How do Hedge Fund "Stars" Create Value? Evidence from Their Daily Trades

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Abstract

I use transaction-level data to investigate the magnitude and source of hedge funds' equity trading profits. Bootstrap simulations indicate that the trading profits of the top 10% of hedge funds cannot be explained by luck. Similarly, superior performance persists. Outperforming hedge funds tend to be short-term contrarians with small price impacts, and their profits are concentrated over short holding periods and in their more contrarian trades. Further, I find that performance persistence is significantly stronger for contrarian funds with small price impacts. My findings suggest that liquidity provision is an important channel through which outperforming hedge funds persistently create value.

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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 skilled trading. The view that hedge funds are skilled traders seems plausible. Compared to other institutional investors, hedge funds have greater flexibility in their investment choices, better liquidity management tools, and stronger performance incentives. Additionally, it is commonly believed that hedge funds are able to attract the most talented managers. For example, Mario Gabelli, a top mutual fund executive, admitted, "[t]he brain drain to hedge funds from the traditional money management industry is real."[2]

Consistent with this view, the academic literature generally finds that the average hedge fund delivers net-of-fee alphas of roughly 3-5% (see, e.g., Ibbotson, Chen, and Zhu, 2011; Kosowski, Naik, and Teo, 2007; and Fung et al., 2008).[3] Ultimately, hedge funds' ability to generate abnormal returns must stem from their ability to profitably trade on mispriced securities.[4] However, relatively little is known about *how* hedge funds exploit mispricing.

There are at least four mechanisms through which hedge funds could create value. First, hedge funds may be skilled *shareholder activists* (Clifford 2008; Brav et al. 2008). Second, hedge funds may have a comparative advantage in collecting and processing *public information*. Third, hedge funds may profit through *insider trading*. Finally, hedge funds may outperform by

[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/Funds05/idUSHAR76019620050907
[3] Not all of the academic literature has been as kind to hedge funds. See, for example, Amin and Kat (2003), Griffin and Xu (2009), and Dichev and Yu (2011).
[4] This, of course, assumes that the hedge fund alphas are not spurious. Some papers argue that the hedge fund alphas can be explained by misspecified risk models (Asness, Krail, and Liew, 2001) or biases in commercial databases (Aiken, Clifford, and Ellis, 2013).

providing liquidity to other investors who demand immediacy (Campbell, Grossman, and Wang, 1993). Distinguishing among these explanations is challenging. Hedge funds are notoriously secretive about their investment strategies. Further, existing data on hedge funds are typically limited to self-reported monthly returns or quarterly holdings, neither of which is well-suited for understanding the source of hedge funds' trading profits.

This paper employs transaction-level data to better understand how hedge funds create value. Specifically, I first demonstrate that some “star” hedge funds are able to persistently create value through trading. I then exploit the granularity of transaction data to explore the mechanisms through which these star hedge funds create value.

The analysis relies on data provided by ANcerno Ltd, an execution cost consulting firm. The data include the names of the institutional investors, which allows me to distinguish hedge funds from other institutions. Unfortunately, like 13F holdings, the data do not include non-equity trading. However, roughly 40% of hedge funds are simply invested in long/short equity strategies (Fung and Hsieh, 2006), which suggests that many funds rely exclusively on equity trading to generate abnormal returns. Moreover, the data offer a number of benefits relative to both commercial databases and quarterly holdings. First, the data do not suffer from many of the biases that plague commercial databases (see, e.g., Fung and Hsieh, 2009). Moreover, since I observe hedge funds’ actual trades, I can estimate trading profits more precisely by using characteristic-based benchmarks rather than factor models (Daniel et al., 1997). In addition, unlike quarterly holdings, ANcerno captures all equity trades, including short-sales, confidential filings, and intra-quarter roundtrip trades. Most importantly, the data contain the precise date and execution price of each trade. This allows me to capture short-term dynamic trading strategies (e.g., Patton and Ramdorai, 2013) and enables more powerful tests of short-term trading skill.

I estimate hedge fund performance by computing calendar-time transaction portfolios (see, e.g., Seasholes and Zhu, 2010) with holding periods ranging from 21 to 252 days. Across all holding periods, I find no evidence that the average or median hedge fund outperforms, after accounting for trading commissions. However, I find significant evidence of outperformance in the right-tail of the distribution. Specifically, bootstrap simulations indicate that the annual performance of the top 10-30% of hedge funds cannot be explained by luck. Similarly, I find that superior performance persists. The top 30% of hedge funds outperform by a statistically significant 0.25% per month over the subsequent year. In sharp contrast to my hedge fund findings, both bootstrap simulations and performance persistence tests fail to reveal any outperformance among non-hedge fund institutional investors.

My remaining tests investigate *how* outperforming hedge funds (i.e., “star” hedge funds) create value. My main findings can be summarized as follows. First, star hedge funds’ profits are concentrated over relatively short holding periods. Specifically, more than 25% (50%) of star hedge funds’ annual outperformance occurs within the first month (quarter) after a trade. Second, star hedge funds tend to be short-term contrarians with small price impacts. Third, the profits of star hedge funds are concentrated in their contrarian trades. Finally, the performance persistence of star hedge funds is substantially stronger among funds that follow contrarian strategies (or funds with small price impacts) and is not at all present for funds that follow momentum strategies (or funds with large price impacts).

The results suggest that liquidity provision is a critical source of star hedge funds’ persistent trading profits. Further, the evidence is largely inconsistent with alternative explanations. For example, while the existing literature finds that activist hedge funds target value stocks (Brav et al., 2008), I find that star hedge funds are net buyers of growth stocks. In addition, I find no evidence that star hedge funds trade more frequently or more profitably prior to earnings announcements. This is inconsistent with the view that insider trading is a major determinant of star hedge funds' trading profits. Finally, the short-term nature of the trading profits is inconsistent with many strategies that rely on superior processing of public information (e.g., long-term value investing), as, on average, it would likely take the market several quarters (or years) to recognize the wisdom of such trades.

This study is related to several strands of literature. The first is the nascent literature that examines the high-frequency dynamics of hedge fund trading strategies. Patton and Ramadorai (2013) combine monthly returns with higher-frequency conditioning variables, and conclude that short-term (e.g., daily) dynamics are far more important for hedge funds than mutual funds. In contrast to Patton and Ramadorai (2013), who must infer short-term dynamics from monthly returns, this study offers a direct analysis of high-frequency hedge fund trading.

My findings also contribute to the literature on the determinants of hedge fund performance. Recent work finds that fund characteristics such as managerial incentives, strategy distinctiveness, and lockup periods are correlated with hedge fund returns (see, e.g., Agarwal, Daniel, and Naik, 2009; Sun, Wang, and Zheng, 2012; and Aragon 2007). In contrast to existing work on observable fund characteristics, my findings highlight the importance of a fund's investment strategy. In particular, my evidence suggests that liquidity provision is an important channel through which star hedge funds persistently create value. My findings are distinct from studies that show that hedge funds profit from holding illiquid assets (Aragon, 2007) or bearing illiquidity risk (Sadka, 2010). I find no evidence that star hedge funds are net buyers of illiquid stocks, nor do I find evidence that their profits covary with an illiquidity risk factor. Instead, my findings suggest that star hedge funds profit by both buying and selling illiquid securities at favorable prices from investors who demand immediacy.

My findings are also consistent with recent work that suggests that at least some hedge funds provide liquidity to the market (Aragon and Strahan, 2012; Jylha, Rinne, and Suominen, 2013). However, my emphasis is not on whether hedge funds provide liquidity but rather on whether hedge funds profit from liquidity provision. These questions are distinct, as naïve liquidity providers could incur losses by supplying liquidity to informed traders. My findings suggest that some hedge funds profit through liquidity provision. However, I find that the majority of liquidity-providing hedge funds do not earn abnormal trading profits. This highlights significant cross-sectional variation in the trading skill of liquidity-providing hedge funds.

Finally, my findings contribute to the literature on hedge fund performance persistence. Griffin and Xu (2009) and Brown, Goetzmann, and Ibbotson (1999) find no evidence of performance persistence, while Agarwal and Naik (2000) and Liang (2000) conclude that performance persists only at the quarterly horizon, and Kosowski, Naik, and Teo (2007) and Jagannathan, Malakhov, and Novikov (2010) find evidence of longer-horizon persistence. My results are consistent with those of the final group and also offer some explanations for why other studies fail to find persistence. First, transaction data allow for more accurately estimated alphas relative to factor models. Thus, my 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. In addition, since short-term trading profits explain a large fraction of annual persistence, studies relying on quarterly holdings will likely understate persistence. Most interestingly, my findings suggest that persistence is conditional on the investment strategies employed. In particular, performance persists for liquidity-supplying funds but not for liquidity-demanding funds.

The remainder of this paper is organized as follows. Section 2 discusses the data and presents descriptive statistics. Section 3 examines whether star hedge funds exist. Section 4 explores the source of star hedge funds' outperformance. Section 5 concludes.

2. Data

2.1 Institutional Trading Data

I obtain data on institutional trading from January 1, 1999 to December 31, 2010 from ANcerno Ltd. (formerly the Abel Noser Corp).[5] ANcerno is a consulting firm that works with institutional investors to monitor their trading costs. The ANcerno data include the complete transaction histories of all of its institutional clients. Each observation corresponds to an executed trade. For each execution, ANcerno reports the date of the trade, the stock traded, whether the trade was a buy or a sell, the number of shares traded, the execution price, the stock price at the time of placing the trade, the commissions paid, and identity codes for the institution making the trade. For each stock traded in the ANcerno dataset, I collect returns, share price, trading volume, and shares outstanding from *CRSP*, and I 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., Fidelity and Angelo Gordon). The client identifier corresponds to the plan sponsor or money manager that subscribes to ANcerno. The client

[5] Other papers that use ANcerno include Anand et al. (2012), Green et al. (2013), and Jegadeesh and Tang (2010).

identifier is a permanent numeric code, which allows me to track a client both in the cross-section and over time. However, the names of the clients are not provided.

The manager code identifies a specific money management company.[6] The manager code, like the client code, is a permanent numeric identifier. However, ANcerno also provides a reference file that links manager codes to money management companies (e.g., manager 3 = 'Acadian Asset Management'). The identification is at the fund-family level, and it is not possible to distinguish different funds within a money management company.

2.2 Descriptive Statistics

I begin by identifying hedge fund managers within the ANcerno sample. Following the literature (see, e.g., Brunnermeier and Nagel, 2004; Griffin and Xu, 2009), I classify a money management company as a hedge fund if the *majority* of its business consists of hedge fund operations. Specifically, for all 653 management companies in the ANcerno database, I search for Form ADV on the SEC website.[7] I find Form ADV for 534 of the managers. For these companies, I 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. In addition, I require that the manager charge a performance-based fee (item 5.E). For the remaining 119 funds for which I could not find Form ADV, I manually review the company names and conduct Google and Factiva searches. The overwhelming majority of the funds are banks, trusts, and internal pension funds (all of which are exempt from filing Form ADV), and I find no evidence that any of the remaining managers are primarily hedge funds.

[6] 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.
[7] Beginning in March 2012, the Dodd-Frank Act has required that nearly all investment advisors, including hedge funds, file Form ADV. In addition, a 2004 SEC investment advisor rule required all hedge funds to file Form ADV for a short period in 2006. Thus, I obtain Form ADV for nearly all hedge fund families that had operations in 2006, or from 2012 onwards, plus any funds that voluntarily filed Form ADV. Form ADVs can be downloaded from the SEC website: http://www.adviserinfo.sec.gov/IAPD/Content/Search/iapd_Search.aspx

Panel A of Table 1 provides summary statistics. The sample consists of 74 hedge fund management companies that manage money for 253 different clients. There are 361 different client/hedge fund manager pairs. Hereafter, I will loosely refer to a client/manager pair as a *fund*. The sample also consists of 579 non-hedge fund management companies (e.g., banks, insurance companies, mutual funds, etc.), managing 4,061 different funds.

There are two ways a hedge fund can enter the database. First, the hedge fund can invest on behalf of a plan sponsor that subscribes to ANcerno. Second, the hedge fund can subscribe directly to ANcerno. In the first case, I observe hedge fund trading for a specific plan sponsor, while in the latter case, I observe the aggregate trading of the hedge fund company. 63 of the 74 hedge fund companies manage money on behalf of a plan sponsor that subscribes to ANcerno, while 22 of the 74 hedge fund companies directly subscribe to ANcerno, with 11 hedge fund companies entering as both. There are 337 different hedge funds trading on behalf of plan sponsors and 24 different hedge funds trading on behalf of their own account.[8] Thus, tests are skewed toward hedge fund trading on behalf of plan sponsors. 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.[9]

Panel B of Table 1 shows the average number of funds that appear in the sample each quarter across all sample years. In the average quarter in 1999, there are roughly 110 hedge funds. This number is relatively stable until around 2006, at which point the sample of funds steadily decreases. In 2010, the average quarter contains only 38 hedge funds. I find a similar decay in the sample size of other institutional investors. In untabulated analysis, I find that the

[8] As money managers typically only make trades on their own behalf, there will typically be one manager code for a given money management firm. Of the 207 different money manager clients in the sample, only nine have multiple manager codes. These may correspond to sub-advised funds.

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

declining sample size is driven entirely by the plan sponsor portion of the sample; the sample size of money managers slightly increases from 1999 to 2010.

I also examine how long the average fund remains in the ANcerno sample (unreported). The average hedge fund remains in the sample for just over 12 quarters, although there is significant cross-sectional variation. Funds at the 75th and 25th percentiles remain in the sample for roughly 18 and four quarters, respectively. The distribution is similar for other institutional investors and does not significantly vary depending on whether the client is a plan sponsor or a money manager.

Panel B also presents the average and median quarterly trading volume for hedge funds by year. Average hedge fund trading volume has increased dramatically over time. Much of the increase in average trading volume is due to a larger fraction of the sample consisting of money managers, which are responsible for much more trading than plan sponsors. There is also an increase in the trading volume of the median fund (which always reflects trading on behalf of plan sponsors), although this increase is less dramatic.

Table 2 shows the cross-sectional distribution of quarterly trading of hedge funds and other institutions. When trading on behalf of plan sponsors, the average hedge fund executes roughly $36 million in total trading in the average quarter. However, there is substantial cross-sectional dispersion, with the largest 1% of hedge funds trading nearly $400 million, while the smallest 1% trades less than $19,000 per quarter. Naturally, the aggregate trading of hedge fund management companies (i.e., their trading as money management companies) is substantially larger. The average hedge fund management company trades roughly $2.5 billion per quarter.

Panel B reports 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 fund-stock-quarter, aggregated across all stocks traded by the fund over the quarter. For example, if a fund purchased $50,000 of Microsoft and $100,000 of Apple in January 2008 and sold $20,000 of Microsoft in February 2008, the fund's total trading volume in quarter 1 of 2008 would be $170,000, while its implied trading volume would be $130,000.[10] The implied trading volume more closely reflects the trading volume that would be reported in 13F filings. The ratio of actual to implied trading volume is a measure of the extent to which 13F filings understate actual trading volume.[11] This analysis also provides some insights into whether a significant fraction of hedge fund trading is motivated by relatively short-term considerations.

I find that the ratio of actual to implied quarterly trading is 147% for the money manager sample of hedge funds. This suggests that intra-quarter trading accounts for a large fraction of hedge funds' total trading. However, 'intra-quarter' trading may simply reflect two different funds within the same family taking opposing positions during a quarter. For trading on behalf of a specific plan sponsor, the ratio of actual to implied quarterly trading is only 119%. Further, most of this measure is driven by a few funds in the far right-tail of the distribution. The corresponding measure for the median fund is only 103%, indicating that nearly half of all hedge funds engage in virtually no intra-quarter trading. Thus, while high frequency trading hedge funds account for a large fraction of total trading volume, they account for a small fraction of total funds.

[10] In computing implied trading volume, I use the actual transaction price. Using end-of-quarter prices would more accurately reflect the extent to which quarterly holdings misstate trading volume; however, it also makes it more difficult to obtain a sense of what fraction of funds engage in no intra-quarter trading because the ratio of actual to implied trading volume will generally not be equal to 1 for these funds. Using end-of-quarter prices yields very similar average effects.

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

2.3 Database Integrity

As noted in the introduction, hedge fund commercial databases suffer from several biases, including backfill bias, survivorship bias, unreliable returns, and self-selected reporting. Similarly, quarterly holdings miss a significant amount of trading activity, including intra-quarter trades, short-sales, confidential filings, and derivative positions. In this section, I discuss the extent to which the ANcerno data are likely to suffer from similar biases. Figure 1 summarizes the discussion.

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

I also have no reason to doubt the reliability of the reported trades. First, there is little incentive for institutions to lie about their transactions. Unlike in 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.

An additional concern is that the ANcerno dataset captures only a subset of trades. For example, hedge funds may attempt to conceal their most informed trades (Agarwal et al., 2013). However, ANcerno representatives believe it would be very difficult for institutions to conceal trades. Once an institution subscribes to ANcerno, a system is installed through which all trades must be routed. ANcerno representatives have also confirmed that the dataset does include short-sales, although it is not possible to distinguish short-sales from other sales. Unfortunately, like 13F filings, ANcerno only captures equity trading.

A final concern is that hedge funds that subscribe to ANcerno are not representative of the population of hedge 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 that chooses to hire ANcerno. However, it is still possible that the plan sponsor's decision to subscribe to ANcerno is correlated with important hedge fund characteristics. To examine this possibility, I compare the sample of ANcerno hedge funds to the universe of 13F filing hedge funds and hedge funds that report to TASS. Appendix B provides details of the analysis and presents the results. I find that ANcerno hedge funds are largely representative of 13F filing hedge funds with respect to the characteristics of the stocks they hold and trade as well as in the performance of their holdings and trades. I also find that ANcerno hedge funds are similar to TASS funds along a number of dimensions, including performance, incentive fees, lockup periods, and high-water marks.

ANcerno hedge funds do differ from other hedge funds along a few dimensions. First, compared to both 13F hedge funds and TASS hedge funds, ANcerno hedge funds are significantly larger. This is consistent with Puckett and Yan (2011), who find that ANcerno institutions are larger than 13F filing institutions. This is also intuitive. Larger funds tend to have more clients. The more clients a fund has, the more likely it is that the fund manages money for a client that subscribes to ANcerno. ANcerno funds are more likely than others to be contrarian traders. They are also less likely than others to hold derivatives. Because ANcerno monitors equity trading costs, it is not surprising that the sample is tilted away from funds that trade non-equity assets. Finally, ANcerno hedge funds tend to charge lower management fees. Perhaps plan sponsors that are conscientious monitors of trading costs are also more likely to avoid high fee funds. In section 4.4, I investigate how the sample's tilt towards larger, low-derivative, low management fee funds could influence my conclusions.

3. Do Star Hedge Funds Exist?

3.1 Measuring Trading Performance

In contrast to most studies on hedge fund performance, my emphasis is not on measuring the actual returns investors realize from holding a fund. Instead, my focus is on the trading skill of hedge funds. In particular, I ask two questions. First, are some hedge funds star traders? Second, if star traders exist, how do they create value?

To answer the first question, I create a fund-level measure of trading performance. Specifically, I follow Seasholes and Zhu (2010) and compute transaction-based, calendar-time portfolios.[12] Each time a fund buys a stock, I place the same number of shares in the calendar-time buy portfolio. Similarly, each a time a fund sells a stock, I place the same number of shares in the calendar-time sell portfolio. In contrast to Seasholes and Zhu (2010), I include day 0 (the transaction day) in the 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.[13] I consider holding periods of 21, 63, 126, and 252 trading days. I emphasize the 252 day holding period because this is closest to the average holding period of a typical hedge fund.[14] In addition, for funds that trade infrequently, shorter horizon calendar-time portfolios may consist of very few stocks,

[12] Seasholes and Zhu (2010) emphasize the benefits of calendar-time portfolios relative to alternative approaches.
[13] An alternative approach would be to simply hold the share until the position is reversed, essentially computing a realized trading profit. However, many positions are never reversed, and focusing on the subset of round-trip trades could generate significant bias, particularly if some hedge funds are subject to the disposition effect (Cici, 2012).
[14] 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. In appendix B, I find that the average ANcerno hedge fund has a turnover of 70%.

resulting in noisy performance estimates. To reduce the impact of noisy estimates, for each holding period, I require that each fund-day have at least 10 stocks in both the buy and sell portfolios.[15]

My approach generates a time-series of daily buy and sell portfolios. For each day, I compute the principal-weighted return on the buy and sell portfolios, as well as the difference between the buy and sell portfolios. I compute returns using three measures: *gross returns*, *DGTW-adjusted returns*, and *DGTW-adjusted returns less commissions*. *Gross returns* simply measures the raw (i.e., unadjusted) return on a stock. *DGTW-adjusted returns* is the return on a stock less the value-weighted return on a benchmark portfolio with the same size, book-to-market, and momentum characteristics as the stock. Daniel et al. (1997) and Wermers (2004) provide more detailed discussions of the construction of the DGTW benchmark portfolio. Finally, *DGTW-adjusted return less commission* subtracts the commissions paid to the broker (as a percentage of the dollar volume traded) from the DGTW-adjusted return. I report the time-series average of daily returns, expressed as monthly returns, in percent.

To further illustrate the 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 gross return is 2.45% (60.96% * 3% + 7.08% * -1% +

[15] Using a 252-day (21-day) holding period, this filter eliminates roughly 12% (68%) of all fund-day observations, and less than 1% (35%) of total trading volume.

31.96% * 2.16%). Note that the weight and return of Google are based on the execution price. Computing the return for a 126-day holding period would be analogous, but the weight on Apple would drop to zero because no shares of Apple were purchased in the past 126 trading days.

3.2 Average Fund Performance

I begin by presenting descriptive statistics of average hedge fund performance. Following most hedge fund studies, I estimate average performance as the equal-weighted average performance across funds. However, the literature typically views a fund as a specific product (e.g., Falcon Point Long/Short). Since I do not have product-level information, I define a fund as a money management company (e.g., Falcon Point Capital) trading for a specific client (e.g., CalPERS). As a result, I treat a money management company's trade on behalf of two different clients as two separate funds, although it may or may not reflect the trading of the same fund. Thus, my average performance estimates are value-weighted by the number of clients that use the fund. To account for the correlated performance across funds, all standard errors are clustered by both time and management company.

Panel A of Table 3 reports the trading performance of the average hedge fund trading for different holding periods. Over the one-month (21-day) holding period, there is modest evidence that the average hedge fund outperforms. Specifically, the average hedge fund generates trading profits of roughly 52 bps, and the estimate is statistically significant at the 10% level. However, the DGTW-adjusted returns fall to (a statistically insignificant) 42 bps, and incorporating trading commissions reduces average profits to just 4 bps. Over longer holding periods, there is no evidence that average hedge fund performance is significantly different from zero.

Panel B presents analogous results for other institutional investors. Like hedge funds, other institutions trade profitably over the one-month period. However, like hedge funds, the trading profits are eliminated after accounting for commissions. Further, over longer holding periods, other institutions trade less profitably than hedge funds. For example, after accounting for trading commissions, other institutions earn negative trading profits. Even prior to accounting for trading commissions, there is some evidence that the trades of other institutions underperform over a one-year holding period. One possible explanation is that other institutions follow other funds into and out of the same stocks (possibly due to reputational concerns) and thus trade at unfavorable prices (Dasgupta, Prat, and Verardo, 2011; Gutierrez and Kelley, 2009).

3.3 Bootstrap Simulations

Although there is little evidence that the trades of the average hedge fund outperform, it is still possible that some hedge funds are star traders. To test for star hedge fund traders, I follow Kosowski et al. (2006) and Fama and French (2010) and conduct bootstrap simulations. Specifically, I compare the actual distribution of precision-adjusted abnormal returns, $\hat{t}_{\hat{a}_i}$, to its simulated distribution under the null hypothesis that all hedge funds have no trading skill. I focus on $\hat{t}_{\hat{a}_i}$ rather than $\hat{\alpha}_i$ to control for disparities in the precision of $\hat{\alpha}_i$ that arise from differences in the variance of $\hat{\alpha}_{it}$ across days and from differences in the number of days the fund appears in the sample. Nevertheless, using $\hat{\alpha}_i$ generates very similar results.

I define $\hat{\alpha}_i$ as the average DGTW-adjusted return of the buy-sell portfolio of a fund across all days for which the fund holds at least 10 stocks in both the buy and sell portfolios, while $\hat{t}_{\hat{a}_i}$ is $\hat{\alpha}_i$ scaled by its standard error. To ensure a sufficient time-series of returns, I exclude funds that appear in the sample for less than one year. I specifically focus on the one-year holding period (results for other holding periods are available upon request).

My simulation approach follows Fama and French (2010). Specifically, for each fund, I subtract its average alpha ($\bar{\hat{\alpha}}_i$) from its daily estimate of alpha ($\hat{\alpha}_{it}$), yielding a time-series of daily residuals. A simulation run is a random sample of 3,271 days (with replacement), drawn from all trading days between 1999 and 2011.[16] For each fund, I estimate the funds' average return based on its residual on the day of the random draw. By choosing the same random sample of days for all funds, the simulations capture the cross-correlation of fund returns. I perform 10,000 simulation runs to produce the distribution of t-statistics for a world in which the true α_i is 0 for all funds.

Panel A of Table 4 presents the simulation results for hedge funds. I first compare the actual and simulated distributions of hedge fund performance using DGTW-adjusted returns excluding trading commissions. I 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 has an average t-statistic of –3.35 (3.84) compared to a simulated t-statistic of -2.63 (2.63). More interestingly, I find strong evidence that top hedge funds are skilled traders. Specifically, the actual trading performance of the top 30% of hedge funds is significantly better than the simulated trading performance.

I next repeat the simulation after incorporating trading commissions. Even after accounting for commissions, I continue to find evidence of hedge fund skill in the right tail, with the top 10% of hedge funds exhibiting outperformance at the 5% significance level. There is

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

weaker evidence that the trading performance of the top 10-30% of hedge funds is significantly better than would be expected by chance, with (one-sided) p-values that are slightly less than 10%.

In Panel B of Table 4, I repeat the analysis for other institutional investors. Before accounting for trading commissions, I find evidence that the middle of the distribution performs significantly worse than would be expected by chance. Further, I find no evidence of skill in the right tail of the distribution. Thus, while a significant fraction (10-30%) of hedge funds is star traders, there is no evidence of star traders among other institutional investors. After accounting for trading commissions, I find that, with the exception of the top 1%, other institutional investors are unable to generate enough value through trading to compensate for trading commissions.

4.4 Performance Persistence

The bootstrap simulations suggest that 10-30% of hedge funds are star traders. As an alternative test, in this section, I examine whether superior performing hedge funds continue to outperform in the future. I estimate performance persistence using calendar-time transaction portfolios with one-year holding periods. Specifically, for each year, I sort funds into three groups based on their performance, using a 252-day holding period. The top (bottom) group consists of the top (bottom) 30% of funds, and the middle group consists of the remaining 40% of funds.[17] I then examine the performance of each group over the subsequent one, two, or three years. Performance measures (in both the ranking and post-ranking period) include trading

[17] I sort funds into three groups rather than quintiles or deciles, due to the relatively small sample of hedge funds and because subsequent tests require further partitioning of the top group. Sorts using quintiles or deciles generate larger spreads but correspondingly larger standard errors.

commissions. Using pre-commission performance results in very similar conclusions, although the performance of each quintile improves by two to four basis points per month.

Table 5 presents the results, which suggest that top performing hedge funds continue to outperform in the future. Hedge funds in the top 30% of annual trading performance outperform by 0.25% per month (3% per year) over the next year and by 0.19% per month over the next three years. There is no evidence that poorly performing hedge funds continue to underperform. There is also no evidence of performance persistence for other institutional investors. Overall, the results are consistent with the bootstrap simulations and further suggest that some hedge funds are able to persistently create value through their trading.

I next examine whether star hedge funds' trading profits are concentrated in specific periods or whether their profits may be compensation for taking on significant tail risk (Jiang and Kelly, 2012). I examine the performance of star funds (i.e., funds in the top 30% of annual trading performance in the prior year) in each quarter, from Q1 2000 to Q4 2011. The quarterly performance is computed as the daily DGTW-adjusted performance less commissions, averaged across all star hedge funds over the quarter.

Figure 2 presents the results. Star hedge funds earned large trading profits in 2000, particularly in the first quarter. This is consistent with prior work (Griffin and Xu, 2009; Fung et al. 2008), which finds that hedge funds performed very well during the tech bubble. However, even after excluding 2000 (or just Q1 of 2000), I find that star hedge funds earn significant trading profits. There is, however, evidence that hedge fund profits are declining over time. Increased competition, due to the rapid growth of the hedge fund industry and limited profitable investment opportunities, may be driving the average alpha of skilled hedge funds closer to zero (Naik, Ramadorai, and Stromqvist 2007; Zhong, 2008).

There is no evidence that star hedge funds profit by taking on significant left-tail risk. The distribution of quarterly returns is positively skewed. In only four quarters did star hedge funds earn average monthly returns of less than 50 bps (with their worst performance being -97 bps), while there were 14 months in which star hedge funds outperformed by over 50 bps per month (with the top performance being 225 bps).

To further investigate whether star hedge funds' profits correlate with any passive benchmark portfolios, I compute a time-series of average monthly returns and regress them on the monthly returns of passive portfolios. I then run the following time-series regression:

$$r_{p,t} = \alpha_p + \sum_{j=1}^{k} \beta_{pj} r_{j,t} + \varepsilon_{p,t} \ , \qquad (1)$$

where $r_{p,t}$ is the monthly return of the star hedge fund portfolio, and $r_{j,t}$ are the returns on the k factors. The return on the star hedge fund portfolio ($r_{p,t}$) is the average daily return for all star hedge funds over one month. Returns are computed as either gross returns or DGTW-adjusted returns, both of which subtract trading commissions. As $r_{p,t}$ is already a long-short portfolio (i.e., the performance of stocks bought by star hedge funds less the performance of stocks sold by star hedge funds), I do not subtract the risk free rate from $r_{p,t}$. The five independent variables represent factors related to the market, firm size, book-to-market ratio, momentum, and liquidity. I obtain factor returns for the first four factors from Ken French's website and use the Pastor and

Stambaugh (2003) traded liquidity factor as my liquidity risk factor. The intercept, α_p , measures the average return achieved by a fund in excess of the return on the passive portfolios.[18]

The time-series regression is estimated using weighted least squares, where the weight of each monthly observation is given by the number of observations used to compute the monthly return. This approach allows for more direct comparisons with my panel estimates, which implicitly value-weight each time period by the number of observations. However, using OLS does not significantly alter the results. Table 6 presents the results. Specification 1 indicates that the performance of star hedge funds is positively correlated with the performance of the market. However, the alpha of star hedge funds remains a statistically significant 30 bps per month over the subsequent year. Specifications 2 and 3 indicate that star hedge funds do not have significant net exposure to small stocks or value stocks, although there is evidence that star hedge funds tend to be contrarian. I investigate this finding in greater detail in the next section.

Specification 4 suggests that star hedge funds do not have significant exposure to liquidity risk. This finding may seem to conflict with Aragon (2007) and Sadka (2010), who find that outperforming funds tend to hold illiquid stocks and have significant liquidity betas. However, my performance measure is based on trading, not holdings. Thus, star hedge funds may tend to skew their holdings toward illiquid stocks, but once they reach their optimal portfolio composition, there is no reason to expect that they will continue to be net buyers of illiquid securities. In specification 5, I regress DGTW-adjusted returns on the five-factor model and continue to find a significant alpha. Across all five specifications, the alpha ranges from 27 bps to 30 bps per month and is very similar to the panel estimate of 25 bps per month. This

[18] There is some debate over whether the returns on these portfolios are compensation for risk or simply mispricing. I do not take a stance on this issue. Rather, my focus is on whether star hedge funds have the ability to generate trading profits above and beyond these known factors.

suggests that star hedge funds' outperformance cannot be explained by exposure to passive benchmark returns. Given the similarities in alpha across all specifications, the remainder of the paper will focus exclusively on DGTW-adjusted returns.

4. How Do Star Hedge Funds Create Value?

4.1 Performance of Star Hedge Funds by Holding Period

The results from the bootstrap simulations and performance persistence tests suggest that some hedge funds can persistently create value through their trading. A natural question is: what is the source of this trading skill? I consider four prominent explanations: *shareholder activism*, *skilled processing of public information*, *insider trading*, and *liquidity provision.*

To distinguish between these explanations, I first examine the holding periods over which star hedge funds create value. Profits from liquidity provision and insider trading (i.e., trading ahead of major information events) should be concentrated over relatively short periods. Profits from shareholder activism are also likely to be concentrated over relatively short holding periods, as most of the abnormal returns occur around the announcement of activism (Brav et al., 2008b). In contrast, profits from superior processing of public information may accrue over relatively long holding periods. For example, a manager may take positions in stocks that he believes are undervalued and wait several quarters (or several years) until the market eventually agrees with his positions.

Each year I divide hedge funds into star funds, funds that were in the top 30% of annual trading performance over the previous year, and all other hedge funds. For each fund-year, I decompose the annual trading profits across different holding periods. I measure trading performance as the principal-weighted return on all stocks purchased less the principal-weighted return on all stocks sold during the year over a given holding period. This approach provides an estimate of a fund's return (for different holding periods) in each year. I use this approach, rather than calendar-time portfolios, because many funds trade infrequently, which results in noisy estimates of short-term performance.

Table 7 decomposes the annual trading profits of hedge funds into their trading profits over each of the four quarters. Panel A presents the results during the ranking period. In the ranking period, star hedge funds outperform by roughly 8.3% (2.07 * 4). The outperformance is strongest in the first quarter (3.37%) and declines in each subsequent quarter until it reaches 1.02% in the fourth quarter.

Panel B presents the decomposition for the year following the ranking period. In the year following the ranking period, star hedge funds outperform by approximately 3.4%. This estimate is similar to (but slightly larger than) the estimate based on calendar-time transaction portfolios (12 * 0.25 = 3%), suggesting that the persistence results are robust to alternative performance methodologies. Further, comparing the outperformance in the ranking period to the post-ranking period suggests that top performing funds retain approximately 40% (3.4/8.3) of their outperformance. Consistent with the results during the ranking period, star hedge funds' profits are strongest in the first quarter. In fact, the first quarter accounts for the majority (50.1%) of star hedge funds' annual trading profits. In addition, star hedge funds significantly outperform the worst hedge funds only in the first quarter.

The results suggest that the trading profits of star hedge funds are concentrated in the first quarter. In unreported results, I further decompose the first quarter trading profits of star hedge funds. I find that nearly 60% of star hedge funds' first quarter trading profits (0.94/1.64) are concentrated in the first month. The monthly outperformance of 94 bps is roughly evenly distributed across the first four weeks. Overall, the results suggest that star hedge funds' profits are concentrated over relatively short holding periods. This finding is inconsistent with hedge funds profiting from taking long-term positions while patiently waiting for the market to correct mispricing over the span of several quarters. This finding also has implications for studies that estimate performance persistence using quarterly holdings (e.g., Griffin and Xu, 2009). In particular, because star hedge funds' outperformance accrues over holding periods of one quarter or less, studies using quarterly holdings may significantly understate persistence.[19]

4.2 Performance of Star Hedge Funds by Stock Characteristic

I next investigate the performance of hedge funds' trades across stocks with differing characteristics. I consider the following characteristics: *size, book-to-market (bm), Amihud illiquidity (illiquidity), idiosyncratic volatility (ivol), past one month return (mom1/contrarian1), past2_12 month return (mom2_12/contrarian2_12),* a dummy variable if the trade occurred ten days prior to an earnings announcement (*pre_earnings*), and a dummy variable if the trade occurred in the 10 days following an earnings announcement (*post_earnings).* A more detailed discussion of the above variables is presented in Appendix A.

Since activist funds tend to target value companies, if star hedge funds profit primarily through activism, their profits should be concentrated in high book-to-market stocks. If star hedge funds' comparative advantage stems from processing public information, their profits are

[19] This finding is similar to Kacperczyk, Sialm, and Zheng (2008) and Puckett and Yan (2011), who find persistent differences in the interim trading skill of institutional investors. Although not the focus of this study, in untabulated analysis, I also examine the interim trading skill of hedge funds. I find that the top 30% of hedge funds outperform the bottom 30% of hedge funds by a statistically significant 60 bps per quarter over the subsequent four quarters. The results for other institutional investors are also statistically significant, but the magnitude is roughly half that found for hedge funds.

likely to be concentrated in firms with good information environments (e.g., large firms) or after public information releases (e.g., after earnings announcements). In contrast, if star hedge funds' outperformance stems from private information, their profits will likely be concentrated in stocks with more opaque information environments (e.g., small firms) and in periods prior to information releases (e.g., prior to earnings announcements). Finally, if hedge funds primarily profit through liquidity provision, then outperformance may be stronger in their more contrarian trades (i.e., purchases of losing stocks and sales of winning stocks). Regardless of the source of star hedge funds' profits, such profits are likely to be larger when limits to arbitrage are greater. Following Pontiff (1996, 2006), I use idiosyncratic volatility as a measure of arbitrage risk. I also consider illiquidity as a proxy for arbitrage costs, although illiquidity is also strongly correlated with firm size and therefore with a firm's information environment.

I begin by assigning a decile rank to each stock based on NYSE breakpoints for all of the above characteristics (except for the dummy variables, *pre_earnings* and *post_earnings*). I then divide the stocks into two groups. For all characteristics except size and illiquidity, stocks are divided based on the median NYSE breakpoint. For example, value stocks are stocks with *bm* decile rankings of 6-10, while growth stocks have *bm* decile rankings of 1-5. Because hedge funds (like all institutional investors) tend to trade large and liquid stocks, I define a stock as large (or liquid) if the stock is in the top 30% of NYSE size (or liquidity). All other stocks are defined as small (illiquid). Note that the classifications of *mom1* and *mom2_12* depend on the side of the trade. Stocks with *mom1* decile rankings of 1-5 are considered contrarian when a fund is purchasing but momentum when a fund is selling.

I next divide all buy and sell trades into two portfolios based on the characteristic breakpoints. Following the methodology used in Table 7, I compute the principal-weighted, DGTW-adjusted performance for each stock characteristic portfolio. I report results for both star hedge funds and other hedge funds in the year after the ranking period. I report results for the first quarter and the average quarterly return over the year (quarters 1 through 4).

Table 8 presents the results. The table shows that star hedge funds' outperformance is robust across different stock characteristics. Over the annual holding period, star hedge funds outperform other hedge funds across all 14 characteristics, and the difference is statistically significant (at the 10% level) for five of the 14 characteristics. Star hedge funds' annual trading profits are statistically significant in small stocks, growth and value stocks, high volatility stocks, *contrarian1* stocks, and *contrarian2_12* stocks.

The fact that star hedge funds' profits are similar in both growth and value stocks is inconsistent with the view that most star hedge funds profit through activism. This is not surprising, given that activist hedge funds make up a small fraction of the hedge fund universe. For example, Brav et al. (2008b) find that of the 11,530 hedge funds on HedgeFund.net, only 95 engaged in any activism over the 2001-2006 period. The lack of informed trading prior to earnings announcements is also inconsistent with the view that informed trading is a major determinant of hedge funds' trading profits. Hedge funds' stronger outperformance in contrarian stocks is consistent with hedge funds profiting from liquidity provision. Finally, the fact that hedge funds' profits are concentrated in volatile stocks is consistent with the notion that limits to arbitrage create more profitable investment opportunities for hedge funds.

Across most characteristics, the performance of other hedge funds is not significantly different from zero. However, there is some evidence that both other hedge funds and star hedge funds perform better in their *contrarian1* trades. This is consistent with the profitability of short-term reversal strategies (e.g., Lehman, 1990; Jegadeesh 1990), presumably due to liquidity provision. If liquidity provision is an important mechanism through which star hedge funds create value, then star hedge funds should tilt their trading towards *contrarian1* trades. I explore this possibility next.

4.3 Characteristics of Star Hedge Funds – Univariate Results

In this section, I examine the characteristics of star hedge funds. I first investigate the characteristics of the *total trading* (i.e., (buys + sells)/2) of hedge funds. Examining the characteristics of the stocks traded provides some sense of the holdings of star hedge funds. For example, if star hedge funds tend to focus on small-cap stocks (perhaps because the profits from insider trading or liquidity provision are greater in these stocks), then I would expect both the buying and selling of hedge funds to be tilted toward small stocks. Similarly, if hedge funds primarily profit from insider trading, I would expect abnormal trading volume in the period prior to earnings announcements. I also examine the characteristics of the *net trading* (i.e., buys – sells) of star hedge funds. For example, I would expect activist hedge funds to be net buyers of value stocks, while I would expect liquidity-providing funds to be contrarian traders (Nagel, 2012).

Panels A and B of Table 9 compare the total trading and net trading of star hedge funds and other hedge funds. I examine the trading of star hedge funds in the year prior to the ranking period. Thus, the analysis is predictive. Examining trading in the ranking period or in the year after the ranking period generates similar results. For each fund, I compute the principal-weighted value of the stock characteristics for both the buy and sell portfolios. The total trading value is computed as the average of the buy and sell portfolios, while the net trading value is the difference between the buy and sell portfolios.

Panel A indicates that the total trading of star hedge funds and other hedge funds do not significantly differ. For example, star hedge funds trade slightly smaller and more illiquid stocks, but neither estimate is significantly different from zero. Panel B reveals some significant differences in the net trading of star hedge funds. Star hedge funds are net buyers of growth stocks. This is inconsistent with most star hedge funds profiting from activism. Star hedge funds are also net buyers of liquid securities. This suggests that star hedge funds are not profiting by earning an illiquidity premium on their trades. Star hedge funds are also contrarians. The stocks bought by star hedge funds have significantly lower returns than the stocks sold, both over the past one month and the past two to 12 months. Using shorter periods of past returns, such as the past five days or one day, yields similar results. This finding is consistent with star hedge funds profiting from liquidity provision.

I next examine the *fund-level* characteristics of star hedge funds. For example, if star hedge funds were liquidity providers, I would expect them to be patient traders with small price impacts, as measured by execution shortfall (Anand et al., 2012). Panel C of Table 8 investigates fund characteristics. I use ANcerno data to compute a decile ranking of *execution shortfall (*a measure of implicit trading costs). I also merge the ANcerno data with 13F holdings to compute *management company size* and management company *turnover*. In addition, I merge the ANcerno and TASS data to obtain information on *average fund size*, *management fees, incentive fee, high-water mark,* a dummy variable for the existence of a lockup period (*dlockup),* the sum of the notice and redemption period (*restrictions),* and a dummy variable for whether the fund has any derivative positions (*derivative).* A detailed description of all fund characteristics is presented in Appendix A. A discussion of the merging of ANcerno with the 13F and TASS data is available in Appendix B.

Panel C indicates that there are significant differences between star hedge funds and other hedge funds. First, star hedge funds have significantly smaller execution shortfalls than other hedge funds. The relatively low execution shortfall suggests that star hedge funds are relatively patient traders. This finding is again consistent with star hedge funds acting as liquidity providers.[20]

Star hedge funds are also more likely to have lockups and longer restriction periods. This finding is consistent with Aragon (2007). Aragon offers two explanations for why funds with long lockup periods outperform*: a reduction in costly liquidity trading* and *an illiquidity premium due to* a *more illiquid asset base.* I find no evidence that the trading profits of star hedge funds are due to an illiquidity premium. In fact, star hedge funds tend to be net buyers of liquid stocks. However, I do find a significantly negative correlation between lockup periods and execution shortfall (ρ=-0.35). This is consistent with a lockup period allowing funds to reduce their price impact through more patient trading. For example, frequent redemption requests may place pressure on funds to immediately sell poorly performing assets at discount prices (Coval and Stafford, 2007). Having lockup periods and longer restriction periods may give star funds the flexibility they need to liquidate positions at more favorable prices. Consistent with this view, Franzoni and Plazzi (2013) find that hedge funds' price impact increases when funding conditions deteriorate, but such affects are attenuated for hedge funds with higher redemption restrictions.

[20] An alternative explanation is that high ability managers may have absolute advantages in minimizing price impact and creating value over longer horizons (Anand et al., 2012).

4.4 Characteristics of Star Hedge Funds – Regression Results

The previous section suggests that certain trading and fund characteristics are significantly correlated with being a star hedge fund. Since many of the attributes are correlated, in this section, I use logit regressions to assess the relationship between these attributes and the likelihood of being a star hedge fund. I continue to measure trade and fund characteristics in the year prior to the performance ranking period.

The logit regressions only include a subset of the characteristics considered in the univariate analysis in Table 7. First, I omit all of the total trading variables (i.e., Panel A of Table 7), as none of these variables are significant. Second, since the fund-level correlation between *net size* and *net illiquidity* is 0.92, I only include *net_size.* I also exclude *ave_fund_size* due to its high correlation with *management_size*, and I drop *restrictions* due to its correlation with *dlockup*. The results are not sensitive to which of the two correlated variables I choose to include. Of the 74 hedge fund management companies in ANcerno, I am able to collect quarterly holdings data for 54, and I collect data from TASS for 48 of the hedge fund companies. In order to run the regression for the full sample of money management companies, I include a corresponding *missing13F (*or *missingTass*) dummy which equals one if I was unable to match the fund to 13F (or TASS) data and zero otherwise.

The dependent variable of the logit regression equals one if the hedge fund is a star hedge fund and zero otherwise. Table 10 reports the coefficients and marginal effects. The marginal effects estimate the change in the predicted probability when the independent variable of interest changes by one standard deviation and all other variables are at their average values. Standard errors are clustered by management company. Panel A reports the results when only net trading characteristics are included. The results are consistent with the univariate results in Table 9. Specifically, funds that are net buyers of growth stocks and contrarian funds are more likely to be star funds in the subsequent year.

Panel B reports the results when only fund characteristics are included. Both *dlockup* and *execution shortfall* remain statistically significant. The economic magnitudes of both effects are also large. For example, a one standard deviation increase in *dlokcup (shortfall)* is associated with an 11.74% increase (5.74% decrease) in the likelihood of being a star hedge fund. All other fund variables are statistically insignificant. That the other variables are not statistically significant may alleviate some concerns regarding potential sample biases. For example, since my sample includes only equity trading, one possible concern is that funds may be using equity positions as hedges against their more informed derivative positions. However, this argument is inconsistent with the insignificant coefficient on *derivative*. In addition, ANcerno funds tend to be tilted towards larger funds and funds with low management fees. Thus, the observation that fund size and management fees are not significantly correlated with being a star hedge fund is reassuring. In untabulated analysis, I also include interactions of fund size and other significant variables, including *mom1*, *mom2_12*, *shortfall,* and *dlockup.* All of the interaction terms are statistically insignificant, suggesting that my findings do not differ significantly for large and small funds. This provides reassurance that the sample's tilt towards larger funds is not driving my findings.

Panel C reports the results when both net trading characteristics and fund characteristics are included. After including fund characteristics, the coefficient on *mom1* is no longer statistically significant. This is largely driven by the strong negative correlation of *mom1* with *execution shortfall* (ρ *= -0.60).* Intuitively, funds that follow short-term contrarian strategies, such as patient liquidity provision strategies, tend to have small price impacts. Overall, the results are largely consistent with the univariate results in Table 9 and continue to suggest that liquidity provision is an important determinant of star hedge funds' trading profits.

4.5 Performance Persistence by Trading Strategy

The results thus far suggest that star hedge funds tend to be contrarians with small price impacts whose trading profits are concentrated over short holding periods and in their contrarian trades. The results suggest that many star hedge funds profit from liquidity provision. As a final test, I revisit the performance persistence results documented in Table 5 but now report results separately for liquidity-supplying and liquidity-demanding star hedge funds. If liquidity provision is one channel through which skilled hedge funds create value, then the superior performance of liquidity suppliers should persist. In contrast, it is unclear that the superior trading performance of star liquidity-demanding hedge funds will persist. It is possible that there are some liquidity-demanding hedge funds that persistently create value through strategies other than liquidity provision (e.g., *insider trading*). However, it is also possible that top-performing liquidity demanders are simply lucky, in which case their subsequent performance should revert.

To investigate this issue, I partition star hedge funds into three groups: liquidity suppliers, liquidity neutral, and liquidity demanders. I use two proxies to distinguish liquidity suppliers from liquidity demanders: *mom1 trading* and *execution shortfall*. Funds in the top 30% of *mom1 trading* (*execution shortfall*) are considered liquidity demanders, while funds in the bottom 30% of *mom1* trading (*execution shortfall*) are considered liquidity suppliers. All other funds are considered liquidity neutral.

Panel A of Table 11 presents the results. The performance of liquidity-supplying star hedge funds is highly persistent. Using *execution shortfall* as a proxy for liquidity provision, I find that star hedge funds that are liquidity suppliers outperform by a statistically significant 0.41% per month over the subsequent year and by 0.29% over the subsequent three years. In contrast, there is no evidence of performance persistence among liquidity-demanding funds. Star liquidity demanders outperform by only 0.03% per month over the first year and actually earn negative (albeit statistically insignificant) returns over the subsequent three years. Similarly, star liquidity suppliers significantly outperform star liquidity demanders over the subsequent one- and three-year periods. The results using *mom1* trading as a proxy for liquidity provision yield similar results.

The results from Panel A of Table 11 suggest that star liquidity-supplying hedge funds outperform "star" liquidity-demanding hedge funds. A natural question is whether other hedge funds (i.e., funds outside the top 30% of past performance) that supply liquidity consistently outperform other liquidity-demanding hedge funds. Panel B of Table 11 explores this question. I find that other liquidity-supplying funds tend to exhibit slightly positive, but statistically insignificant, performance. Similarly, liquidity-supplying funds tend to perform slightly better than liquidity-demanding funds, but the difference is relatively small and typically statistically insignificant. Thus, not all liquidity-providing hedge funds outperform. This result highlights the existence of significant cross-sectional variations in trading skill, even among liquidity-providing hedge funds. Further, my findings suggest that interacting past performance and trading strategy can help identify hedge fund managers with superior trading skill.

5. Conclusion

This paper uses transaction-level data to offer a fresh perspective on the magnitude and source of hedge fund trading profits. To my knowledge, this is the first paper to use transaction-level data to investigate issues of hedge fund trading skill. Transaction data avoid many of the biases associated with commercial databases (e.g., unreliable returns, backfill bias, survivorship bias, etc.) and provide more powerful tests of trading skill than quarterly holdings (e.g., transaction data captures intra-quarter trading, short-selling, and confidential fillings).

I find that at least 10% (and at most 30%) of hedge funds are skilled traders. Similarly, I find that the trading profits of top performing hedge funds persist. This finding is consistent with studies that reach similar conclusions using commercial databases (e.g., Kosowski, Naik, and Teo, 2007; Jagannathan, Malakhov, and Novikov 2010). This out-of-sample support is reassuring, given the well-documented biases in commercial databases and because studies using quarterly holdings fail to find similar results (Griffin and Xu, 2009). My results also offer an explanation for the considerably weaker evidence of persistence in studies using quarterly holdings. Specifically, because a large portion of the trading profits of superior performing hedge funds accrue over relatively short holding periods (e.g., one quarter), quarterly holdings will generally understate the trading performance of star hedge funds.

I also exploit the granularity of transaction data to better understand the source of star hedge funds' trading profits. I find that star hedge funds tend to be contrarians with small price impacts and that their profits are concentrated over relatively short holding periods and in their more contrarian trades. All of these findings are consistent with the notion that star hedge funds profit from liquidity provision. In addition, my evidence is largely inconsistent with alternative sources of profitability, such as shareholder activism, insider trading, or skilled processing of public information. Of course, it is still possible (and even likely) that some hedge funds do profit from strategies other than liquidity provision. Nevertheless, my findings highlight the importance of liquidity provision as a channel through which many star hedge funds create value. Further, I find that performance persistence is very strong for liquidity-supplying hedge funds but not at all present for liquidity-demanding hedge funds. This finding points to the possibility that hedge fund investors can better identify star funds by screening on both past performance and investment strategy.

Appendix A: Description of the Control Variables

Stock Characteristics:

- *Size:* market capitalization (share price * total shares outstanding) at the end of the year prior to 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 divided by 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.

- *IVOL:* the square root of the mean squared residual from an annual regression of a firm's daily returns on market (value-weighted CRSP index) returns. Computed in 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).

Fund Characteristics:

- *Shortfall*: the principal-weighted shortfall of a fund. Following Anand et al. (2012), I measure execution shortfall as:

$$\frac{P_{1t} - P_{0t}}{P_{0t}} \times D_t$$

  where P_{1t} measures the value-weighted execution price of ticket t, P_{0t} is the price at the time when the broker receives the ticket, and D_t is an indicator variable that equals one for a buy ticket and minus one for a sell ticket (Source: ANcerno).

- *Management Co. Size:* The total value (shares held * price per share) of long-only equity holdings, computed quarterly. (Source: 13F Filings)

- *Turnover:* Following Griffin and Xu (2009), turnover is computed as: $\min(Buy_{it}, Sale_{it})/Holdings_{it-1}$, where Buy_{it} ($Sale_{it}$) is the total value of stocks bought (sold) by fund i in quarter t and $Holdings_{it-1}$ is the total equity holdings of fund i in quarter t-1. (Source: 13F Filings)

- *Stocks Held:* the number of long-only equity positions reported by the management company per quarter. (Source: 13F Filings)

- *Holding Return:* the one-quarter ahead DGTW-adjusted return of the equity holdings, as reported by the management company. (Source: 13F Filings)

- *Trading Return:* the one-quarter ahead DGTW-adjusted return of the equity trades (i.e.; changes in quarterly holdings) of the management company. (Source: 13F Filings)

- *Fund Size* – the equal-weighted average total assets under management across all funds within a given money management company. (Source: TASS)

- *Management Fee:* the AUM-weighted average management fee of funds within a money management company. (Source: TASS)

- *Incentive Fee:* the AUM-weighted average incentive fee of funds within a money management company. (Source: TASS)

- *High-water Mark:* a dummy variable equal to one if the fund has a high-water mark provision. This measure is the AUM-weighted average across funds within a money management company. (Source: TASS)

- *Dlockup:* a dummy variable equal to one if the fund imposes any lockup period. This measure is the AUM-weighted average across funds within a management company. (Source: TASS)

- *Restrictions:* the sum of the notice period and the redemption period. The notice period is the time the investor has to give notice to the fund of an intention to withdraw money from the fund, and the redemption period is the time taken by the fund to return money to investors after the notice period has expired. This measure is the AUM-weighted average across funds within a money management company. (Source: TASS)

- *Derivatives:* a dummy variable equal to one if the fund has any exposure to derivatives (including futures). This measure is the AUM-weighted average across funds within a money management company. (Source: TASS)

- *Leverage:* a dummy variable equal to one if the fund uses any leverage. This measure is the AUM-weighted average across funds within a management company. (Source: TASS)

- *Return Ranking:* a decile ranking of the fund's performance in a given month relative to all other funds in the same TASS primary category. The primary categories include: Convertible Arbitrage, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Long/Short Equity, Managed Futures, Multi-Strategy, and Other. This measure is averaged for each fund over the year prior to the ranking period. I then report the AUM-weighted average across funds within a money management company. (Source: TASS)

- *Equity Focused:* A dummy variable equal to one if the fund has a primary TASS category of Equity Market Neutral or Long/Short Equity. This measure is the AUM-weighted average across funds within a money management company. (Source: TASS)

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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, (i.e., plan sponsors or money managers) and manager-client pairs during the full sample period from 1999 to 2010. Panel B reports the number of managers, manager-client pairs (funds), and the average and median dollar trading volume per fund averaged across the four quarters in each year. I report the results separately for hedge funds and other institutional investors.

Panel A: Aggregate Sample Size

	Hedge Funds				Other Institutions			
Manager Type	Managers	Clients	Man-Clients	Clients Per Man	Managers	Clients	Man-Clients	Clients Per Man
All	74	253	361	4.88	579	733	4061	7.01
Plan Sponsor	63	229	337	5.35	527	554	3853	7.31
Money Man.	22	24	24	1.09	185	179	209	1.13

Panel B: Time-Series of Quarterly Averages

	Hedge Funds				Other Institutions			
Year	Managers	Man-Clients	Ave Vol ($m)	Med Vol ($m)	Managers	Man-Clients	Ave Vol ($m)	Med Vol ($m)
1999	46.50	110.50	71.49	16.14	387.00	1418.50	354.21	21.09
2000	41.50	110.75	56.39	19.60	372.25	1329.25	557.03	24.49
2001	38.50	111.75	71.30	17.69	371.50	1331.75	465.75	19.21
2002	43.75	127.75	81.55	10.11	389.75	1348.25	485.88	17.15
2003	39.50	117.50	73.19	8.93	375.50	1252.50	432.98	15.41
2004	40.75	114.75	111.06	10.58	367.75	1175.25	563.40	17.37
2005	41.50	109.50	338.71	13.05	342.50	1033.25	451.78	18.96
2006	38.00	97.50	432.60	19.61	323.50	883.50	710.79	20.71
2007	39.00	95.25	484.35	21.27	304.50	759.25	960.69	25.32
2008	36.00	73.00	548.57	17.67	252.25	559.50	1134.65	21.90
2009	27.50	50.25	428.37	10.02	205.75	408.00	667.81	13.89
2010	25.25	38.25	525.61	15.26	166.00	273.75	672.87	16.28

Table 2: The Cross-Sectional Distribution of Quarterly Trading and Intra-Quarter Trading

This table reports the cross-sectional distribution of quarterly trading for hedge funds and other institutional investors (Other). This measure is computed each quarter. The table presents the time-series average across the 48 quarters in the sample. I also report the ratio of actual to implied quarterly trading. Actual trading is based on actual transaction data. Implied quarterly trading is computed as the net dollar volume (buys-sells) of a stock, aggregated across all stocks traded by the fund 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: Quarterly Trading Volume Per Client-Manager Quarter

	Mean	Std Dev	99	95	75	50	25	5	1
					Plan Sponsors				
HF	35.97	74.03	389.58	151.54	35.20	12.88	4.41	0.74	0.19
Other	63.45	396.63	519.38	189.55	47.55	16.78	5.60	0.64	0.08
					Money Managers				
	Mean	Std Dev	99	95	75	50	25	5	1
HF	2,488.05	2,721.96	7,747.61	7,747.61	3,413.91	1,817.20	736.19	391.74	391.74
Other	9,624.91	23,484.74	132,622.8	50,145.97	6,605.73	1,276.77	260.84	22.43	3.60

Panel B: Ratio of Actual to Implied Quarterly Trading

	Mean	Std Dev	99	95	75	50	25	5	1
					Plan Sponsors				
HF	1.19	0.69	4.22	1.65	1.16	1.03	1.00	1.00	1.00
Other	1.31	4.77	2.32	1.48	1.18	1.06	1.00	1.00	1.00
					Money Managers				
	Mean	Std Dev	99	95	75	50	25	5	1
HF	1.47	0.40	2.29	2.29	1.60	1.34	1.21	1.13	1.13
Other	1.51	1.26	9.40	2.14	1.53	1.30	1.13	1.01	1.00

Table 3: Fund-Level Performance by Investor Type

This table reports the average trading profits based on transaction-based calendar-time portfolios, with holding periods ranging from 21 days to 252 days. I estimate performance for each fund and report the equally-weighted average across funds for both hedge funds (Panel A) and other institutional investors (Panel B). For each institution type, I estimate performance using gross returns, DGTW-adjusted returns, and DGTW-adjusted returns less commissions. For each holding period, I exclude fund-days on which there are fewer than 10 stocks in both the buy and sell portfolios. Returns are inclusive of 'Day 0' returns, where Day 0 returns are computed based on the reported execution price. This table reports the average return across all days in the sample period, expressed as monthly returns in percent. T-statistics, based on standard errors clustered by fund and day, are reported in parentheses.

Panel A: Hedge Funds

	Holding Period			
	21	63	126	252
Gross Returns				
Buys	1.27	0.72	0.71	0.72
Sells	0.75	0.63	0.66	0.64
Buys - Sells	0.52	0.10	0.05	0.08
	(1.74)	(0.60)	(0.51)	(1.00)
DGTW Adjusted Returns				
Buys	0.40	0.04	0.03	0.01
Sells	-0.01	-0.05	-0.03	-0.06
Buys - Sells	0.41	0.09	0.06	0.07
	(1.63)	(0.60)	(0.66)	(1.11)
DGTW Adjusted Returns Less Commissions				
Buys	0.22	-0.02	0.00	-0.01
Sells	0.18	0.01	0.00	-0.04
Buys - Sells	0.04	-0.03	-0.01	0.04
	(0.14)	(-0.23)	(-0.06)	(0.57)

Panel B: Other Institutions

	Holding Period			
	21	63	126	252
Gross Returns				
Buys	0.90	0.60	0.56	0.52
Sells	0.63	0.58	0.58	0.57
Buys - Sells	0.27	0.02	-0.02	-0.05
	(3.55)	(0.64)	(-0.66)	(-1.98)
DGTW Adjusted Returns				
Buys	0.23	0.00	-0.06	-0.08
Sells	0.08	0.01	-0.03	-0.04
Buys - Sells	0.15	-0.01	-0.03	-0.04
	(2.54)	(-0.35)	(-1.17)	(-2.33)
DGTW Adjusted Returns Less Commissions				
Buys	0.11	-0.04	-0.08	-0.10
Sells	0.21	0.05	-0.01	-0.03
Buys - Sells	-0.10	-0.10	-0.07	-0.07
	(-1.72)	(-3.09)	(-3.10)	(-3.83)

Table 4: The Cross-Section of Fund Performance

For each fund, I estimate performance using transaction-based calendar time portfolios with a 252-day holding period. I exclude fund-days in which there are fewer than 10 stocks in both the buy and sell portfolios. I 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. I estimate returns based on DGTW-adjusted returns both excluding and including trading commissions. For each fund in the sample, I compute the actual t-statistic of alpha, based on the entire time-series of the fund's returns. *Actual* reports the distribution of t-statistics across all hedge funds (Panel A) or other institutional investors (Panel B). I 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. I also show the percentage of simulation draws that produce a t-statistic greater than the corresponding actual value.

Panel A: Hedge Funds

	Excluding Commissions			Including Commissions		
Pct	Actual	Simulated	% Act	Actual	Simulated	% Act
1	-3.35	-2.63	97.5%	-3.40	-2.62	97.9%
2	-2.70	-2.22	96.5%	-2.78	-2.21	98.1%
3	-1.74	-1.98	11.7%	-1.83	-1.97	23.8%
4	-1.56	-1.82	7.7%	-1.65	-1.81	18.1%
5	-1.48	-1.71	9.0%	-1.60	-1.71	26.6%
10	-1.20	-1.32	21.3%	-1.31	-1.32	48.4%
20	-0.83	-0.86	42.0%	-0.88	-0.86	58.4%
30	-0.43	-0.53	18.7%	-0.51	-0.53	44.1%
40	-0.11	-0.26	10.4%	-0.23	-0.26	40.1%
50	0.15	0.00	9.7%	0.01	0.00	48.1%
60	0.43	0.26	7.0%	0.30	0.26	34.9%
70	0.81	0.54	1.0%	0.70	0.53	7.9%
80	1.09	0.86	3.5%	1.02	0.86	9.3%
90	1.74	1.32	0.4%	1.63	1.32	2.0%
95	2.15	1.72	1.4%	2.06	1.72	3.7%
96	2.46	1.82	0.2%	2.41	1.82	0.4%
97	2.83	1.99	0.1%	2.75	1.98	0.2%
98	3.17	2.23	0.1%	3.06	2.22	0.3%
99	3.84	2.63	0.2%	3.68	2.63	0.4%

Panel B: Other Institutions

	Excluding Commissions			Including Commissions		
Pct	Actual	Simulated	% Act	Actual	Simulated	% Act
1	-2.73	-2.66	71.9%	-2.87	-2.66	94.1%
2	-2.27	-2.18	83.2%	-2.34	-2.17	94.6%
3	-2.05	-1.96	84.1%	-2.12	-1.96	95.8%
4	-1.91	-1.81	88.1%	-1.99	-1.81	97.8%
5	-1.79	-1.69	88.3%	-1.87	-1.69	97.8%
10	-1.42	-1.31	93.6%	-1.50	-1.31	99.6%
20	-0.99	-0.85	98.8%	-1.07	-0.85	99.9%
30	-0.64	-0.53	97.9%	-0.72	-0.53	100.0%
40	-0.36	-0.26	97.3%	-0.43	-0.26	100.0%
50	-0.10	0.00	97.7%	-0.17	0.00	100.0%
60	0.16	0.26	97.1%	0.07	0.26	100.0%
70	0.41	0.53	98.7%	0.34	0.53	100.0%
80	0.75	0.85	96.4%	0.66	0.86	100.0%
90	1.25	1.31	79.2%	1.17	1.31	98.7%
95	1.61	1.70	84.3%	1.53	1.70	98.7%
96	1.76	1.81	72.7%	1.66	1.81	97.1%
97	1.92	1.96	64.7%	1.82	1.96	94.9%
98	2.12	2.18	71.7%	2.01	2.18	96.0%
99	2.70	2.66	37.4%	2.58	2.67	74.2%

Table 5: Persistence in Annual Trading Skill

I estimate fund performance using calendar-time transaction portfolios with 252-day holding periods. Returns are reported as DGTW-adjusted returns less trading commissions and are inclusive of Day 0 returns. I sort funds into three groups according to the DGTW-adjusted performance over the prior year. Group 3 (1) consists of funds that were in the top (bottom) 30% of performance. Group 2 consists of the remaining 40% of funds. I exclude fund-days on which there are fewer than 10 stocks in both the buy and the sell portfolio. I hold the portfolios for post-ranking periods ranging from one year to three years. I rebalance the portfolios at the end of each year. I 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. I report the results for both hedge funds and other institutional investors. T-statistics, based on standard errors clustered by fund and day, are reported in parentheses.

Annual Persistence (Including Commissions)

	Hedge Funds				**Other Institutions**			
	Holding Period (in Quarters)				Holding Period (in Quarters)			
Past Year Ranking	[1,4]	[5,8]	[9,12]	[1,12]	[1,4]	[5,8]	[9,12]	[1,12]
1	0.01	0.01	0.02	0.01	-0.08	-0.05	-0.08	-0.07
	(0.12)	(0.14)	(0.39)	(0.24)	(-1.82)	(-1.69)	(-2.69)	(-2.38)
2	-0.04	0.06	0.05	0.01	-0.06	-0.05	-0.04	-0.05
	(-0.97)	(1.23)	(0.98)	(0.42)	(-3.44)	(-1.79)	(-1.94)	(-2.90)
3	0.25	0.14	0.12	0.19	-0.04	-0.06	-0.02	-0.04
	(2.75)	(1.46)	(1.22)	(2.14)	(-1.11)	(-1.99)	(-0.48)	(-1.60)
3-1	0.24	0.13	0.10	0.17	0.04	-0.01	0.07	0.03
	(2.59)	(1.32)	(1.08)	(2.59)	(0.59)	(-0.29)	(1.56)	(0.78)

Table 6: Persistence in Annual Trading Skill of "Star" Hedge Funds - Alternative Risk Adjustments

This table examines the performance of "star" hedge funds using alternative risk-adjustments. I define a star hedge fund as a fund that was in the top 30% of performance (as defined in Table 5) over the prior year. I estimate the performance of the star hedge funds over the subsequent year. I estimate performance as the average daily return (expressed as monthly returns in percent) for all star hedge funds over the month. I exclude fund-days in which there are fewer than 10 stocks in both the buy and the sell portfolios. I then estimate the following monthly time-series regression for the period from January 2000 to December 2011: $R_{pt}=\alpha_i+\boldsymbol{\beta}\mathbf{F}_t+\varepsilon_t$. R_{pt} is the monthly return on the aggregate star hedge fund portfolio, and $\mathbf{F_t}$ is a matrix of returns on the MKTRF, SMB, HML, WML, and LIQ factors. In specifications 1-4, the dependent variable is the gross performance of star hedge funds, and in specification 5, the dependent variable is the DGTW-adjusted performance of star hedge funds. Both performance measures incorporate trading commissions. The time-series regression is estimated using weighted least squares, where the weight is given by the number of observations used to compute the monthly return. T-statistics are reported in parentheses.

	Return Measure	Alpha	MKTRF	SMB	HML	WML	LIQ	Adj R-squared
1	Gross Return	0.30	0.07					6.48%
		(2.83)	(3.30)					
2	Gross Return	0.30	0.08	-0.01	0.02			5.65%
		(2.65)	(3.38)	(-0.39)	(0.55)			
3	Gross Return	0.30	0.05	0.01	0.01	-0.05		9.74%
		(2.71)	(1.79)	(0.30)	(0.31)	(-2.71)		
4	Gross Return	0.28	0.04	0.01	0.01	-0.05	0.01	9.23%
		(2.52)	(1.73)	(0.28)	(0.34)	(-2.73)	(0.48)	
5	DGTW-Adj Return	0.27	0.05	-0.01	-0.03	0.00	0.01	4.60%
		(3.08)	(2.69)	(-0.52)	(-1.07)	(0.21)	(0.60)	

Table 7: Performance of Star Hedge Funds by Holding Period

This table sorts hedge funds into 3 groups, based on performance (as defined in Table 5) in the current year (Panel A) or the prior year (Panel B). Group 3 (1) consists of funds that were in the top (bottom) 30% of performance. Group 2 consists of the remaining 40% of funds. For each fund and year, I examine the DGTW-adjusted returns of the stocks purchased by the fund less the DGTW-adjusted returns of the stocks sold by the fund over the subsequent one, two, three, or four quarters or the entire year (1,4). Returns are expressed as percent per quarter and do not incorporate trading commissions. T-statistics, reported in parentheses, are based on standard errors clustered by management company and year.

Panel A: Ranking Period					
	Holding Period in Quarters				
Current Year Rank	Q1	Q2	Q3	Q4	[1,4]
1	-2.68	-1.22	-1.36	0.63	-1.16
2	0.44	-0.16	-0.09	-0.28	-0.24
3	3.37	2.11	1.79	1.02	2.07
3-1	6.04	3.33	3.15	0.39	3.23
t-stat	(8.00)	(7.83)	(4.96)	(0.73)	(12.70)

Panel B: Subsequent Period					
	Holding Period in Quarters				
Past Year Rank	Q1	Q2	Q3	Q4	[1,4]
1	-0.17	0.23	-0.53	0.54	0.02
2	0.24	-0.31	-0.20	-0.01	-0.07
3	1.69	0.72	0.46	0.50	0.84
3-1	1.86	0.48	0.99	-0.04	0.82
t-stat	(2.22)	(0.66)	(1.26)	(-0.06)	(2.01)

Table 8: Performance of Hedge Funds by Stock Characteristics

This table reports the trading performance of star hedge funds and other hedge funds. Star hedge funds are funds that were in the top 30% of performance (as defined in Table 5) over the prior year. I assign stocks to size, book-to-market, idiosyncratic volatility, and momentum groups based on NYSE breakpoints. For all characteristics except size and illiquidity, stocks are divided based on the median NYSE breakpoint. I define a stock as large (or liquid) if the stock is in the top 30 of NYSE size (or bottom 30% of NYSE illiquidity). All other stocks are defined as small (or illiquid) stocks. I also define stocks according to the time of the most recent earnings announcements. Pre-earnings stocks are stocks that will announce earnings within the next 10 trading days, and post-earnings stocks are stocks that announced earnings within the past 10 trading days. For each fund and stock characteristic, I compute the principal-weighted DGTW-adjusted returns on the stocks bought less the stocks sold. The sample includes all funds with at least five buys and five sells over the calendar year for both groups (i.e., both small and large stocks). I report the equal-weighted average across all star hedge funds or other hedge funds. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. T-statistics, based on standard errors clustered by management company and year, are reported in parentheses.

	Star HF Holding Period (in Quarters)		Other HF Holding Period (in Quarters)		Star - Other HF Holding Period (in Quarters)	
	[1]	[1,4]	[1]	[1,4]	[1]	[1,4]
Small	1.28	1.24*	1.31**	-0.02	-0.03	1.26
Large	1.16	0.93	-0.34	0.14	1.50	0.79
Small - Large	0.11	0.31	1.64**	-0.16	-1.53	0.48
	(0.07)	(0.41)	(2.11)	(-0.45)	(-0.90)	(0.61)
Growth	1.46**	0.93*	-0.05	0.06	1.51**	0.87*
Value	1.73	0.53	0.11	-0.25	1.62	0.78*
Growth - Value	-0.27	0.40	-0.17	0.31	-0.10	0.08
	(-0.22)	(0.53)	(-0.28)	(0.94)	(-0.09)	(0.14)
High IVol	1.88**	1.24*	-0.02	0.04	1.90**	1.20*
Low IVol	1.54**	0.24	-0.07	0.02	1.61**	0.22
High - Low IVol	0.34	1.00**	0.05	0.02	0.29	0.98*
	(0.56)	(2.00)	(0.10)	(0.08)	(0.34)	(1.68)
Illiquid	1.52	0.52	-0.31	0.04	1.83*	0.48
Liquid	1.76*	1.12	0.41	0.25	1.35	0.87
Illiquid - Liquid	-0.24	-0.60	-0.72	-0.21	0.48	-0.39
	(-0.18)	(-0.79)	(-0.93)	(-0.41)	(0.41)	(-0.57)
Pre_Earnigns	0.15	1.19	-0.83	-0.19	0.98	1.38
Post_Earnings	1.71	1.06	0.46	0.61	1.25	0.45
Pre-Post Earnings	-1.55	0.13	-1.27	-0.80	-0.26	0.92
	(-1.33)	(0.24)	(-1.88)	(-1.59)	(0.24)	(1.33)
Contrarian21_252	2.23**	1.26***	0.37	0.62**	1.86*	0.64*
Momentum21_252	1.06	0.41	0.12	-0.65	0.94	1.06
Con21_252- Mom21_252	1.17	0.85	0.25	1.27***	0.92	-0.42
	(1.15)	(0.98)	(0.50)	(2.97)	(0.95)	(-0.52)
Contrarian21	2.19*	1.10**	1.07***	0.26	1.13	0.84**
Momentum21	0.28	0.42	-0.87**	-0.16	1.15*	0.58
Con21 - Mom21	1.91	0.69**	1.93***	0.42*	-0.02	0.27
	(1.66)	(2.06)	(4.28)	(1.92)	(-0.02)	(0.90)

Table 9: The Characteristics of Star Hedge Funds

The table below compares the characteristics of star hedge funds to those of other hedge funds. Star hedge funds are funds that were in the top 30% of performance (as defined in Table 5) over the subsequent year. For each hedge fund with at least 10 buys and 10 sells during a given calendar year, I compute the principal-weighted characteristics of the stocks traded (i.e., (buys + sells)/2). Panel A reports the average across all star hedge funds and all other hedge funds. Panel B reports a similar metric for net trading (i.e., buys – sells). Panel C reports fund-level characteristics. The construction of all variables is described in Appendix A. T-statistics, reported in parentheses, are based on standard errors clustered by management company and year.

Panel A: Total Trading

	Star HF	Other HF	Star- Other	t(Star-Other)
Size	6.81	7.12	-0.31	(-1.00)
BM	4.22	4.09	0.13	(0.94)
IVol	5.75	5.78	-0.03	(-0.23)
Illiquidity	3.90	3.61	0.29	(1.04)
Mom21	5.71	5.74	-0.03	(-0.41)
Mom21_252	6.01	6.14	-0.13	(-0.95)
Pre_Earnings (%)	13.29	12.99	0.30	(0.77)
Post_Earnings (%)	16.04	16.31	-0.27	(-0.48)

Panel B: Net Trading

	Star HF	Other HF	Star- Other	t(Star-Other)
Size	0.00	-0.08	0.08	(1.59)
BM	-0.40	-0.17	-0.23	(-3.34)
IVol	0.15	0.04	0.11	(0.96)
Illiquidity	-0.02	0.10	-0.12	(-1.97)
Mom21	-0.82	-0.26	-0.56	(-3.67)
Mom21_252	-1.11	-0.74	-0.37	(-2.31)
Pre_Earnings (%)	0.53	0.33	0.20	(0.36)
Post_Earnings (%)	1.41	0.00	1.41	(1.49)

Panel C: Fund Characteristics

	Star HF	Other HF	Star- Other	t(Star-Other)
Log (Fund Size)	*3.88*	*3.98*	*-0.10*	*(-0.26)*
Management Fee	1.34	1.27	0.07	(0.61)
Incentive Fee	15.17	15.66	-0.49	(-0.44)
High-water Mark	67.84	60.92	6.92	(0.99)
Dlockup	52.63	29.33	23.30	(2.91)
Restrictions	*202.33*	*154.18*	*48.15*	*(2.34)*
Derivatives	6.16	8.32	-2.16	(-0.74)
Execution Shortfall	4.80	5.88	-1.08	(3.86)
Turnover	0.62	0.74	-0.12	(-1.96)
Log (Management Co.Size)	8.45	8.15	0.30	(1.87)

Table 10: Predicting Star Hedge Funds

The dependent variable is a dummy variable equal to one if the hedge fund is in the top 30% of performance (as defined in Table 5) over the subsequent year. The explanatory variables are computed in the year prior to observed performance. Descriptions of the control variables are presented in Appendix A. Specification 1 uses the various net trading (i.e., buys – sells) characteristics to predict whether a hedge fund is a star. Specification 2 examines whether characteristics of the money manager company can forecast star hedge funds. Specification 3 includes both net trading and fund characteristics. All specifications are estimated using logistic regressions. For each specification, in the first column, I report the coefficient and, in parentheses, the z-score. Z-scores are computed based on standard errors clustered by management company. In the second column, I report the marginal effects. The marginal effects estimate the change in the predicted probability when the independent variable of interest changes by one standard deviation and all other variables are at their average values.

	1		2		3	
	Coeff	Marg. Eff	Coeff	Marg. Eff	Coeff	Marg. Eff
Intercept	-112.19		-95.01		-128.78	
	(-9.28)		(-0.89)		(-1.23)	
Net_Size	1.62	0.28%			3.19	0.59%
	(0.21)				(0.43)	
Net_BM	-11.41	-2.53%			-8.22	-1.30%
	(-2.03)				(-1.81)	
Net_Mom21	-8.94	-3.61%			-1.75	-0.77%
	(-2.63)				(-0.40)	
Net_Mom21_252	-11.42	-3.17%			-12.60	-3.72%
	(-1.58)				(-2.14)	
Net_IVol	9.43	2.41%			10.07	2.73%
	(1.12)				(1.02)	
Net_Pre_Earnings	0.11	0.26%			0.02	0.05%
	(0.24)				(0.04)	
Net_Post_Earnings	0.85	2.21%			0.72	2.00%
	(1.46)				(1.32)	
Log (Management Size)			1.97	0.55%	4.10	1.19%
			(0.28)		(0.61)	
Turnover			-87.07	-1.95%	-41.45	-0.96%
			(-0.78)		(-0.37)	
Management Fee			37.36	3.11%	33.37	2.84%
			(0.69)		(0.61)	
Incentive Fee			0.75	1.02%	0.65	0.90%
			(0.40)		(0.34)	
High-water Mark			-0.57	-4.93%	-62.20	-5.47%
			(-1.39)		(-1.55)	
Dlockup			1.17	11.74%	1.16	11.80%
			(2.57)		(2.62)	
Derivatives			-0.63	-3.10%	-0.74	-3.69%
			(-0.82)		(-0.80)	
Shortfall			-9.56	-5.81%	-7.67	-4.88%
			(-2.60)		(-1.91)	
Obs	3023		3023		3023	
Pseudo R-squared	2.85%		4.72%		5.99%	

Table 11: Performance Persistence of Liquidity-Supplying versus Liquidity-Demanding Hedge Funds

This table revisits the performance persistence of star hedge funds (i.e., hedge funds in the top 30% of performance in Table 5) and other hedge funds (i.e., hedge funds in the bottom 70% of performance in Table 5). The methodology is identical to Table 5, except I now partition funds into three groups: liquidity demanders (LD), liquidity neutral (LN) and liquidity suppliers (LS). I create two liquidity proxies: execution shortfall and short-term momentum trading. Funds in the bottom (top) 30% of execution shortfall (as defined in the Appendix) or funds in the bottom (top) 30% of net trading based on past one month returns (as defined in the Appendix) are defined as liquidity suppliers (liquidity demanders). Funds in the middle 40% are classified as liquidity neutral. Panel A reports the results for star hedge funds, and Panel B reports the results for all other hedge funds. T-statistics, based on standard errors clustered by management company and day, are reported in parentheses.

Panel A: Star Hedge Fund Persistence by Liquidity Group

	Annual Performance (+ Commissions) **Liquidity Proxy: *Execution Shortfall***				Annual Performance (+ Commissions) **Liquidity Proxy: *Mom1* Trading**			
Group	Year 1	Year 2	Year 3	Year [1-3]	Year 1	Year 2	Year 3	Year [1-3]
Star LS	0.41	0.26	0.07	0.29	0.36	0.37	0.06	0.30
	(3.56)	(2.42)	(0.44)	(2.87)	(2.84)	(2.52)	(0.52)	(2.41)
Star LN	0.24	0.14	0.32	0.22	0.32	0.16	0.29	0.27
	(1.83)	(0.87)	(2.06)	(1.82)	(3.06)	(1.04)	(1.98)	(2.39)
Star LD	0.03	-0.05	-0.17	-0.04	0.01	-0.19	-0.13	-0.09
	(0.43)	(-0.51)	(-1.37)	(-0.74)	(0.06)	(-2.39)	(-1.29)	(-0.98)
LS – LD	0.38	0.31	0.23	0.33	0.35	0.56	0.18	0.39
	(2.51)	(1.99)	(1.19)	(2.61)	(2.12)	(3.09)	(1.37)	(2.99)

Panel B: Other Hedge Fund Persistence by Liquidity Group

	Annual Performance (+ Commissions) **Liquidity Proxy: *Execution Shortfall***				Annual Performance (+ Commissions) **Liquidity Proxy: *Mom1* Trading**			
Group	Year 1	Year 2	Year 3	Year [1-3]	Year 1	Year 2	Year 3	Year [1-3]
Other LS	0.04	0.07	0.03	0.05	-0.03	0.18	0.12	0.08
	(0.44)	(0.84)	(0.41)	(0.68)	(-0.27)	(2.41)	(1.83)	(1.10)
Other LN	-0.02	0.11	0.05	0.04	-0.01	0.02	0.11	0.03
	(-0.29)	(1.24)	(0.61)	(0.68)	(-0.19)	(0.33)	(1.09)	(0.42)
Other LD	-0.07	-0.07	0.03	-0.05	-0.02	-0.06	-0.12	-0.06
	(-1.26)	(-1.72)	(0.48)	(-1.13)	(-0.41)	(-1.32)	(-1.93)	(-1.53)
LS – LD	0.11	0.14	0.00	0.10	-0.01	0.25	0.23	0.14
	(1.03)	(1.42)	(-0.03)	(1.12)	(-0.06)	(2.54)	(2.44)	(1.54)

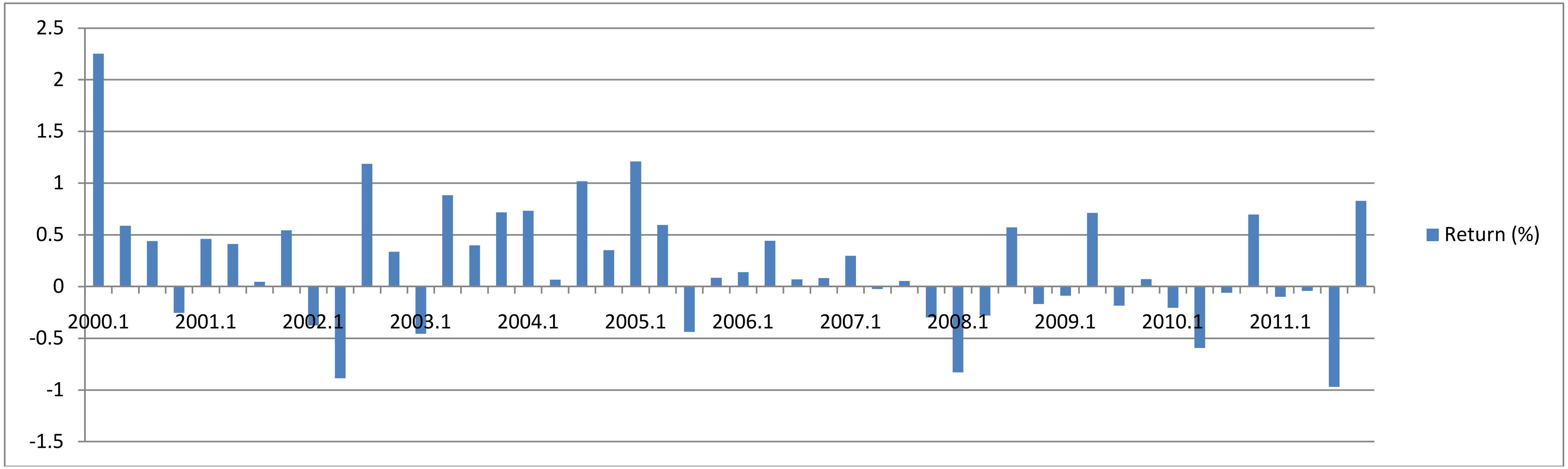
Figure 1: The Advantages of ANcerno Data

This figure highlights some limitations of the existing hedge fund data sources and comments on whether the limitations are also present in ANcerno data. Panel A highlights the shortcomings of commercial hedge fund databases (e.g., TASS), and Panel B highlights the shortcomings of 13F filings (i.e., quarterly holdings).

Panel A: Problems in Commercial Databases	**Problem in ANcerno?**
Backfill Bias	No
Survivorship Bias	No
Smoothing Bias	No
Distinguishing Beta vs. Alpha	No
Reliable Returns	No
Self-Selection Bias	See Appendix Tables A.1 & A.2
Panel B: Problems with 13F	**Problem in ANcerno?**
Missing Intra-quarter Trades	No
Window Dressing	No
Unclear Execution Price	No
Missing short-sales	No
Missing Confidential Filings	No
Missing Derivative Positions	Yes

Figure 2: Time-Series Variation in the Performance of Star Hedge Funds

I estimate fund performance using calendar-time transaction portfolios with 252-day holding periods. I exclude fund-day observations in which there are fewer than 10 stocks in both the buy and the sell portfolios. Returns are reported as DGTW-adjusted returns less trading commissions and are inclusive of Day 0 returns. I define a star hedge fund as a fund that was in the top 30% of performance (as defined in Table 5) over the prior year. This figure plots the performance of the star hedge funds each quarter in the year subsequent to the ranking year. Returns are expressed as % per month.



Appendix B: Representativeness of ANcerno Hedge Funds

A.1 Comparisons to Quarterly Holdings

In this section, I compare 13F filing hedge funds that appear in ANcerno to 13F filing hedge funds that do not report to ANcerno. I begin by collecting a list of all institutional investors that filed form 13F (and thus report quarterly equity holdings) over the period from 1999 to 2010. I then use the hedge fund classification procedure (as discussed in section 2.2) to classify 13F filing institutions into hedge funds and other institutions. Specifically, I classify a 13F filing institution as a hedge fund if more than 50% of its clients are categorized as "high net worth individuals" or "other pooled investment vehicles," and the manager charges a performance-based fee. I initially identify 1,171 hedge fund management companies (hereafter hedge funds). I limit the sample to hedge funds that hold at least 10 equity positions in a given quarter. The final sample consists of 1,013 hedge funds and 19,840 hedge fund quarters.

The ANcerno sample consists of 74 hedge fund management companies and 1,524 management-company quarters. For each ANcerno hedge fund, I manually search for the corresponding 13F filing hedge fund based on management company name. I am able to identify 54 ANcerno hedge funds and 1,191 ANcerno hedge fund quarters in the 13F filings.

For each hedge fund quarter, I use quarterly holdings data to compute the following fund-level variables: *total net assets (TNA), stocks held, holding return, size, bm, illiquidity, volatility, mom1* and *mom2_12*. The details of the variable construction are described in Appendix A. *Mom1* and *mom2_12* are computed relative to the first day of the quarter. All stock characteristics (e.g., size, bm, etc.) reflect the principal-weighted characteristics of the stocks *held* by the fund.

Panel A compares the characteristics of ANcerno hedge funds to other 13F Filing hedge funds that do not appear in ANcerno (*Other).* ANcerno hedge funds are significantly larger than other hedge funds. Specifically, the average ANcerno hedge fund has total net assets of roughly $5 billion, while other hedge funds on average have assets of slightly less than $1 billion. The distribution of assets under management is highly skewed, and taking the natural log of total net assets results in a less dramatic, but still highly significant, difference. This finding is similar to Puckett and Yan (2011), who also find that ANcerno institutions are substantially larger than non-ANcerno institutions.[22] Given the structure of ANcerno data, it is not surprising that the sample is tilted towards larger funds. Most ANcerno hedge funds enter the sample because they manage money on behalf of a plan sponsor that subscribes to ANcerno. Larger hedge funds manage money for more plan sponsors, which increases the likelihood that they will appear in the ANcerno sample.

On average, hedge funds in ANcerno have DGTW-adjusted quarterly holdings that are nearly identical to those of other hedge funds in the 13F universe (42 bps vs. 39 bps). The characteristics of the stocks they hold are also very similar. In particular, compared to other hedge funds, ANcerno hedge funds show no significant tilt towards firm size, bm, illiquidity, or volatility, although they do exhibit a slight preference for recent winners.

I also examine whether the trading of ANcerno hedge funds is similar to that of the universe of 13F filing hedge funds. Trading is computed as changes in quarterly holdings. For each fund, I estimate the fund's *turnover* and the principal-weighted DGTW-adjusted returns on stocks bought less returns on stocks sold over the subsequent quarter (*trading return)*. I also compute *size, bm, illiquidity, volatility, mom1,* and *mom2_12* for the stocks traded by each fund (i.e., total trading) and net trading (i.e., buys – sells). Additional information regarding variable construction is presented in Appendix A.

Panel B presents the results. I find that ANcerno hedge funds have lower turnover than other hedge funds (70% vs. 97%). Their trading performance is also lower (0.05% vs.

[22] At the time of Puckett and Yan's (2011) study, the ANcerno data were anonymous; however the authors were able to obtain a list of the names of 68 institutions from ANcerno. Their analysis does not distinguish hedge funds from other institutions.

0.43%), although the estimates do not differ significantly. If anything, the slightly weaker performance of ANcerno funds suggests the possibility that more than 10% of hedge funds may be star traders. The characteristics of stocks traded (i.e., buys + sells) by ANcerno hedge funds are very similar to those traded by other hedge funds. Similarly, net trading (i.e., buys – sells) of ANcerno hedge funds is typically very similar to that of other hedge funds, although ANcerno hedge funds tilt towards more contrarian trading strategies. This finding suggests that my sample may be biased towards liquidity-supplying funds. However, my emphasis is not on whether the average hedge fund provides liquidity, but on whether liquidity provision generates persistent trading profits for some hedge funds.

A.2 Comparisons to TASS

I next compare my sample of ANcerno hedge funds to funds that report to TASS. I identify 17,272 live and graveyard funds that reported to the TASS database between 1999 and 2010. To make these data congruent with the ANcerno data, I aggregate across all funds that belong to a given management company and compute management company averages by weighting each fund by its assets under management. The sample includes 4,693 management companies and 237,638 management company-months. For each observation, I compute the following management-company variables: *fund size, management fee, incentive fee, high-water mark, dlokcup, restrictions, derivatives, return ranking,* and *equity focused.* Details of the variable construction are presented in Appendix A.

I manually search for ANcerno hedge funds within TASS, identifying 48 such funds. The intersection of ANcerno and TASS yields a sample of 35 management companies for which the TASS and ANcerno reporting periods overlap, resulting in a total of 1,630 company-month observations.

I compare the sample of ANcerno hedge funds reporting to TASS to other TASS hedge funds that do not report to ANcerno. Table A.2 presents the results. Along most dimensions, there is no significant difference between ANcerno hedge funds and other TASS hedge funds. The two groups are similar with respect to performance (*return ranking),* incentive fees, lockup periods, restrictions, leverage, and high-water marks.

There are, however, some notable differences. First, there is evidence that ANcerno hedge funds are larger than TASS hedge funds. This is consistent with the comparison to 13F holdings, although the difference here is less dramatic. Second, ANcerno hedge funds charge significantly lower management fees (1.2% compared to 1.4%). In a competitive equilibrium, one might expect net of fee alphas to be zero for all funds (Berk and Green, 2004). As the trading analysis is performed gross of management fees, this may bias the sample towards less skilled funds. However, in Table 9, I find no significant relationship between management fees and the likelihood of being a star hedge fund trader.

Finally, I find that ANcerno hedge funds are significantly less likely to use derivatives. In fact, only 6% of ANcerno hedge funds use derivatives. This is not surprising, as funds that primarily trade derivatives would have less need to use an equity-focused transaction cost consulting firm. The fact that the majority of hedge funds in the sample do not use derivatives is reassuring, as this mitigates concerns about bias caused by the omission of derivative trades (Aragon and Martin, 2012). It does, however, raise a concern that the sample is tilted towards specific types of hedge fund strategies. Consistent with this view, 57% of the hedge funds in the ANcerno sample are either *equity market neutral* or *long/short equity* strategies (i.e., equity-focused strategies), compared to 37% in the universe of hedge funds.[23] Nevertheless, existing studies find that equity-focused hedge funds generate similar outperformance compared to most other hedge fund styles (Kosowski, Naik, and Teo, 2007), and this subset of hedge funds reflects a sizeable fraction of the hedge fund universe.

[23] The 57% estimate is likely an understatement. Many funds offer multiple products, and it is likely that the ANcerno funds are more likely to be equity products. If I limit the sample to funds that offer only one product, the sample of equity-focused funds increases to 72% (compared to 44% for non-ANcerno funds).

Table A.1: Comparison of ANcerno Hedge Funds and 13F Hedge Funds

This table compares 13F filing hedge funds that report to ANcerno to hedge funds that do no report to ANcerno (Other). Panel A compares characteristics of the holdings of the two groups of funds. Panel B compares trading characteristics. Definitions of the variables and details of their construction are presented in Appendix A. T-statistics, based on standard errors clustered by management company and quarter, are reported in parentheses.

Panel A: Holdings

	ANcerno	Other	Dif	t(Dif)
Mean TNA ($ Millions)	4935.17	973.41	3961.76	(2.37)
Log (TNA)	7.54	5.74	1.80	(8.74)
Stocks Held	287.23	113.94	173.29	(3.49)
Holding Return (Quarterly)	0.42	0.39	0.03	(0.15)
Size	7.41	7.18	0.23	(0.91)
BM	4.17	4.28	-0.11	(-0.62)
Illiquidity	3.42	3.67	-0.25	(-1.06)
Volatility	5.26	5.37	-0.11	(-0.52)
Mom1	5.90	5.71	0.19	(2.57)
Mom2_12	6.42	6.13	0.29	(2.07)

Panel B: Trading

	ANcerno	Other	Dif	t(Dif)
Turnover	0.69	0.97	-0.28	(-3.63)
Trading Return	0.05	0.43	-0.38	(-1.54)
Total Trading (Buys + Sells)				
Size	7.35	7.35	-0.04	(-0.16)
BM	4.06	4.08	-0.02	(-0.11)
Illiquidity	3.45	3.44	0.01	(0.03)
Volatility	5.64	5.47	0.17	(0.88)
Mom1	5.79	5.68	0.11	(1.54)
Mom2_12	6.39	6.14	0.25	(1.92)
Net Trading (Buys - Sells)				
Size	-0.01	-0.04	-0.01	(-0.22)
BM	-0.05	-0.01	-0.05	(-0.67)
Illiquidity	0.07	0.06	0.01	(0.11)
Volatility	0.12	0.03	0.09	(2.04)
Mom1	-0.18	-0.15	-0.03	(-0.32)
Mom2_12	-0.42	-0.05	-0.37	(-3.08)

Table A.2 Comparison of ANcerno Hedge Funds and TASS Hedge Funds

This table compares TASS hedge funds that report to ANcerno to TASS hedge funds that do not report to ANcerno (Other). Definitions of the variables and details of their construction are presented in Appendix A. T-statistics, based on standard errors clustered by management company and month, are reported in parentheses.

	ANcerno	Other	Dif	T(Dif)
Manager Size $Millions	273	182	91	(0.62)
Log (Manager Size)	4.57	3.90	0.67	(1.98)
Log (Ave_Fund_Size)	3.83	3.44	0.39	(1.36)
Return Ranking	4.40	4.49	-0.09	(-0.87)
Mgmt Fee	1.20	1.40	-0.20	(-2.72)
Incentive Fee	16.83	16.54	0.29	(0.23)
Dlockup	0.35	0.31	0.04	(0.43)
Restrictions	154.86	112.97	41.89	(1.53)
Leverage	0.43	0.60	-0.17	(-1.55)
Derivatives	0.06	0.28	-0.22	(-6.13)
Equity Focused	0.57	0.37	0.20	(1.53)
High-water Mark	0.63	0.71	-0.08	(-0.75)