.82	8.6%	-1.92	-1.81	85.1%	-1.92	-1.81	83.4%
5	-1.55	-1.69	21.4%	-1.79	-1.70	84.8%	-1.80	-1.69	86.3%
10	-1.15	-1.31	13.1%	-1.37	-1.31	78.0%	-1.47	-1.31	96.1%
20	-0.76	-0.86	21.4%	-0.96	-0.85	93.0%	-1.06	-0.85	99.3%
30	-0.41	-0.53	14.8%	-0.61	-0.53	90.7%	-0.70	-0.53	98.6%
40	-0.12	-0.26	10.7%	-0.33	-0.26	88.9%	-0.39	-0.26	96.5%
50	0.14	0.00	10.6%	-0.07	0.00	90.5%	-0.12	0.00	95.0%
60	0.38	0.26	12.5%	0.21	0.26	79.0%	0.09	0.26	99.0%
70	0.72	0.54	6.6%	0.50	0.53	67.8%	0.35	0.53	99.6%
80	1.07	0.86	5.4%	0.80	0.85	78.0%	0.67	0.85	99.0%
90	1.71	1.32	0.7%	1.27	1.31	66.7%	1.22	1.31	82.1%
95	1.96	1.70	6.6%	1.62	1.69	79.8%	1.61	1.69	77.3%
96	2.26	1.83	1.7%	1.75	1.81	73.4%	1.77	1.82	64.3%
97	2.48	2.00	1.9%	1.94	1.96	57.4%	1.92	1.96	63.7%
98	2.83	2.20	1.0%	2.20	2.18	39.7%	2.07	2.18	78.5%
99	3.43	2.61	1.2%	2.86	2.65	10.4%	2.60	2.66	59.9%

Panel B : 252 Day Holding Period With Commissions (Table 5 continued)

	Hedge Funds			**Mixed Funds**			**Non Hedge Funds**		
Pct	Actual	Simulated	% > Act	Actual	Simulated	% > Act	Actual	Simulated	% > Act
1	-3.06	-2.61	91.8%	-2.88	-2.65	92.0%	-2.91	-2.65	92.3%
2	-2.00	-2.19	21.2%	-2.38	-2.17	94.9%	-2.39	-2.17	94.1%
3	-1.75	-1.98	12.8%	-2.14	-1.96	94.3%	-2.14	-1.96	93.3%
4	-1.65	-1.81	17.9%	-2.00	-1.81	96.7%	-1.98	-1.81	93.8%
5	-1.62	-1.69	36.6%	-1.88	-1.69	97.0%	-1.87	-1.69	94.8%
10	-1.28	-1.31	44.4%	-1.45	-1.31	96.2%	-1.55	-1.30	99.4%
20	-0.82	-0.86	40.4%	-1.03	-0.85	99.2%	-1.13	-0.85	99.9%
30	-0.51	-0.53	41.5%	-0.68	-0.53	99.1%	-0.78	-0.53	99.9%
40	-0.23	-0.25	39.9%	-0.42	-0.26	99.6%	-0.45	-0.26	99.6%
50	0.01	0.00	46.4%	-0.16	0.00	99.6%	-0.18	0.00	99.5%
60	0.27	0.26	46.2%	0.13	0.26	98.6%	0.03	0.26	100.0%
70	0.58	0.54	36.7%	0.43	0.53	95.7%	0.28	0.53	100.0%
80	1.01	0.86	12.0%	0.72	0.86	98.2%	0.60	0.86	100.0%
90	1.60	1.31	3.3%	1.17	1.31	96.3%	1.16	1.31	96.4%
95	1.91	1.70	11.1%	1.52	1.70	97.3%	1.54	1.70	93.8%
96	2.16	1.83	4.3%	1.66	1.82	93.9%	1.66	1.82	92.4%
97	2.43	2.00	2.6%	1.85	1.96	85.5%	1.82	1.97	89.8%
98	2.75	2.20	1.9%	2.06	2.18	83.6%	1.98	2.18	94.7%
99	3.23	2.62	4.3%	2.74	2.66	28.5%	2.51	2.66	80.5%

Table 6: Persistence in Interim Trading Skill

We sort funds into quintiles according to the DGTW-adjusted interim trading skill during the ranking period of one quarter. We exclude funds with fewer than 10 buys and 10 sells in a given quarter. We hold the quintile portfolios for post-ranking periods ranging of one quarter, two to four quarters, five to eight quarters, and two years (quarters 1 through 8). We rebalance the portfolios at the end of every quarter. We present results where both the ranking period and post ranking period returns exclude commissions (interim skill) as well as when both the ranking period and post ranking period returns include commissions (interim skill + commissions). The post ranking returns reflect the average quarterly return, expressed in percent. Panel A reports the results for hedge funds. Panels B and C report the results for mixed funds and non hedge funds, respectively. T-statistics, based on standard errors clustered by fund and quarter, are reported in parentheses.

Panel A: Hedge Funds

	Interim Skill Holding Period (in Quarters)				Interim Skill + Commissions Holding Period (in Quarters)			
Quintile	[1,1]	[2,4]	[5,8]	[1,8]	[1,1]	[2,4]	[5,8]	[1,8]
1	-0.02	0.30	-0.20	0.04	-0.36	-0.06	-0.56	-0.32
	(-0.04)	(1.05)	(-0.86)	(0.37)	(-1.03)	(-0.20)	(-2.16)	(-1.28)
2	0.08	0.31	0.30	0.27	-0.32	-0.12	-0.07	-0.13
	(0.22)	(1.26)	(1.47)	(1.41)	(-0.93)	(-0.47)	(-0.32)	(-0.63)
3	0.70	0.20	0.27	0.31	0.36	-0.05	-0.02	0.03
	(2.39)	(1.04)	(1.52)	(1.94)	(1.17)	(-0.26)	(0.12)	(0.19)
4	0.30	0.46	0.24	0.34	0.00	0.11	-0.09	0.01
	(1.13)	(2.27)	(1.08)	(1.94)	(0.01)	(0.61)	(-0.39)	(0.07)
5	1.42	1.07	0.54	0.91	1.04	0.68	0.13	0.52
	(3.60)	(3.00)	(1.72)	(3.32)	(2.51)	(1.87)	(0.41)	(1.85)
5-1	1.43	0.77	0.74	0.87	1.40	0.74	0.69	0.83
	(2.97)	(1.71)	(2.02)	(2.84)	(2.95)	(1.66)	(1.85)	(2.73)

Panel B: Mixed Funds

	Interim Skill Holding Period (in Quarters)				Interim Skill + Commissions Holding Period (in Quarters)			
Quintile	[1,1]	[2,4]	[5,8]	[1,8]	[1,1]	[2,4]	[5,8]	[1,8]
1	-0.05	-0.03	0.08	0.01	-0.33	-0.30	-0.17	-0.25
	(-0.34)	(-0.27)	(0.85)	(0.09)	(-2.07)	(-2.30)	(-1.26)	(-2.21)
2	0.21	0.19	0.12	0.16	-0.02	-0.03	-0.12	-0.06
	(1.66)	(1.85)	(1.22)	(1.94)	(-0.16)	(-0.24)	(-1.26)	(-0.76)
3	0.23	0.28	0.17	0.23	0.04	0.03	-0.07	-0.01
	(1.76)	(3.03)	(2.25)	(2.93)	(0.29)	(0.37)	(0.92)	(-0.11)
4	0.28	0.24	0.31	0.28	0.00	0.02	0.08	0.04
	(2.39)	(2.18)	(3.59)	(3.21)	(0.03)	(0.23)	(0.89)	(0.50)
5	0.32	0.32	0.30	0.31	0.07	0.03	0.03	0.04
	(2.32)	(3.05)	(2.60)	(3.20)	(0.55)	(0.31)	(0.26)	(0.40)
5-1	0.37	0.35	0.22	0.30	0.40	0.33	0.20	0.29
	(1.99)	(2.66)	(1.92)	(3.49)	(2.15)	(2.46)	(1.79)	(3.36)

Panel C: Non Hedge Funds (Table 6 continued)								
	Interim Skill Holding Period (in Quarters)				Interim Skill + Commissions Holding Period (in Quarters)			
Quintile	[1,1]	[2,4]	[5,8]	[1,8]	[1,1]	[2,4]	[5,8]	[1,8]
1	-0.31	-0.01	0.06	-0.03	-0.55	-0.29	-0.21	-0.30
	(-1.29)	(-0.08)	(0.43)	(-0.24)	(-2.30)	(-1.88)	(-1.46)	(-2.21)
2	0.33	0.25	0.20	0.24	0.09	0.02	-0.06	-0.01
	(2.42)	(2.25)	(2.06)	(2.76)	(0.62)	(0.20)	(-0.60)	(-0.01)
3	0.29	0.19	0.16	0.19	0.02	-0.03	-0.06	-0.03
	(2.33)	(1.41)	(1.35)	(1.77)	(0.13)	(-0.21)	(-0.53)	(-0.32)
4	0.44	0.38	0.27	0.34	0.22	0.09	0.00	0.07
	(2.51)	(3.05)	(2.82)	(3.99)	(1.21)	(0.71)	(0.00)	(0.71)
5	0.61	0.39	0.44	0.45	0.30	0.11	0.14	0.15
	(3.28)	(2.84)	(3.99)	(4.29)	(1.58)	(0.83)	(1.26)	(1.49)
5-1	0.93	0.40	0.38	0.48	0.84	0.40	0.34	0.45
	(3.06)	(2.02)	(2.57)	(3.61)	(2.77)	(2.08)	(2.37)	(3.46)

Table 7: Persistence in Annual Trading Skill

We estimate annual fund performance using two approaches: *actual* and *implied*. The *actual* measure uses actual transaction data and thus adds the purchased (or sold) stock into the buy (sell) portfolio on the day of the trades (and includes day 0 returns). The implied measure adds stocks to the portfolio at the end of every quarter based on net quarterly trading and assumes all trades occur at the end of quarter closing price. Both approaches hold the stock for 252 trading days.
We sort funds into quintiles according to the actual (or implied) DGTW-adjusted performance over the prior year. We exclude fund-days observations in which there are fewer than 10 stocks in both the buy and the sell portfolio. We hold the quintile portfolios for post-ranking periods ranging from one year to three years. We rebalance the portfolios at the end of every year. We report the results for one, two, and three year separately, as well as the cumulative three year holding period. The post ranking returns reflect the average daily return, expressed as monthly returns in percent. Panel A reports the results for hedge funds. Panels B and C report the results for mixed funds and non hedge funds, respectively. T-statistics, based on standard errors clustered by fund and day, are reported in parentheses.

Panel A: Hedge Funds

	Actual Annual Performance				*Implied* Annual Performance			
Quintile	Year 1	Year2	Year 3	Year [1-3]	Year 1	Year2	Year 3	Year [1-3]
1	0.01	0.03	0.04	0.02	-0.06	0.06	0.05	0.00
	(0.11)	(0.30)	(0.37)	(0.34)	(-0.55)	(0.60)	(0.50)	(0.04)
2	-0.06	0.07	0.07	0.01	0.07	0.15	0.07	0.09
	(-0.71)	(0.86)	(0.79)	(0.23)	(0.69)	(1.63)	(0.79)	(1.37)
3	0.02	0.05	0.02	0.03	-0.02	0.12	0.15	0.06
	(0.33)	(0.65)	(0.28)	(0.60)	(-0.35)	(1.59)	(1.91)	(1.23)
4	0.00	0.11	0.11	0.06	0.08	0.07	0.18	0.10
	(0.02)	(1.57)	(1.53)	(1.20)	(0.98)	(0.99)	(2.12)	(1.79)
5	0.40	0.19	0.13	0.27	0.25	0.21	0.03	0.19
	(3.57)	(1.43)	(1.02)	(2.85)	(2.00)	(1.63)	(0.25)	(1.93)
5-1	0.39	0.16	0.09	0.24	0.31	0.15	-0.02	0.18
	(2.51)	(0.95)	(0.58)	(2.40)	(1.80)	(0.94)	(-0.11)	(1.61)

Panel B: Mixed Funds

	Actual Annual Performance				*Implied* Annual Performance			
Quintile	Year 1	Year2	Year 3	Year [1-3]	Year 1	Year2	Year 3	Year [1-3]
1	-0.07	-0.06	-0.10	-0.07	-0.07	-0.05	-0.06	-0.06
	(-1.19)	(-1.24)	(-2.28)	(-1.83)	(-1.26)	(-1.13)	(-1.04)	(-1.57)
2	-0.08	-0.05	-0.06	-0.07	-0.08	-0.03	-0.07	-0.06
	(-2.86)	(-1.87)	(-2.01)	(-3.18)	(-2.61)	(-0.87)	(-2.24)	(-2.59)
3	-0.06	-0.04	-0.06	-0.05	-0.09	-0.08	-0.04	-0.08
	(-2.46)	(-1.49)	(-2.31)	(-2.77)	(-3.08)	(-2.59)	(-1.38)	(-3.24)
4	-0.02	-0.05	-0.01	-0.03	-0.02	-0.04	0.01	-0.02
	(-0.51)	(-1.67)	(-0.40)	(-1.10)	(-0.49)	(-1.08)	(0.32)	(-0.68)
5	-0.01	-0.05	0.02	-0.01	0.00	-0.05	0.03	-0.01
	(-0.14)	(-1.17)	(0.52)	(-0.38)	(-0.02)	(-1.07)	(0.58)	(-0.25)
5-1	0.06	0.01	0.12	0.06	0.07	0.01	0.08	0.05
	(0.67)	(0.11)	(2.14)	(1.23)	(0.77)	(0.09)	(1.29)	(1.11)

Panel C: Non Hedge Funds (Table 7 continued)								
	Actual Annual Performance				*Implied* Annual Performance			
Quintile	Year 1	Year2	Year 3	Year [1-3]	Year 1	Year2	Year 3	Year [1-3]
1	-0.07	-0.07	-0.07	-0.07	-0.04	-0.02	-0.06	-0.04
	(-0.85)	(-1.28)	(-1.46)	(-1.41)	(-0.45)	(-0.38)	(-1.04)	(-0.72)
2	-0.10	-0.05	-0.06	-0.08	-0.10	-0.10	-0.05	-0.09
	(-2.64)	(-1.30)	(-1.48)	(-2.48)	(-2.59)	(-2.31)	(-1.08)	(-2.73)
3	-0.07	0.00	-0.04	-0.04	-0.08	-0.04	-0.01	-0.05
	(-2.20)	(0.03)	(-1.16)	(-1.54)	(-2.35)	(-0.98)	(-0.30)	(-1.76)
4	-0.05	-0.07	-0.02	-0.05	-0.09	-0.02	-0.05	-0.06
	(-1.45)	(-1.77)	(-0.50)	(-1.76)	(-2.33)	(-0.59)	(-1.24)	(-2.00)
5	-0.08	-0.08	-0.07	-0.08	-0.09	-0.09	-0.09	-0.09
	(-1.65)	(-1.46)	(-1.10)	(-1.89)	(-1.74)	(-1.81)	(-1.51)	(-2.29)
5-1	-0.01	-0.01	0.00	-0.01	-0.06	-0.07	-0.03	-0.05
	(-0.12)	(-0.10)	(0.06)	(-0.12)	(-0.60)	(-0.93)	(-0.39)	(-1.09)

Table 8: Performance by Stock Characteristic

This table reports the trading performance of different types of institutions across stocks with different characteristics. Mixed Funds (Mixed) and Non Hedge Funds (Non HF) are defined as in section 2.1. Hedge funds, as defined in section 2.1, are further partitioned in Smart Hedge Funds (Smart HF) and Other Hedge Funds (Other HF). Smart HFs are hedge funds that were in the top quintile of annual performance in the prior year. Other HFs are all remaining hedge funds. We assign stocks to size, book-to-market, illiquidity and volatility groups based on median NYSE breakpoints. All stock characteristics are defined in Appendix A. We also define stocks according to the time of the most recent earnings announcements. Pre-earnings stocks are stocks which will announce earnings within the next 10 trading days, and post earnings announcement stocks announced earnings within the past 10 trading days. For each fund and stock characteristic, we compute the principal-weighted DGTW-adjusted returns on the stocks bought less the stocks sold. We report the equal-weighted average across all funds for a given institution type. Panel A reports the results for the end-of-quarter holding period and Panel B reports the results for the annual holding period. Both measures compute returns inclusive of commissions. T-statistics, based on standard errors clustered by fund and quarter are reported in parentheses.

Panel A: Interim Trading Performance (+ Commissions)

	Smart HF	Other HF	Mixed	Non HF	Smart - Other	Smart - Non HF
Small	2.21	0.00	-0.14	0.01	2.21	2.20
	(2.01)	(0.00)	(-0.82)	(0.06)	(2.05)	(1.99)
Large	-0.06	-0.12	-0.29	-0.19	0.06	0.13
	(-0.07)	(-0.48)	(-2.14)	(1.14)	(0.08)	(0.15)
Small - Large	2.26	0.12	0.15	0.20	2.14	2.07
	(2.12)	(0.35)	(0.71)	(0.92)	(2.15)	(2.09)
Growth	1.30	-0.20	-0.04	-0.23	1.49	1.52
	(0.82)	(-0.59)	(-0.29)	(-1.37)	(0.92)	(0.97)
Value	0.98	-0.31	-0.14	-0.11	1.29	1.08
	(1.63)	(-1.37)	(-1.47)	(-0.92)	(2.04)	(1.80)
Growth - Value	0.32	0.12	0.10	-0.12	0.20	0.44
	(0.22)	(0.30)	(0.56)	(-0.71)	(0.14)	(0.32)
Illiquid	3.42	0.11	0.04	0.00	3.31	3.42
	(2.85)	(0.34)	(0.19)	(-0.01)	(2.56)	(2.62)
Liquid	0.35	-0.09	-0.26	-0.29	0.44	0.64
	(0.35)	(-0.31)	(-1.63)	(-1.88)	(0.43)	(0.63)
Illiquid - Liquid	3.07	0.20	0.30	0.29	2.87	2.78
	(2.48)	(0.65)	(1.14)	(1.18)	(1.85)	(1.94)
High Volatility	0.24	-0.27	-0.09	-0.19	0.50	0.42
	(0.37)	(-1.01)	(-0.93)	(-1.00)	(0.75)	(0.67)
Low Volatility	0.60	0.06	-0.14	-0.01	0.54	0.61
	(0.89)	(0.24)	(-1.27)	(-0.09)	(0.74)	(0.85)
High - Low Vol.	-0.36	-0.32	0.05	-0.18	-0.04	-0.18
	(-0.38)	(-0.95)	(0.34)	(-0.99)	(-0.04)	(-0.20)
Pre_Earnings	2.29	0.03	-0.15	-0.40	2.26	2.69
	(2.52)	(0.08)	(-1.02)	(-2.45)	(3.05)	(3.16)
Post_Earnings	1.87	0.14	0.00	0.02	1.73	1.84
	(1.49)	(0.55)	(-0.01)	(0.14)	(1.37)	(1.58)
Non Earnings	1.22	0.02	-0.19	0.10	1.20	1.21
	(1.46)	(0.09)	(-1.98)	(0.08)	(1.54)	(1.47)
Pre - Post	0.42	-0.11	-0.15	-0.43	0.53	0.85
	(0.38)	(-0.29)	(-0.60)	(-2.19)	(0.50)	(0.83)

Panel B: Annual Trading Performance (+ Commissions)						
	Smart HF	Other HFs	Mixed	Non HF	Smart - Other	Smart - Non HF
Small	6.89	1.03	-1.13	-0.23	5.86	7.12
	(2.33)	(1.23)	(-1.81)	(-0.41)	(2.07)	(2.41)
Large	3.21	0.78	0.32	-0.19	2.42	3.39
	(1.08)	(0.82)	(0.89)	(-0.42)	(0.89)	(1.18)
Small - Large	3.68	0.25	-1.45	-0.04	3.43	3.75
	(0.95)	(0.26)	(-2.14)	(-0.06)	(0.88)	(1.01)
Growth	2.74	0.44	-1.15	-0.74	2.29	3.48
	(1.05)	(0.44)	(-3.48)	(-1.72)	(0.91)	(1.36)
Value	5.67	-0.35	-0.19	-0.34	6.02	6.01
	(2.53)	(-0.45)	(-0.75)	(-1.07)	(2.90)	(2.62)
Growth - Value	-2.93	0.80	-0.96	-0.40	-3.72	-2.53
	(-0.82)	(0.60)	(-2.90)	(-0.76)	(-1.01)	(-0.69)
Illiquid	6.31	0.66	-0.88	-0.36	5.64	6.67
	(1.70)	(0.74)	(-1.41)	(-0.65)	(1.56)	(1.78)
Liquid	1.96	0.50	-0.30	0.06	1.46	1.89
	(0.91)	(0.55)	(-0.95)	(0.14)	(0.78)	(0.95)
Illiquid - Liquid	4.35	0.16	-0.57	-0.42	4.19	4.78
	(1.19)	(0.15)	(-0.90)	(-0.57)	(1.14)	(1.36)
High Volatility	7.08	1.21	-1.01	-1.07	5.87	8.16
	(3.19)	(1.96)	(-2.59)	(-3.19)	(2.44)	(3.22)
Low Volatility	3.21	0.25	-0.26	-0.03	2.96	3.22
	(2.05)	(0.35)	(-1.20)	(-0.09)	(1.54)	(1.88)
High - Low Vol.	3.88	0.96	-0.75	-1.05	2.92	4.92
	(1.27)	(0.90)	(-1.94)	(-3.03)	(0.88)	(1.55)
Pre_Earnings	5.30	-0.76	-0.32	-0.10	6.06	5.40
	(2.14)	(-0.76)	(-0.90)	(-0.21)	(2.50)	(2.20)
Post_Earnings	2.17	0.89	-1.03	-0.53	1.32	2.70
	(1.21)	(1.02)	(-2.90)	(-1.05)	(0.71)	(1.47)
Non Earnings	4.34	0.82	-0.61	-0.32	3.52	4.68
	(2.10)	(1.44)	(-2.26)	(-1.20)	(1.68)	(2.01)
Pre - Post	3.13	-1.62	0.71	0.42	4.75	2.69
	(1.12)	(-1.24)	(1.61)	(0.83)	(1.59)	(0.95)

Table 9: Execution Shortfall by Institution Type

This table reports the results of panel regressions of measures of execution shortfall on institution type. The institution types considered are smart hedge funds (Smart HF), other hedge funds (other HF), mixed funds, and non-hedge funds. Institution types are defined in Table 8. The non-hedge funds are the omitted group (i.e. the intercept) in the regression. We consider four dependent variables. The first is the average execution shortfall (shortfall). Shortfall is defined as the execution price of the trade less the price at the time the broker receives the trade, scaled by the price at the time the broker receives the trade. Shortfall is multiplied by negative one for sell trades. For each fund, shortfall is computed as the principal-weighted average shortfall across all trades within a quarter less the average execution shortfall across all funds in a given quarter. We report the average shortfall across all funds for a given institution type. We create 3 additional dummy variables: liquidity supplier (LS), liquidity neutral (LN), and liquidity demander (LD). LS (LD) equals one if the fund is in the bottom (top) quintile of execution shortfall for a given quarter. LN equals 1 if the fund is in the middle three quintiles. We report results for both year 0 (i.e. the formation period year for assigning smart hedge funds) and year 1. T-statistics, based on standard errors clustered by fund and quarter, are reported in parentheses.

	Year 0				*Year 1*			
	Shortfall	**% LS**	**% LN**	**% LD**	**Shortfall**	**% LS**	**% LN**	**% LD**
Smart HF	-0.07	13.35	-13.42	0.06	-0.04	13.58	-17.38	3.81
	(-1.02)	(3.53)	(-4.15)	(0.02)	(0.48)	(3.18)	(-4.52)	(0.98)
Other HF	0.18	-0.51	-10.54	11.15	0.14	1.76	-11.28	9.52
	(3.11)	(-0.20)	(-4.15)	(3.69)	(2.09)	(0.59)	(-3.65)	(2.78)
Mixed Fund	0.10	-6.06	3.24	2.81	0.08	-5.57	2.72	2.85
	(4.68)	(-5.17)	(2.61)	(2.51)	(3.63)	(-4.14)	(1.91)	(2.22)
Intercept	-0.06	22.93	59.25	17.82	-0.05	22.52	59.63	17.85
	(-4.04)	(25.33)	(67.36)	(2.51)	(-3.12)	(21.79)	(59.17)	(20.84)
Smrt HF - Other HF	-25.01	13.83	-2.88	-10.98	-0.18	11.82	-6.11	-5.71
	(-3.64)	(3.80)	(-0.87)	(3.48)	(2.28)	(2.95)	(-1.53)	(-1.48)

Table 10: Annual Performance Persistence of Liquidity Supplying versus Liquidity Demanding Hedge Funds

This table revisits the performance persistence of smart hedge funds (i.e. hedge funds in the top quintile of performance in Table 7) and other hedge funds (i.e. hedge funds in the bottom four quintiles of performance in Table 7). The methodology is identical to the '*actual annual performance*' reported in Table 7, except we now partition funds into three groups: liquidity demanders (LD), liquidity neutral (LN) and liquidity suppliers (LS). We create two liquidity proxies: execution shortfall and short-term momentum trading. Funds in the bottom (top) quintile of execution shortfall (as defined in Table 8) or funds in the bottom (top) quintile of net trading based on past one month returns (as defined in Figure 1) are defined as liquidity suppliers (liquidity demanders). Funds in the middle three quintiles are defined as liquidity neutral. Panel A reports the results for smart hedge funds (quintile 5 of past performance) and Panel B reports the results for all other hedge funds (quintiles 1 through 4). T-statistics, based on standard errors clustered by fund and day, are reported in parentheses.

Panel A: 'Smart' Hedge Fund Persistence by Liquidity Group

	Annual Performance (+ Commissions) **Liquidity Proxy: Execution Shortfall**				Annual Performance (+ Commissions) **Liquidity Proxy: Short-term Momentum Trading**			
Group	Year 1	Year2	Year 3	Year [1-3]	Year 1	Year2	Year 3	Year [1-3]
Q5 LD	0.07	-0.36	-0.08	-0.11	0.04	-0.39	-0.03	-0.11
	(0.38)	(-1.92)	(-0.42)	(-0.92)	(0.21)	(-2.11)	(-0.18)	(-0.85)
Q5 LN	0.35	0.25	0.24	0.29	0.43	0.10	0.26	0.28
	(2.39)	(1.33)	(1.29)	(2.60)	(2.91)	(0.56)	(1.38)	(2.45)
Q5 LS	0.63	0.43	0.08	0.43	0.48	0.55	0.04	0.40
	(3.05)	(2.12)	(0.31)	(2.77)	(2.56)	(2.78)	(0.20)	(2.74)
LS - LD	0.56	0.79	0.16	0.55	0.44	0.94	0.07	0.51
	(1.79)	(2.86)	(0.50)	(2.58)	(1.38)	(3.49)	(0.26)	(2.41)

Panel B: 'Other' Hedge Fund Persistence by Liquidity Group

	Annual Performance (+ Commissions) **Liquidity Proxy: Execution Shortfall**				Annual Performance (+ Commissions) **Liquidity Proxy: Short-term Momentum Trading**			
Group	Year 1	Year2	Year 3	Year [1-3]	Year 1	Year2	Year 3	Year [1-3]
Q1-Q4 LD	-0.01	-0.01	-0.02	-0.01	-0.07	-0.04	-0.03	-0.05
	(-0.09)	(-0.09)	(-0.31)	(-0.17)	(-1.01)	(-0.54)	(-0.35)	(-0.86)
Q1-Q4 LN	-0.02	0.09	0.08	0.04	0.04	0.04	0.06	0.04
	(-0.24)	(1.31)	(1.09)	(0.72)	(0.70)	(0.73)	(0.99)	(0.95)
Q1-Q4 LS	0.06	0.11	0.15	0.10	-0.01	0.22	0.15	0.11
	(0.46)	(1.22)	(1.25)	(1.03)	(-0.04)	(1.69)	(1.17)	(0.96)
LS - LD	0.06	0.12	0.17	0.11	0.07	0.26	0.18	0.16
	(0.41)	(0.98)	(1.23)	(0.91)	(0.38)	(1.63)	(1.12)	(1.18)

Figure 1: Trading by Stock Characteristics

The figures below present trading by different investor types across different stock characteristics. We consider four investor types: smart hedge funds (Smart HF), other hedge funds (Other HF), mixed funds (Mixed), and non hedge funds (Non HF). Institution types are defined as in Table 8. We assign stocks to size, book-to-market, illiquidity, volatility, and past return deciles based on NYSE breakpoints. The construction of all variables are presented in Appendix A. We also create two dummy variables: Pre Earnings and Post Earnings. *Pre-Earnings (Post Earnings)* equals 10 if the trade was made in the 10 trading days prior to (after) an earnings announcement and zero otherwise. For each fund, we compute the principal-weighted average decile ranking of the stocks bought and the stocks sold. For each fund, we compute total trading (i.e. (buys + sells)/2) and net trading (i.e. buys - sells). The figures reports the average decile ranking by stock characteristic across all funds in a given institution type.

Figure 1a: Total Buying by Stock Characteristics

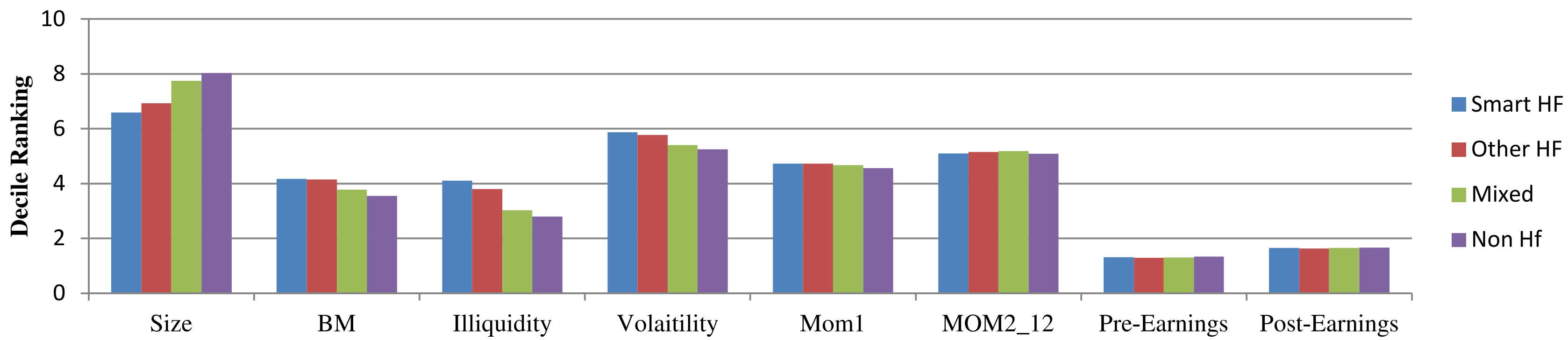

Figure 1b: Net Buying by Stock Characteristics