Internet Appendix for

"Liquidity Provision and the Cross-Section of Hedge Fund Returns"

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This document contains supplementary material for the paper titled: *Liquidity Provision and the Cross-Section of Hedge Fund Returns*. It consists of six sections. Section IA.1 outlines the identification of hedge fund management companies. Section IA.2 discusses database integrity issues, including the representativeness of the ANcerno sample. Section IA.3 reports robustness tests for the results reported in Tables 3 and 4 of the paper. Section IA.4 compares the ability of *Mom1&5* and *Shortfall* to correctly classify trades against mutual fund fire-sales and fire-purchases as liquidity-supplying trades. Section IA.5 examines hedge funds' 13F stockholdings to study the relationship between liquidity provision and returns on long-only equity holdings. Finally, Section IA.6 examines whether liquidity-supplying funds in TASS and Barclays experience higher fund flows.

IA.1. Identifying Hedge Fund Management Companies

I use Form ADV to identify hedge fund managers within the ANcerno sample. I find Form ADV for 534 of 653 managers in the ANcerno sample.[1] Following Brunnermeier and Nagel (2004) and Griffin and Xu (2009), I classify a manager as a hedge fund if more than half of its investors are categorized as *high net worth individuals* or *pooled investment vehicles* in item 5.D. In addition, I require that the manager charge a performance-based fee (item 5.E). However, this approach incorrectly includes some funds with no hedge fund operations. I thus visit each company's website and eliminate any firms that do not report any hedge funds on their website. This filter eliminates private equity firms (e.g., New Harbor Capital), real estate firms (e.g., ERE Rosen), and investment advisors who have high net worth investors but do not offer

[1] Beginning in March 2012, the Dodd-Frank Act 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

hedge fund products (e.g., Denver Investment Advisors). I also exclude large banks (e.g., Bank of America). After these filters, the sample includes 55 hedge fund management companies.

An additional concern is that Form ADV fails to capture many hedge funds. I examine the Form ADV of *Institutional Investor's* Top 100 Hedge Funds and find that the Form ADV approach correctly classifies 78 of the 100 hedge funds.[2] Of the 22 remaining funds, the majority list *pensions and profit sharing plans* as part of their investor base (see, e.g., Bridgewater Associates). To capture additional hedge funds that do not meet the Form ADV criteria, I examine a list of roughly 1000 13F-filing hedge funds provided by Morningstar. According to Morningstar, the list is self-reported by the money management company, and typically reflects whether the management company is predominantly a hedge fund manager.[3] I find that 27 management companies appear on the Morningstar list of hedge funds, but fail to meet the Form ADV hedge fund criteria. Of the 27 hedge funds, 24 charged performance-based fees and had over 50% of their investors as high net worth individuals, pooled investment vehicles, or pensions and profit sharing plans. For the other three funds, Form ADV was unavailable, but inspection of the company's website indicated significant hedge fund operations. Based on this information, I classify all 27 companies as hedge funds. Thus, the final sample includes 82 hedge fund management companies, of which 70 offer at least one-equity focused fund.[4]

IA.2. Database Integrity

IA.2.1 Survivorship Bias, Backfill Bias, and Unreliable Returns

ANcerno does not suffer from many of the biases that plague commercial databases such as backfill bias and survivorship bias (Fung and Hsieh, 2000), or unreliable reported returns (Patton, Ramadorai, and

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[2] The list of top 100 hedge funds is here: http://www.institutionalinvestorsalpha.com/Research/4270/Hedge-Fund-100-Ranking.html.

[3] Unfortunately, the Morningstar list also fails to capture some hedge funds. For example, the Morningstar list identifies 55 of Institutional Investors top 100 hedge fund companies. However, using a combination of Form ADV and Morningstar correctly identifies 83 of the top 100 hedge fund companies.

[4] The list of 82 hedge funds, as well as an identifier to eliminate 12 non-equity focused hedge funds, are available on my webpage: http://russelljame.com/research.html

Streatfield, 2015). ANcerno collects 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, the trades of non-surviving funds remain in the historical data.

I also have no reason to doubt the reliability of the reported trades. There is little incentive for institutions to lie about their transactions. Unlike commercial databases, these transactions are not disclosed to potential investors. Moreover, institutions incur a significant expense when hiring ANcerno, and the benefits of ANcerno's services would be significantly reduced if the institution did not provide ANcerno with reliable data. A related concern is that ANcerno 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. Thus, in contrast to quarterly holdings, ANcerno data include intra-quarter roundtrip trades, confidential filings, and short sales.

A final concern is that ANcerno hedge funds are not representative of the population of hedge funds. To explore this possibility, I compare the sample of ANcerno funds to the sample of funds in commercial databases (i.e., TASS and Barclays) and to the sample of 13F-filing hedge funds.

IA.2.2 Comparison to Hedge Funds in TASS and Barclays

I begin by comparing hedge funds in TASS and Barclays (hereafter TASS/Barclays) that appear in ANcerno to funds in TASS/ Barclays that do not appear in ANcerno. I start with the sample of 191,911 fund-month observations used in Table 13 of the paper. I then limit the sample to the 1999 to 2010 sample period for which ANcerno data are available. I exclude funds of funds since such funds would not appear in ANcerno. I also exclude management companies that offer no equity funds since such funds are dropped from the ANcerno sample. To make the TASS/Barclays data congruent with the ANcerno data, I aggregate multiple funds within a management company into one observation by computing AUM-weighted averages across all funds. The final sample includes 63,878 management company-month observations and 1,244 unique management companies.

I manually search for ANcerno hedge funds within TASS/Barclays. The intersection yields a sample of 19 management companies for which the TASS/Barclays and ANcerno reporting periods overlap, resulting in a total of 1,137 management company-month observations. I compare TASS/Barclays funds that appear in ANcerno to those that do not appear in ANcerno. Specifically, for each management company month, I compare following characteristics *AUM, Age, Excess Return, Sharpe Ratio, Management Fee, Incentive Fee, High-Water Mark, Minimum Investment, Restrictions, Leverage, Asset Illiquidity, Fund* R^2, β_{SP500} *Rank,* and β_{RLP} *Rank.* Definitions of all the variables are provided in the Appendix.

Table IA.1 reports the average values of the fund characteristics across all management-company months for the two samples. Along most dimensions, TASS/Barclays hedge funds that appear in ANcerno do not significantly differ from TASS/Barclays funds that do not appear in ANcerno. For example, the two groups do not differ significantly with respect to assets under management, excess returns, Sharpe ratios, asset illiquidity, leverage, high-water marks, or their tendency to provide liquidity, as measured by β_{RLP} *Rank*. The most notable difference is with respect to fees. ANcerno hedge funds tend to charge lower management fees and higher incentives fees. This suggests that plan sponsors that chose to monitor execution costs also prefer more incentivized compensation contracts.

IA.2.3 Comparison to 13F-Filing Hedge Funds

I next compare 13F-filing hedge fund management companies (hereafter: funds) that appear in ANcerno to 13F-filing hedge funds that do not appear in ANcerno. I begin by collecting a list of all institutional investors that report quarterly holdings over the period from 1999 to 2010. I then use the hedge fund classification procedure, as described in Section IA.1, to identify hedge funds. The final sample consists of 1,168 hedge funds and 25,714 hedge-fund quarters. I manually search for ANcerno hedge funds in the 13F data, and I find 61 hedge funds that appear in both samples.

For each hedge fund-quarter, I use the holdings data to compute the following fund-level variables: *Total Net Assets (TNA*), *Stocks Held*, *Holding Return, Size, BM, Idiosyncratic Volatility (IVOL*) *and Mom21*. *Mom21* is computed relative to the first day of the quarter. All stock characteristics (e.g., *Size*, *BM*, etc.) are measured as percentile rankings. Additional details of the variable construction are described in the Appendix.

Panel A of Table IA.2 compares the characteristics of ANcerno hedge funds to other 13F-filing hedge funds that do not appear in ANcerno. I report the average values across all fund-quarters, and t-statistics are based on standard errors clustered by management company and quarter. Within a fund, all the stock characteristics are based on the principal-weighted average of the characteristic.

ANcerno hedge funds are significantly larger than other hedge funds as measured by both *TNA* and *Stocks Held*. This finding is consistent with Puckett and Yan (2011), who also find that ANcerno institutions are substantially larger than non-ANcerno institutions.[5] Given the structure of ANcerno data, it is not surprising that the sample is tilted towards larger funds. Most ANcerno funds enter the sample because they manage money on behalf of a plan sponsor that subscribes to ANcerno. Larger funds manage money for more plan sponsors, which increases the likelihood that they appear in the ANcerno sample.

On average, hedge funds in ANcerno have one-quarter ahead DGTW-adjusted returns on their holdings that are similar to those of other hedge funds in the 13F universe (0.08% vs. 0.19%). There are some differences in the characteristics of the stock held by ANcerno and Non-ANcerno hedge funds. Specifically, ANcerno hedge funds tend to hold larger stocks, less volatile stocks, and stocks with stronger past one-month returns.

[5] 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.

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 *Portfolio Turnover* and the principal-weighted DGTW-adjusted returns on stocks bought less the principal-weighted DGTW-adjusted returns on stocks sold over the subsequent quarter (*Trading Return*). I also examine principal-weighted stock characteristics of the portfolio of stocks bought less the portfolio of stocks sold. As in Panel A, I examine the following characteristics: *Size, BM, IVOL,* and *Mom21*.

Panel B of Table IA.2 presents the results. The *Trading Return* of ANcerno hedge funds is not significantly different from other hedge funds. (0.31% vs. 0.55%), There is also no evidence that the net trading (i.e., buys – sells) of ANcerno hedge funds differs from non-ANcerno hedge funds along any dimension. The only significant difference is that ANcerno hedge funds have lower turnover than other hedge funds (82% vs. 132%). This suggests that the long holdings periods I document in ANcerno may be overstated relative to the average hedge fund. However, even the average turnover of 132% for non-ANcerno hedge funds implies a holding period of over 9 months.

IA.3. Liquidity Provision and Equity Trading Returns: Robustness Tests

In this section, I examine the robustness of the findings that hedge funds that follow liquidity-supplying strategies earn significantly larger *ETR1* (Table 3) and *EHR* (Table 4). I now only consider Specification 3 from Tables 3 and 4 and only report the coefficient on the main variable of interest (i.e., *Mom1&5* or an alternative liquidity-provision measure). For reference, the first row of Table IA.3 reports the baseline estimates from Specification 3 of Tables 3 and 4.

In Rows 2 through 4, I examine whether the results are robust to alternative measures of liquidity provision. In particular, I replace *Mom1&5*, with *Mom1*, *Mom5*, and *Mom21*, as defined in Table 2. These alternative measures yield similar conclusions. Specifically, when the dependent variable is *ETR1*, the coefficient on the alternative liquidity provision variables range from -0.39 to -0.48, and when the dependent variable is *EHR* the coefficients range from -0.13 to -0.17. In all cases, the coefficients are significantly different from zero at a 5% level.

In Row 5, I report the results net of trading commissions. Trading commissions are subtracted from the day 0 return. For example, if a fund paid total commissions of $100 (as reported in ANcerno), on a $10,000 transaction, then 1% would be subtracted from the day 0 return for that transaction. Row 5 indicates that incorporating trading commissions does not influence the coefficient on *Mom1&5*.[6]

In Rows 6, I replace DGTW-adjusted returns with raw returns and find slightly stronger results. In Rows 7 and 8, I compute ETR using factor-model alphas rather than DGTW-adjusted returns. Specifically, I compute *ETR* by estimating the following time-series regression:

$$ETR^{*}_{f,\mathrm{t}} = \alpha_f + \sum_{j=1}^{n} \beta_{f,j} R_{j,t} + \varepsilon_{f,t.} \qquad \text{(IA.1)}$$

$ETR^{*}_{f,t}$ is computed similarly to $\mathrm{ETR}_{f,t}$, however it is computed using raw returns rather than DGTW-adjusted returns. Further, I aggregate $ETR1^{*}_{f,t}$ to a monthly measure by averaging across all daily estimates in a given month. I aggregate to a monthly frequency since the returns on some of the factor portfolios are available only at a monthly frequency. As $ETR^{*}_{f,t}$ already reflects the returns of a long-short portfolio, I do not subtract the risk-free rate from $ETR^{*}_{f,t}$.

$R_{j,t}$ captures the return on the factors. I consider two factor models: a five-factor alpha and a hedge fund index alpha. In the five-factor model, $R_{j,t}$ includes the returns on the Fama-French (1993) three-factors, plus the Carhart (1997) momentum factor, and the Sadka (2006) liquidity-risk factor. In the hedge fund index alpha, the factors include the excess market return and the average excess return of equity-oriented hedge funds that report to TASS and Barclays. I estimate Equation (IA.1) for each fund and compute the fund's monthly alpha as the sum of the intercept plus the monthly residual. The results, reported in Rows 7 and 8, indicate that replacing DGTW-adjusted returns with five-factor alphas or hedge fund index alphas generally yield slightly stronger results.

[6] While trading commissions does not influence measures of relative *ETR*, they do reduce absolute *ETR*. Incorporating trading commissions reduces *ETR1 (EHR)* by roughly 0.30% (0.03%) per month.

Rows 9 and 10 decompose the *buy minus sell* portfolios used throughout the paper into the *buy* and *sell* portfolios. The ability of *Mom1&5* to predict *ETR1* is slightly stronger among buys trades (0.29%) relative to sell trades (0.16%). However the relationship between *Mom1&5* and *EHR* is evenly split among buy and sell trades (0.08% each).

Row 11 confirms that the results are similar after excluding the small sample of hedge funds that directly subscribe to ANcerno (i.e., money managers), and Row 12 shows that the results are robust to including hedge fund management companies that are less likely to have an all-equity focus. In Row 13, I exclude July through December of 2008 (i.e., the period surrounding the financial crisis) and find similar results. In Row 14, I estimate the results using a panel regression. Following Petersen (2009), standard errors are clustered by both management company and time. The estimates from the panel regressions are slightly smaller than the Fama-Macbeth estimates, but the coefficients remain statistically significant at a 5% level.

In Tables 3 and 4, if a fund drops out of the sample, I simply exclude the fund from the analysis. However, if funds that drop out of the sample (hereafter: non-surviving funds) have different *ETR* than funds that remain in the sample (hereafter: surviving funds), then estimates of *ETR* can be biased. Following ter Horst, Nijman, and Verbeek (2001) and Baquero, ter Horst, and Verbeek (2005), I attempt to correct for this "look-ahead bias" by modelling the probability of hedge fund survival. This approach allows for surviving and non-surviving funds to have different expected returns, and instead assumes that the return of a fund is independent of survival after conditioning upon determinants of a fund's survival.

I model a fund's survival using the following logistic regression:

$$Survive_{f,t} = A_t + \beta_1\, ETR1_{f,t-1} + \beta_2\, EHR_{f,t-1} + \beta_3 Mom1\&5_{f,t-1} + \beta_4 Holdings\ Size_{f,t-1} + \beta_5 \mathrm{Age}_{f,t-1} + e_{f,t.} \quad \text{(IA.2)}$$

$Survive_{f,t}$ is a dummy variable equal to one if fund f appears in the sample period during year t. A_t allows for different intercepts for each year of the sample (i.e., year fixed effects). *Holdings Size* and *Age* are in natural logs. In untabulated analysis, I find that *Age* and *Holdings Size* have significant positive coefficients.

Thus, funds that have appeared in ANcerno for a longer period of time or larger funds are more likely to remain in the ANcerno sample.

The results from Equation (IA.2) provide estimates of the conditional probability of survival. I re-weight each observation by the unconditional probability of survival, scaled by the fund's conditional probability of survival. Intuitively, funds that have a lower conditional probability of survival (e.g., funds that just recently joined ANcerno or smaller funds) are less likely to appear in ANcerno in the post-ranking period. To correct for their underrepresentation, the returns on these funds are given greater weight. Row 15 indicates that the results are virtually identical after correcting for look-ahead bias.

IA.4. Mom1&5, Shortfall, and Forced Mutual Fund Trading

Table 4 of the paper shows that *Mom1&5* is a stronger predictor of *EHR* than *Shortfall*. One possible explanation for this finding is that *Mom1&5* better reflects trading against more long-lived mispricing. One such example is mispricing due to forced trading by mutual fund flows experiencing extreme flows (Coval and Stafford, 2007).

To explore this possibility, I repeat the analysis conducted in Panel A of Table 7 of the paper using both the *Mom1&5* and *Shortfall* measures of liquidity provision. Specifically, following Coval and Stafford (2007), I define flow-induced sales (purchases) as reductions (increases) in shares owned by mutual funds experiencing severe outflows (inflows). Fund f is considered to have severe flows if its flows are below the 10th percentile ($<P10$) or above the 90th percentile ($>P90$) of the cross-sectional distribution. For each stock i and quarter t, I compute the fraction of average volume due to extreme flow-motivated trading as *pressure:*

$$pressure_{i,t} = \frac{\sum_{f} \max\left(0, \Delta Holdings_{f,i,t}\right) | \text{flow}_{f,t} > \text{P}90 - \sum_{f} \max\left(0, -\Delta Holdings_{f,i,t}\right) | \text{flow}_{f,t} < P10}{AvgVolume_{i,t-12:t-6}}. \tag{IA.3}$$

I define a stock as experiencing fire-sale (fire-purchase) pressure if the stock is in the bottom (top) quintile of *pressure*. I limit the sample of traded stocks to those experience fire-sale or fire-purchase pressure. For each fund-quarter with at least five trades, I report the average fraction of a fund's dollar volume that trade against pressure (i.e., buying fire sale stocks and selling fire purchase stocks). I report the results for all funds and for *LS*, *LN*, and *LD* funds, separately. I also report the results across all trades and for *LS*, *LN*, and *LD* trades. Standard errors are clustered by management company and quarter. Panel A of Table IA.4 classifies *LS, LN,* and *LD* funds and trades using the *Mom1&5* measure (and is identical to the results reported in Panel A of Table 7). Panel B classifies *LS, LN,* and *LD* funds and trades using the *Shortfall* measure.

A comparison of Panels A and B of Table IA.4 indicates that while the *Mom1&5* and *Shortfall* measures yield qualitatively similar patterns, the magnitudes are stronger using *Mom1&5.* For example, across all funds, using the *Mom1&5* measure, *LS* trades are 2.90 percentage points more likely to trade against pressure than *LD* trades. The corresponding estimate for the *Shortfall* measure is only 0.93 percentage points and the estimate is not reliably different from zero. The accuracy of both measures increases at the fund level. This is not surprising since the fund-level measure typically aggregates across hundreds of trades and is thus estimated more precisely. However, even at the fund level, the magnitudes remain stronger for *Mom1&5.* Specifically, across all trades, using the *Mom1&5* measure, *LS* funds are 7.24 percentage points more likely to trade against pressure than *LD* funds, while the corresponding estimate using the *Shortfall* measure is 4.68 percentage points. Overall, the evidence suggests that *Mom1&5* measure does a better job of capturing liquidity-provision around mutual fund forced trading.

IA.5. Liquidity Provision and Equity Holding Returns – Evidence from 13F Fillings

In the body of the paper, I rely on two data sources to establish that *LS* hedge funds exhibit superior performance. First, using transaction data from ANcerno, I show that *LS* funds earn significantly higher returns on their equity trades and holdings. Second, using data on realized returns from TASS and Barclays, I show that *LS* hedge funds earn significantly higher excess returns, Sharpe ratios, alphas, and style-adjusted returns.

A third possible data source is the long-only equity holdings reported at a quarterly frequency by 13F-filing hedge funds. Relative to ANcerno data, 13F data provide a much larger sample and offer information on the fund's holdings as long as the fund has at least $100 million in assets. However, the lower-frequency data result in less accurate estimates of a fund's tendency to provide liquidity and less accurate estimates of trading returns, particularly since the *ETR* advantage of *LS* funds is most pronounced over shorter holding periods. In addition, the 13F holdings do not capture intra-quarter trading, confidential fillings, or short-sales. Relative to TASS and Barclays, 13F holdings likely provide more accurate estimates of a fund's tendency to provide liquidity and are less prone to selection-biases. However, since 13F holdings do not include non-equity positions, short-positions, or information on expenses, the holdings data are not well suited for studying the realized returns that accrue to investors. Since the 13F data offer both costs and benefits relative to the alternative data sources, in this section I examine whether my main conclusions continue to hold using 13F data.

I begin by collecting a list of all institutional investors that report quarterly holdings from 1996 to 2013. The 1996 to 2013 sample period corresponds to TASS and Barclays sample used in Section 5 of the paper. I then use the hedge fund classification procedure, as described in Section IA.1, to classify 13F-filing institutions into hedge funds and other institutions. The final sample consists of 1,246 unique hedge funds.

To estimate a fund's tendency to supply liquidity, I use a measure closely related to *Mom1&5*. Specifically, each quarter, I estimate a fund's trades based on changes in quarterly holdings. Since I do not know the exact date of the trade, I compute the *Mom1&5* for each trading day in the quarter and average the *Mom1&5* across all trading days in the quarter. I label this measure *Mom1&5Q*. For each fund-year, I compute a fund-level measure of liquidity provision by computing the principal-weighted average *Mom1&5Q* of stocks purchased less the principal-weighted average *Mom1&5Q* of stocks sold.

I begin by comparing the correlation between *Mom1&5Q* (as computed from 13F data) and *Mom1&5* (as computed from ANcerno data). For each year and each management company in ANcerno, I compute a manager-level measure of *Mom1&5* by taking an equal-weighted average of *Mom1&5* across all of the manager-client pairs. I then merge the ANcerno data with 13F-filling hedge funds at the management company level. The sample includes 258 fund-year observations. I find that the correlation between *Mom1&5Q* and *Mom1&5* is 0.72, indicating that the two measures are capturing a similar aspect of fund behavior.

Differences in *Mom1&5Q* and *Mom1&5* can stem from two sources. The first is measurement error in *Mom1&5Q* due to not knowing the exact date of the trade. The second is that the trading of a given management company may be different across the two databases. For example, Angelo Gordon's trading in ANcerno reflects their trading for a specific client, while their trading in 13F data reflects their trading across all clients. To abstract from the second factor, I also compute *Implied Mom1&5Q* using ANcerno data. Specifically, for each fund and stock, I aggregate all trades within the quarter and calculate net trading positions as of the quarter end. For each position, I then compute *Mom1&5Q* by averaging the *Mom1&5* across all trading days in the quarter and compute a corresponding fund-level measure of

Mom1&5Q (Implied Mom1&5Q). I find the correlation between *Mom1&5* and *Implied Mom1&5Q* is 0.86.

I next examine whether a fund's tendency to supply liquidity can be used to predict the returns on its equity holdings. Specifically, at the beginning of year *t*, I sort funds into quintiles based on their *Mom1&5Q* estimated over the prior year. I then examine the principal-weighted return of the fund's holdings each month in year *t* and report the equal-weighted average across all funds in the portfolio. I repeat this procedure each year, resulting in 212 estimates of monthly returns, from January 1996 to August 2013, for each *Mom1&5Q* quintile.

Table IA.5 reports the average return of each portfolio. Standard errors are computed from the time-series standard deviation. Columns 1 through 4 measure returns using four different benchmarks. Column 1 reports the results using excess returns (i.e., raw returns less the risk-free rate), while Column 2 reports the results using DGTW-adjusted returns. Column 3 reports the alphas from the Carhart (1997) four-factor model augmented to include the Sadka (2006) liquidity-risk factor, and Column 4 reports the alphas from a model that includes the excess market return and the average excess return of equity-oriented hedge funds that report to TASS and Barclays.

The results across the four columns are qualitatively similar. In particular, the returns on *LS* funds' equity holdings tend to be significantly positive, although the outperformance using hedge fund index alphas is only marginally significant (p-value = 0.10). On the other hand, the returns on *LD* funds' equity holdings are generally insignificantly different from zero. The difference in the return on the equity holdings of *LS* and *LD* funds ranges from 0.15% to 0.34% per month, with t-statistics ranging from 1.59 to 2.83. Overall, the evidence is consistent with *LS* funds earning superior returns on their quarterly holdings relative to *LD* funds.

It is worth noting that quarterly holdings likely underestimate the difference in the return on equity holdings of *LS* and *LD* funds for two reasons. First, quarterly holdings implicitly assume that all trades were made at the end of the quarter. Given that *LS* funds exhibit significant short-term trading skill relative to *LD* funds (i.e., superior *ETR1)*, this assumption likely biases return differences downwards. Second, because quarterly holdings do not provide the exact date of the trade, *Mom1&5Q* is a less precise estimate of a fund's tendency to supply liquidity relative to *Mom1&5*.

To explore the potential impact of these two biases, I repeat the above analysis using ANcerno data. Column 5 reports the results using the *Mom1&5* measure and estimates *EHR* using the exact date and execution price of the trade. These results are identical to those reported in Table 4 and represent the return spread without either source of measurement error. Column 6 repeat the analysis using *Mom1&5* measure, but now assumes that all trades occur at the closing price at the end of the quarter. After imposing this assumption, the spread in the *EHR* between *LS* and *LD* funds falls by about 20% (from 0.37% to 0.29%). In Column 7, I classify a fund's tendency to supply liquidity based on *Implied Mom1&5Q* and continue to compute *EHR* based on the assumption that all trades occur at the closing price at the end of the quarter. The spread in the *EHR* between *LS* and *LD* now falls to 0.21%, representing a roughly 43% decline. These results are consistent with quarterly holdings understating the return difference between the equity holdings of *LS* and *LD* funds by a considerable magnitude.

IA.6. Liquidity Provision and Fund Flows

Table 13 of the paper shows that a fund's tendency to supply liquidity, as measured by β_{RLP} *Rank*, is a useful predictor of fund performance even after controlling for past performance and a host of other fund characteristics. This suggests that investors could benefit from investing more in *LS* funds. In this section, I investigate whether investors exhibit a preference for *LS* funds by examining the relationship between fund flows and β_{RLP} *Rank*.

I begin with the sample of 191,911 fund-month observations used in Table 13. Since information of hedge fund assets is often not updated on a monthly basis, I examine fund flows at a quarterly frequency. I calculate quarterly flows for fund *i* in quarter *t* as follows:

$$Flow_{it=} = \frac{AUM_{it}}{AUM_{it-1}} - (1 + R_{it}). \qquad \text{(IA.4)}$$

I winsorize the flow variable at the -50% and 200%. I also exclude fund-quarter observations where AUM does not change, as this likely indicates that the fund has not updated its AUM. The final sample include 56,933 fund-quarter observations. The mean (median) fund experiences a flow of 0.26% (0.03%) per quarter.

Specifications 1 and 2 of Table IA.6 conduct Fama-Macbeth regressions of *Flow* on β_{RLP} *Rank* and controls. The controls are identical to those used in Table 13 of the paper. Specification 1 excludes style fixed effects, while Specification 2 includes style fixed effects. Standard errors are computed from the time-series standard deviation using a Newey-West adjustment with two lags. Both specifications indicate that a one quintile increase in β_{RLP} *Rank* is associated with a 0.19% increase in *Flow*, however the estimate is not statistically significant. Specifications 3 (4) repeat the analysis using panel regressions with time (time * style) fixed effects. Standard errors are clustered by fund and quarter. The panel regressions yield somewhat stronger results. Specifically, a one quintile increase in β_{RLP} *Rank* is associated with a 0.25% or 0.23% increase in *Flow*, and both estimates are statistically significant at a 5% level. Overall, there appears to be modest evidence that investors exhibit a preference for *LS* funds.

Appendix: Description of the Control Variables

Fund Characteristics obtained from TASS and Barclays Data:

- *Excess Return:* the fund's net-of-fee monthly return less the risk-free rate.

- *Sharpe Ratio:* the fund's monthly excess return scaled by the fund's standard deviation of excess returns over the calendar year. The variable is annualized by multiplying by the square root of 12 and is winsorized at the 1st and 99th percentile.

- *Style-Adjusted Return:* the return of the fund less the average return of all funds in the same styles.

- β_{RLP}*:* a fund's beta with respect to the liquidity-provision factor of Jylhä, Rinne, and Suominen (2014). The beta is estimated from a regression of the fund's excess return on the Fung and Hsieh (2004) seven factors, plus the Sadka (2006) liquidity-risk factor, and the liquidity-provision factor over two-year rolling windows.
    - β_{RLP} *Rank* – the quintile ranking of β_{RLP} across all funds in the sample each year.

- *AUM:* assets under management.

- *Age:* the number of months since the fund first appeared in the sample.

- *Management Fee:* the management fee charged by the fund.

- *Incentive Fee:* the incentive fee charged by the fund.

- *High-water mark:* a dummy variable that equals one if the fund has a high-water mark provision.

- *Leverage:* a dummy variable equal to one if the fund reports using leverage.

- *Minimum Investment:* the minimum initial investment size required to invest in the fund.

- *Restrictions:* the sum of the notice period and the redemption period.

- *Fund* R^2*:* the adjusted r-squared of the fund from a regression of the fund's excess return on the Fung and Hsieh (2004) seven factors, plus the Sadka (2006) liquidity-risk factor, and the liquidity-provision factor of Jylhä, Rinne, and Suominen (2014) over two-year rolling windows.

- β_{SP500} *Rank:* the quintile ranking of a fund's beta with respect to the S&P 500 index. The betas is estimated from a regression of the fund's excess return on the Fung and Hsieh (2004) seven factors, plus the Sadka (2006) liquidity-risk factor, and the liquidity provision factor of Jylhä, Rinne, and Suominen (2014) over two-year rolling windows.

- *Asset Illiquidity:* the first-order serial correlation of a fund's returns.

- *H*edge Fund Styles: Specific strategies listed in TASS and Barclays are mapped into the following nine broad hedge fund styles:

  - ***CTAs**:* CTA/Managed Futures, Commodity-Multi, Currency-Systematic, Managed Futures
  - **Emerging Markets**: Emerging Markets
  - **Equity Focused**: Equity Long Only, Equity Long-Bias, Equity Long/Short, Equity Market Neutral
  - **Event Driven:** Distressed/Restructuring, Event Driven, Merger Arbitrage, Special Situations
  - **Fund of Funds**: Fund of Funds
  - **Global Macro**: Discretionary Thematic, Global Macro, HF Currency, Macro
  - **Multi-Strategy:** Balanced (Stocks & Bonds), Multi-Advisor, Multi-Strategy, Systematic Diversified
  - **Relative Value**: Fixed Income Arbitrage, Fixed Income Asset Backed, Fixed Income Collateralized Debt, Fixed Income Convertible Bonds, Fixed Income High Yield, Fixed Income Mortgage Backed, Fixed Income Sovereign, Option Strategies, Volatility Trading
  - **Sector**: Sector

Fund Characteristics obtained from 13F Data: Characteristics of the Management Company
Note: All stock characteristics are reported as a percentile ranking (ranging from 1 to 100) based on the cross-sectional distribution of all stocks in the sample. At the fund-level, stock characteristics are computed from the principal-weighted average of holdings or trades.

- *Total Net Assets (TNA):* The total value (shares held * price per share) of long-only equity holdings, computed quarterly.

- *Stocks Held:* the number of long-only equity positions reported by the management company per quarter.

- *Holding Return:* the principal-weighted average return on a fund's long-only equity holdings. Returns are computed using four different benchmarks:

  - *Excess return* – the raw return less the risk-free rate
  - *DGTW-adjusted return* – the return less the value-weighted return on a benchmark portfolio matched on size, book-to-market, and momentum (see, e.g., Daniel et al., 1997).
  - *Five-Factor Alphas* – the intercept from a time-series regression of excess returns on the Carhart (1997) four-factors plus the Sadka (2006) liquidity-risk factor.
  - *Hedge Fund Index Alphas* - the intercept from a time-series regression of excess returns on the market excess return and the average excess return on equity-oriented funds reporting to Tass and Barclays.

- *Portfolio Turnover:* The turnover of the fund, 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 $t-1$.

- *Trading Return:* the one-quarter ahead return of the equity buy trades (i.e., changes in quarterly holdings) less the one-quarter ahead return of the equity sell trades.

- *Mom1&5Q: F*or each traded stock, I average the stock's *Mom1&5* across all trading days in the quarter. For each fund-year, I compute principal-weighted average *Mom1&5Q* of stocks purchased less the principal-weighted average *Mom1&5Q* of stocks sold

13F Data: Characteristics of the Stocks Held and Traded by a Fund
Note: All stock characteristics are reported as a percentile ranking (ranging from 1 to 100) based on the cross-sectional distribution of all stocks in the sample. At the fund-level, stock characteristics are computed from the principal-weighted average of holdings or trades.

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

- *BM*: 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. Estimated for the fiscal year prior to the year of the trade.

- *Idiosyncratic Volatility (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.

- *Mom21:* the return on the stock in the 21 trading days prior to the beginning of the quarter.

Liquidity Provision Measures obtained from ANcerno Data:

Note: All trade-level liquidity-provision characteristics are aggregated to a fund characteristic. The fund-level measure is computed as principal-weighted average characteristics (e.g., Mom1) of stocks purchased less the principal-weighted average characteristic (e.g., Mom1) of stocks sold.

- *Mom1:* the market-adjusted return on the stock on the trading day prior to the day of the trade.

- *Mom5:* the market-adjusted return on the stock in the five trading days prior to the day of the trade.

- *Mom1&5:* the average of *Mom1* and *Mom5*.

- *Mom21:* the market-adjusted return on the stock in the 21 trading days prior to the day of the trade.

- *Shortfall*: the principal-weighted implementation shortfall of a trade, measured as $(P_1 - P_0)/P_0$, where P_1 measures the value-weighted execution price of a ticket and P_0 is the price at the time when the broker receives the ticket.

- *Implied Mom1&5Q:* A measure of liquidity provision estimated from implied changes in quarterly holdings. For each fund and stock, I aggregate all trades within a quarter and calculate the cumulative net trading as of the quarter end. I compute the *Mom1&5* for each trading day in the quarter and average the *Mom1&5* across all trading days in the quarter.

Other Fund Characteristics obtained from ANcerno Data:

- *ETR1* (*One-Month Equity Trading Returns*)*:* the DGTW-adjusted returns on a fund's long holdings less the DGTW-adjusted returns on a fund's short holdings, where both long and short holdings are estimated based on a fund's trading over the prior 21 trading days (including the current trading day).

    - *t*(*ETR1*)*: ETR1* scaled by the standard error of *ETR1*.

- *EHR* (*Equity Holding Returns*)*:* the DGTW-adjusted returns on a fund's long holdings less the DGTW-adjusted returns on a fund's short holdings, where both long and short holdings are estimated based on all of a fund's equity trading since entering ANcerno (including the current trading day).

    - *t*(*EHR*)*: EHR* scaled by the standard error of *EHR*.
    - EHR_Q*:* EHR computed under the assumption that all trading occurred at the end of the quarter.

- *Holdings Size1:* the total value of a fund's long holdings and short holdings where both long and short holdings are estimated based on a fund's trading over the prior 21 trading days (including holdings established on the current trading day).

- *Holdings Size:* the total value of a fund's long holdings and short holdings where both long and short holdings are estimated based on all of a fund's historical trading since entering ANcerno (including the current trading day). This measure is computed for all fund-days in which the fund has been in the ANcerno sample for at least one year.

- *Volume:* the average quarterly trading volume of a fund.

- *Actual/Implied:* the ratio of actual quarterly trading volume to implied quarterly trading volume. Actual trading reflects the aggregate quarterly trading of a fund. Implied quarterly trading volume is computed as the absolute net dollar volume, |buys – sells|, for a fund-stock-quarter, aggregated across all stocks traded by the fund over the quarter.

- *Com/Share:* the dollar volume paid in commissions scaled by total share volume traded (reported in cents).

- *Plan Sponsor:* a dummy variable equal to one if the hedge fund enters the ANcerno sample because it manages money on behalf of a plan sponsor client that has hired ANcerno. This value is set to zero for hedge funds that enter the sample because they directly hire ANcerno (i.e., money manager clients).

- *Money Manager:* a dummy variable equal to one if the hedge fund directly subscribes to ANcerno. This value is set to zero for hedge funds that enter the sample because they manager money on behalf of a plan sponsor who subscribes to ANcerno (i.e., *Plan Sponsors*).

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Table IA.1: Comparison of ANcerno Hedge Funds and TASS AND Barclays Hedge Funds

This table rpeorts the average value of different fund characteristics for TASS and Barclays hedge funds that report to ANcerno (N = 1,137 management company-months) and TASS and Barclays hedge funds that do not report to ANcerno (N = 62,741 management company-months). Definitions for all fund characteristics are available in the Appendix. For both ANcerno and Non-ANcerno management companies, I report the AUM-weighted average across all management-company months. Dif. is the difference between ANcerno and Non-ANcerno hedge funds. The final column tests whether the difference is significantly different from zero. Statistical significance is based on standard errors clustered by management company and month.

	ANcerno	Non-ANcerno	Dif.	t(Dif.)
Log (AUM)	18.35	18.55	-0.20	(-0.70)
Log (Age)	5.00	4.64	0.36	(1.44)
Excess Return	0.42	0.49	-0.07	(-0.69)
Sharpe Ratio	1.03	0.90	0.13	(0.41)
Management Fee	1.11	1.42	-0.31	(-4.51)
Incentive Fee	19.47	18.37	1.10	(2.46)
High-Water Mark	0.87	0.81	0.06	(1.00)
Min. Investment ($ mil)	1.33	1.23	0.10	(0.24)
Restrictions	223.22	123.48	99.47	(1.98)
Leverage	0.46	0.59	-0.13	(-0.89)
Asset Illiquidity	0.05	0.05	0.00	(0.07)
R^2	0.42	0.34	0.08	(1.24)
β_{sp500} *Rank*	2.80	2.61	0.19	(0.51)
β_{RLP} *Rank*	2.63	2.56	0.07	(0.35)

Table IA.2: Comparison of ANcerno Hedge Funds and 13F Hedge Funds

This table compares 13F-filing hedge funds that report to ANcerno to 13F-filing hedge funds that do not report to ANcerno. The sample includes 1,168 hedge fund management companies (hereafter hedge funds) and 25,714 hedge fund quarters. For each hedge fund-quarter, I examine whether the hedge fund reports to ANcerno during that quarter. The sample includes 1,406 ANcerno hedge fund-quarters. Panel A compares the average fund characteristics of the stocks held by ANcerno and Non-ANcerno hedge funds. Within a hedge fund-quarter, stock characteristics are based on the principal-weighted averages of the characteristic. The table presents averages across all fund-quarters. In the last column, I also test whether the averages for ANcerno and Non-ANcerno hedge funds are significantly different. T-statistics are based on standard errors clustered by management company and quarter. Panel B compares the trading, estimated from changes in quarterly holdings, of ANcerno and Non-ANcerno hedge funds. For each fund, I estimate the fund's *Portfolio Turnover* and the principal-weighted DGTW-adjusted returns on stocks bought less returns on stocks sold over the subsequent quarter (*Trading Return*). I also examine principal-weighted characteristics of the portfolio of stocks bought less the portfolio of stocks sold. All stock characteristics are reported as percentile rankings. Additional information regarding variable construction is presented in the Appendix.

Panel A: Holdings

	ANcerno	Non-ANcerno	Dif.	t(Dif.)
Log (TNA)	21.63	19.64	1.98	(9.04)
Stocks Held	381.26	130.60	251.66	(4.41)
Holding Return (Quarterly)	0.08	0.19	-0.10	(-0.65)
Size	86.53	83.65	2.87	(2.76)
BM	34.52	36.13	-1.62	(-1.24)
IVOL	33.48	36.80	-3.31	(-2.30)
Mom21	53.72	52.07	1.65	(3.18)

Panel B: Trading

	ANcerno	Non-ANcerno	Dif.	t(Dif.)
Portfolio Turnover	0.82	1.32	-0.50	(-7.57)
	Net Trading (Buys - Sells)			
Trading Return (Quarterly)	0.31	0.55	-0.24	(-1.03)
Size	-0.72	-0.36	-0.37	(-1.15)
BM	0.31	-0.37	0.68	(1.68)
IVOL	0.78	0.46	0.31	(0.97)
Mom21	-2.46	-1.98	-0.47	(-0.45)

Table IA.3: Liquidity Provision and ETR – Robustness

This table presents robustness tests for the finding that a fund's tendency to supply liquidity is related to subsequent *ETR1* (Table 3) or *EHR* (Table 4). Row 1 presents the baseline results as reported in Specification 3 of Tables 3 and 4. In Rows 2-4, I replace *Mom1&5* with liquidity provision proxies based on the stock's return over the prior one, five, or 21 trading days, (*Mom1, Mom5*, and *Mom21*). Row 5 reports DGTW-adjusted returns net of trading commissions, Row 6 reports raw returns, Row 7 reports the five-factor alpha that includes the Carhart (1997) four-factors plus the Sadka (2006) liquidity-risk factor, and Row 8 reports the alpha from a factor model that includes the market excess return and the average excess return of equity-oriented hedge funds that report to TASS and Barclays. Rows 9 and 10 report the results for the buy and sell portfolio separately. Row 11 excludes hedge funds that enter the ANcerno sample as money managers, Row 12 included hedge fund management companies that are less likely to pure equity-oriented funds, and Row 13 excludes July through December of 2008. Row 14 reports estimates from a panel regression with standard errors clustered by both management company and day. Row 15 uses a weighting procedure designed to eliminate the potential bias due to fund attrition (i.e., the look-ahead bias). Obs. reports the average number of funds that are in the portfolio across all trading days in the sample, or in Row 14, the number of fund-days in the panel regression. T-statistics are reported in parentheses.

		ETR1 (Table 3 Robustness)			*EHR* (*Table 4 Robustness*)		
Row	Specification	Obs.	Coeff.	t-stat	Obs.	Coeff.	t-stat
1	*Baseline Results*	71	-0.45	(-2.73)	76	-0.16	(-2.39)
	Alternative Liquidity Provision Proxies						
2	*Mom1*	71	-0.39	(-2.50)	76	-0.13	(-2.04)
3	*Mom5*	71	-0.46	(-2.81)	76	-0.17	(-2.50)
4	*Mom21*	71	-0.48	(-2.92)	76	-0.16	(-2.34)
	Alternative Benchmark						
5	*DGTW-Returns less trading commissions*	71	-0.43	(-2.64)	76	-0.16	(-2.38)
6	*Raw Returns*	71	-0.64	(-3.57)	76	-0.18	(-2.40)
7	*Five-Factor Alpha*	74	-0.61	(-3.48)	76	-0.22	(-3.40)
8	*Hedge Fund Index Alphas*	74	-0.72	(-3.92)	76	-0.15	(-1.98)
	Buy versus Sell Trades						
9	*Buy Trades*	71	-0.29	(-2.62)	76	-0.08	(-1.56)
10	*Sell Trades*	71	0.16	(1.31)	76	0.08	(1.62)
	Alternative Samples						
11	*Exclude Money Managers*	66	-0.47	(-2.81)	70	-0.16	(-2.39)
12	*Include Funds with Pct. Equity =0*	79	-0.50	(-2.92)	88	-0.18	(-2.48)
13	*Exclude Financial Crisis*	72	-0.41	(-2.54)	77	-0.16	(-2.33)
	Alternative Methodologies						
14	*Panel Regression*	197,103	-0.30	(-2.27)	209,581	-0.15	(-2.42)
15	*Correction for "Look-Ahead" Bias*	71	-0.44	(-2.70)	76	-0.16	(-2.41)

Table IA.4: Hedge Fund Trading Around Asset Fire Sales and Purchases

This table reports the percentage of hedge funds' trades that provide liquidity to stocks experiencing extreme selling or extreme buying pressure due to mutual fund flow-induced trading. Specifically, for each stock-quarter I compute *Pressure* defined as the fraction of average volume due to extreme flow-motivated trading (Coval and Stafford, 2007). Stocks in the bottom (top) quintile of *Pressure* are classified as fire sale (fire purchase) stocks. I limit the sample to fire sale and fire purchase stocks. For each fund-quarter with at least five trades across fire sale or fire purchase stocks, I report the average fraction of a fund's dollar volume that trades against pressure (i.e., buying fire sale stocks and selling fire purchase stocks). I report the results for all funds and for *LS, LN,* and LD funds (as defined in Table 2 of the paper) separately. I also report the results across all trades as well as for *LS, LN,* and *LD* trades (as defined in Table 5 of the paper). In Panel A, I use *Mom1&5* to classify a fund or a trade as *LS, LN,* or *LD*. In Panel B, I use *Shortfall* to classify a fund or a trade as *LS, LN,* or LD. T-statistics, based on standard errors clustered by manager and quarter, are reported in parentheses. The number of fund-quarter observations are reported in brackets.

Panel A: Mom1&5

	All Trades	*LS Trades*	*LN Trades*	*LD Trades*	*LS - LD Trades*
All Funds	49.06%	50.83%	48.16%	47.94%	2.90%
	[3,265]	[2,639]	[2,522]	[2,777]	(3.16)
LD Funds	45.95%	46.41%	45.52%	44.71%	1.70%
	[656]	[488]	[467]	[591]	(1.08)
LN Funds	48.75%	50.81%	48.28%	48.17%	2.64%
	[1967]	[1,588]	[1,552]	[1,714]	(2.62)
LS Funds	53.20%	54.72%	50.22%	51.12%	3.60%
	[642]	[563]	[503]	[472]	(2.69)
LS - LD Funds	7.24%	8.30%	4.70%	6.41%	
	(5.00)	(5.58)	(2.32)	(3.53)	

Panel B: Shortfall

	All Trades	*LS Trades*	*LN Trades*	*LD Trades*	*LS - LD Trades*
All Funds	49.06%	49.67%	48.28%	48.74%	0.93%
	[3,265]	[2,737]	[2,343]	[2,769]	(1.43)
LD Funds	47.27%	47.39%	47.35%	47.16%	0.23%
	[655]	[504]	[391]	[604]	(0.17)
LN Funds	48.47%	49.21%	48.10%	48.47%	0.75%
	[1,971]	[1,662]	[1,488]	[1,694]	(0.90)
LS Funds	51.94%	53.00%	49.64%	51.74%	1.26%
	[639]	[571]	[464]	[471]	(1.02)
LS - LD Funds	4.68%	5.60%	2.30%	4.57%	
	(3.46)	(3.14)	(1.08)	(2.70)	

Table IA.5: Liquidity Provision and the Return on Long-Only Equity Holdings

At the beginning of each year *t* from 1996 to 2013, I rank hedge funds reporting quarterly holdings into quintiles based on the fund's tendency to supply liquidity, estimated in year *t-1*. I measure a fund's tendency to provide liquidity as the fund's *Mom1&5Q*. Each quarter, I estimate a fund's trades based on changes in quarterly holdings. I compute the *Mom1&5* for each trading day in the quarter and average the *Mom1&5* across all trading days in the quarter. For each fund-year, I compute principal-weighted average *Mom1&5Q* of stocks purchased less the principal-weighted average *Mom1&5Q* of stocks sold (*Mom1&5Q*). Quintile 1 consists of funds with the highest *Mom1&5Q* (i.e., liquidity-demanding funds) and quintile 5 consists of funds with the lowest *Mom1&5Q* (i.e., liquidity-supplying funds). I compute the principal-weighted return of the fund's holdings each month in year *t* and report the equal-weighted average across all funds in the portfolio. I repeat this procedure each year, resulting in 212 estimates of monthly returns, from January 1996 to August 2013, for each *Mom1&5Q* quintile. Columns 1 through 4 report the results for four different performance metrics (defined in the Appendix). Columns 5 through 7 report the results using ANcerno data. Column 5 reports the results using the *Mom1&5* measure and estimates *EHR* using the exact date and execution price of the trade (and is thus identical to the results reported in Table 4 of the paper). Column 6 repeat the analysis using *Mom1&5* measure, but now assumes that all trades occur at the closing price at the end of the quarter. Column 7 classifies a fund's tendency to supply liquidity based on *Implied Mom1&5Q* and continues to compute *EHR* based on the assumption that all trades occur at the closing price at the end of the quarter. In columns 1 through 4 the sample spans 212 months from January 1996 to August 2013. In the average month, each quintile consists of roughly 79 funds. In Columns 5 through 7 the sample spans 2,767 trading days from January 2000 to December 2010. In the average day, each quintile consists of roughly 15 funds.

Dataset:	**13F**	**13F**	**13F**	**13F**	**ANcerno**	**ANcerno**	**ANcerno**
LS Measure:	*Mom1&5Q*	*Mom1&5Q*	*Mom1&5Q*	*Mom1&5Q*	*Mom1&5*	*Mom1&5*	*Mom1&5Q*
Return Measure:	Excess Returns	DGTW-Adjusted Returns	Five-Factor Alphas	HF Index Alphas	EHR	EHR_Q	EHR_Q
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
1 (*LD* Funds)	0.74	0.04	0.07	-0.15	-0.12	-0.08	-0.03
	(1.86)	(0.39)	(0.83)	(-1.67)	(-0.85)	(-0.55)	(-0.16)
2	0.69	-0.01	0.04	-0.05	0.10	0.09	0.07
	(1.92)	(-0.11)	(0.61)	(-0.65)	(1.18)	(1.08)	(0.81)
3	0.74	0.03	0.14	0.09	0.03	0.04	0.03
	(2.11)	(0.37)	(1.79)	(1.06)	(0.45)	(0.52)	(0.38)
4	0.75	0.02	0.13	0.05	0.07	0.02	0.07
	(2.05)	(0.30)	(1.87)	(0.60)	(0.89)	(0.31)	(0.88)
5 (*LS* Funds)	0.98	0.19	0.32	0.20	0.25	0.21	0.19
	(2.55)	(2.51)	(3.72)	(1.66)	(1.80)	(1.42)	(1.11)
LS - LD	0.24	0.15	0.25	0.34	0.37	0.29	0.21
	(1.79)	(1.59)	(2.83)	(2.49)	(1.71)	(1.29)	(0.81)

Table IA.6: Liquidity Provision and Fund Flows

This table reports the results of regressions of quarterly fund flows on a fund's tendency to supply liquidity and controls. I calculate quarterly flows for fund *i* in quarter t as $Flow_{it} = (AUM_{it}/AUM_{it-1}) - (1 + R_{it})$. I winsorize *Flow* at -50% and 200% and exclude fund-quarter observations where AUM does not change. I measure a fund's tendency to provide liquidity as the fund's beta with respect to a liquidity-provision factor (β_{RLP}). β_{RLP} is estimated each year based on two-year rolling regressions of a fund's excess return on the Fung and Hsieh (2004) seven factors, plus the Sadka (2006) liquidity-risk factor, and the liquidity-provision factor of Jylhä, Rinne, and Suominen (2014). All control variables are defined in the Appendix. The sample includes funds that report to TASS and Barclays and spans from January 1996 to August 2013. Specifications 1 and 2 report the time-series average of Fama-MacBeth regression coefficients and Newey-West t-statistics (in parentheses). Specifications 3 and 4 report the results of panel regressions with t-statistics (in parentheses) computed from standard errors clustered by fund and month.

	Fama-MacBeth Regressions		Panel Regressions	
	[1]	[2]	[3]	[4]
β_{RLP} Rank	0.19	0.19	0.25	0.23
	(1.63)	(1.56)	(2.29)	(1.96)
Past Sharpe Ratio	2.75	2.70	2.72	2.62
	(15.47)	(15.62)	(13.96)	(12.44)
Adjusted R^2	0.25	0.24	-0.05	0.07
	(1.10)	(1.31)	(-0.32)	(0.52)
Log (Aum)	-0.56	-0.57	-0.62	-0.65
	(-2.85)	(-3.20)	(-3.60)	(-4.27)
Age	-0.43	-0.48	-0.39	-0.52
	(-4.11)	(-4.80)	(-3.46)	(-4.91)
Management Fee	0.12	0.08	0.29	0.09
	(0.62)	(0.48)	(2.02)	(0.70)
Incentive Fee	-0.27	-0.39	-0.17	-0.46
	(-1.01)	(-2.48)	(-0.60)	(-3.30)
High Water Mark	0.36	0.32	0.10	0.10
	(1.71)	(1.76)	(0.65)	(0.86)
Leverage Dummy	0.11	0.01	0.26	0.12
	(0.53)	(0.04)	(1.12)	(0.46)
Log (Minimum Investment)	0.64	0.57	0.59	0.45
	(4.36)	(4.10)	(4.97)	(3.78)
Restrictions	-0.11	-0.04	-0.12	0.03
	(-0.76)	(-0.25)	(-1.30)	(0.34)
β_{sp500} Rank	0.42	0.37	0.53	0.43
	(2.74)	(2.47)	(3.38)	(2.76)
Asset Illiquidity	-0.02	-0.09	-0.32	-0.33
	(-0.03)	(-0.13)	(-0.61)	(-0.59)
Fixed Effects	None	Style	Time	Time * Style
Ave Obs./ Obs.	802	802	56,933	56,933
Ave Within R^2/Within R^2	10.35%	8.97%	2.94%	2.70%