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Liquidity Provision and the Cross Section of Hedge Fund Returns

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Abstract. I investigate whether hedge funds that supply liquidity earn superior returns. Using transaction data, I find that hedge funds following short-term contrarian strategies (i.e., liquidity suppliers) earn significantly higher returns on their equity trades and holdings. Similarly, using commercial databases, I find that hedge funds with greater exposure to a liquidity provision factor earn significantly higher excess returns and Sharpe ratios. The superior performance of liquidity-supplying hedge funds arises from strategies that are more complex than mechanical short-term reversal strategies. For example, among stocks with similar past returns, liquidity-supplying funds are more likely to trade against stocks heavily traded by constrained mutual funds and less likely to trade against stocks heavily traded by unconstrained mutual funds. The outperformance of liquidity-supplying funds is also concentrated in periods of low funding liquidity, suggesting that less-binding financial constraints contribute to their superior returns.

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1. Introduction

According to BarclayHedge, the hedge fund industry has grown from \$38 billion in 1990 to over \$2.7 trillion in 2015.[1] Presumably, much of this growth is driven by investors' faith in their ability to identify outperforming hedge funds. Consistent with this view, recent work suggests that a subset of highly skilled hedge funds earn persistent abnormal returns (Kosowski et al. 2007, Jagannathan et al. 2010). However, relatively little is known about the trading styles associated with superior hedge fund performance. In this paper, I examine whether a fund's tendency to supply liquidity is one such style that can help identify better-performing hedge funds.

Liquidity-supplying funds act as counterparties to other investors who are willing to pay a premium in exchange for immediacy. This suggests that liquidity-supplying funds should earn abnormal returns from trading against price-pressure–induced mispricing. Consistent with this view, several papers find that mechanical liquidity provision strategies earn abnormal returns (see, e.g., Jegadeesh 1990, Nagel 2012), and such profits could be amplified if liquidity-supplying funds are skilled at distinguishing between uninformed and informed demand shocks. Furthermore, a fund's ability to provide liquidity may signal that the fund is less financially constrained. Many hedge funds have difficulty attracting and retaining the capital necessary to trade against risky mispricing, particularly during periods of limited funding liquidity, and thus may be unable to consistently supply liquidity (Franzoni and Plazzi 2015). Therefore, a fund's tendency to provide liquidity may be a useful way of aggregating both observable features of the fund (e.g., share restrictions, lockups) and less observable fund characteristics (e.g., connections with prime brokers, the stability and sophistication of the investment base, the risk aversion of the fund manager) that influence funding constraints. If liquidity provision helps predict a fund's (lack of) financial constraints above and beyond existing measures, it can offer incremental value in identifying better-performing funds.

I use transaction-level data to examine the relationship between a fund's tendency to supply liquidity and performance. Transaction data allow for more accurate estimates of a fund's tendency to demand or supply liquidity and enable more precise estimates of trading returns over various holding periods. Furthermore, the granularity of transaction data can shed greater light on the mechanisms driving any performance differentials. However, the transaction data do not include nonequity trading and also do not allow for a precise estimate of the realized returns that accrue to investors. Thus, I supplement transaction data with an analysis of hedge fund realized returns as reported in TASS and Barclays.

I start by proposing a transaction-based measure of a fund's tendency to supply liquidity. Following a large literature, I define liquidity-supplying trades as trades that are contrarian based on the stock's return over the prior day and week.[2] I show that a fund's tendency to supply liquidity is highly persistent, suggesting that this measure captures a dedicated trading strategy of a fund.

I next develop measures of fund performance based on equity transaction data. I estimate *equity trading returns* (*ETR*) using calendar-time transaction portfolios (see, e.g., Seasholes and Zhu 2010) with holding periods ranging from one month (*ETR1*) to one year (*ETR12*). I also compute *equity holding returns* (*EHR*) by aggregating the net trading of a fund beginning when it first appears in ANcerno. All *ETR* measures (i.e., *ETR1*, *EHR*, etc.) are computed as the principal-weighted return on the stocks held in the buy portfolio less the principal-weighted return on the stocks held in the sell portfolio. Following Daniel et al. (1997), I characteristic-adjust all *ETR* measures by subtracting the returns of a benchmark portfolio matched on size, book-to-market, and momentum.

My central finding is that a fund's tendency to provide liquidity is a strong predictor of *ETR*. The difference in *ETR1* (*EHR*) for hedge funds in the top versus bottom quintile of liquidity provision is 1.07% (0.37%) per month. Similarly, after controlling for past *ETR* and other fund characteristics, I find that a one-standard-deviation increase in short-term contrarian trading is associated with a 0.45% per month increase in *ETR1* and a 0.16% per month increase in *EHR*, both of which are highly significant.

Since liquidity-supplying (*LS*) funds follow contrarian strategies, their superior performance is likely related to the abnormal returns associated with short-term reversal strategies. However, I find that mechanical reversal strategies cannot explain the majority of the superior *ETR* of *LS* funds. First, I partition all trading into liquidity-supplying, liquidity-neutral (*LN*), and liquidity-demanding (*LD*) trades. I find that *LS* funds earn higher returns than *LD* funds across all trade types. In addition, *LS* funds' trades continue to earn higher returns well beyond the first month of the trade, long after the returns associated with reversal strategies have dissipated. A performance decomposition indicates that *LS* funds' tendency to overweight mechanical reversal strategies accounts for roughly 25% of their superior *ETR1* and even less of their superior *EHR*.

I next examine whether *LS* hedge funds are skilled at distinguished uninformed versus informed trades. I again partition all trades into liquidity-supplying, liquidity-neutral, and liquidity-demanding trades. Within each trade type, I find that *LS* funds are significantly more likely to trade against stocks experiencing pressure because of constrained mutual fund trades, defined as purchases by funds experiencing extreme inflows or sales by funds experiencing extreme outflows (Coval and Stafford 2007). On the other hand, *LS* funds are significantly less likely to trade against stocks experiencing demand shocks from unconstrained mutual fund trades, defined as purchases by funds experiencing outflows or sales by funds experiencing inflows (Alexander et al. 2007). These findings suggest that *LS* funds skillfully manage the adverse selection risks associated with providing liquidity. Consistent with this view, I find that the *ETR1* of *LS* hedge funds' is particularly large after news stories and earnings announcements, where information asymmetry tends to be elevated (Kim and Verecchia 1994, Krinsky and Lee 1996).

I also examine whether differences in financing constraints contribute to the superior *ETR* of *LS* funds. If *LS* funds benefit from being less financially constrained, such benefits should be particularly pronounced during periods of low funding liquidity. Consistent with this notion, I find that *LS* funds' superior *ETR* is concentrated when the VIX index is above its median. A performance decomposition indicates that the results are not simply a consequence of mechanical reversal strategies generating higher returns during periods of tighter funding constraints (Nagel 2012).

One concern with the findings above is that they rely exclusively on transaction data. While transaction data allow for a more precise estimate of a fund's trading strategy, they are not well suited for estimating the realized returns that accrue to investors. In addition, it is possible that the funds in the ANcerno sample are not representative of the broader hedge fund universe. To address these concerns, I repeat my analysis by examining the realized returns of hedge funds reporting to TASS and Barclays, and continue to find very similar results. Specifically, *LS* funds, as measured by their beta with respect to the liquidity provision factor of Jylhä et al. (2014), significantly outperform *LD* funds. The difference in excess returns between funds in the top and bottom quintile of liquidity provision is a statistically significant 0.31% per month, and this difference grows to 0.66% during periods of more limited funding liquidity. *LS* funds also earn significantly higher Sharpe ratios, alphas, and style-adjusted returns. Furthermore, the superior performance of *LS* funds is robust to controlling for a number of factors known to explain hedge fund performance including past performance, fund age, fund size, minimum investments, share restrictions, asset illiquidity, high watermarks, and the R^2 of the fund.

This paper contributes to a number of literatures. First, the paper adds to the literature on the cross-sectional determinants of hedge fund performance. In particular, I document that a fund's tendency to provide liquidity is associated with future superior returns. I also contribute to the literature that measures the funding constraints of hedge funds. Much of the existing work has emphasized observable fund characteristics such as lockups, share restrictions, asset illiquidity, and leverage (Aragon 2007, Franzoni and Plazzi 2015). My findings suggest that a fund's tendency to provide liquidity contains incrementally useful information about a fund's financing constraints. In addition, unlike lockups or share restrictions which impose trading constraints on investors, there is no obvious cost to investing in *LS* funds. Collectively, these findings suggest that investors are better off investing in *LS* funds.

My findings also relate to the literature that explores the role of hedge funds as liquidity providers. Franzoni and Plazzi (2015), who also use ANcerno data, explore the fund characteristics that constrain hedge funds' ability to provide liquidity (e.g., share restrictions, leverage, fund size). Similarly, Jylhä et al. (2014) show that hedge fund returns covary with a liquidity provision factor. These studies highlight significant time-series and cross-sectional variation in hedge funds' tendency to supply liquidity. I contribute to this literature by documenting that differences in a fund's tendency to supply liquidity are a strong predictor of future performance.

Finally, my study contributes to the debate over whether skilled hedge funds exist. Some studies using commercial databases find evidence of star hedge funds (e.g., Kosowski et al. 2007, Jagannathan et al. 2010). However, these findings may be a consequence of selection-biases in commercial databases (Aiken et al. 2013). Consistent with this view, Griffin and Xu (2009) examine the quarterly holdings of hedge funds and find that the stock-picking ability of the average hedge fund is relatively small. Furthermore, they find only weak evidence of differential ability between hedge funds. My study offers an out-of-sample test that relies on more granular data. My findings indicate that liquidity-supplying funds are skilled equity traders. Further, equity trading returns tend to be stronger over shorter holding periods (i.e., one month), which suggests that studies relying on quarterly holdings will understate hedge funds' *EHR*.

2. Data and Descriptive Statistics

2.1. Transaction Data

I obtain data on institutional equity trading from 1999 to 2010 from ANcerno Ltd. (formerly the Abel Noser Corp), a consulting firm that works with institutional investors to monitor their trading costs.[3] I use the following information from ANcerno: the stock traded (Cusip and ticker), trade direction (buy or sell), shares traded, the execution price, the 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 data set, I collect returns, share price, trading volume, and shares outstanding from CRSP, and I collect book value of equity from Compustat.

Each institution in ANcerno has three identifier variables: an institution- type identifier, a client identifier, and a manager identifier. The institution identifier distinguishes between clients that are plan sponsors (e.g., CalPERS, United Airlines) and clients that are money managers (e.g., Fidelity, Angelo Gordon). The client identifier corresponds to the plan sponsor or money manager that subscribes to ANcerno. The client identifier is a permanent numeric code. However, the names of the clients are not provided. The manager code corresponds to the management company executing the trades. 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.[4] I use the management company name to identify hedge funds within the ANcerno sample. Section IA.1 of the Internet appendix provides a more detailed discussion of the approach used to identify of hedge fund managers. A list of all ANcerno hedge funds (i.e., client–manager pairs) is available at http://russelljame.com/research.html.

ANcerno only reports equity trading, which could bias estimates of *ETR*, particularly for funds following strategies that involve both equity and nonequity trading (e.g., convertible arbitrage). To minimize this bias, I eliminate funds that are unlikely to be equity focused. First, for each ANcerno hedge fund that appears in TASS or Barclays, I examine the fraction of funds within the management company that have an *equity-focused* investment style.[5] If the management company does not offer any equity-focused funds, I drop the management company from the sample. For management companies that do not report to TASS or Barclays, I visit the company's website and exclude companies that do not offer any equity funds. In addition, I exclude funds that average less than five equity trades per quarter, as such funds are less likely to be equity funds.[6]

Table 1 provides summary statistics. The sample consists of 70 hedge fund management companies that offer at least one equity-focused fund. There are 483 different hedge fund client–manager pairs. Hereafter, I will loosely refer to a client–manager pair as a *fund*. Thus, I classify a money management company's trades on behalf of two different clients as two funds, although it may reflect the trading of the same hedge fund product. Panel B of Table 1 shows the average number of funds that appear in the sample each month across all sample years. In the average month in 1999, there are 153 hedge funds. This number is relatively stable until about 2007, at which point the sample of funds steadily decreases. I also examine how long

Table 1. Summary Statistics

Panel A: Aggregate sample size

	Managers	Clients	Man-clients/funds
ANcerno	70	314	483
TASS and Barclays	1,920	NA	3,913

Panel B: Average monthly sample size by year

Year	ANcerno managers	ANcerno funds	TASS and Barclays funds
1996			88
1997			137
1998			205
1999	40	153	287
2000	38	142	373
2001	36	140	954
2002	37	150	573
2003	38	152	702
2004	38	149	825
2005	40	153	953
2006	38	140	1,169
2007	37	133	1,417
2008	33	102	1,508
2009	28	71	1,484
2010	25	48	1,571
2011			1,653
2012			1,608
2013			1,639

Notes. This table presents descriptive statistics for the two primary data sources used in the paper: (1) institutional trading data from ANcerno and (2) realized return data from TASS and Barclays. The first column of panel A reports the total number of managers (i.e., management companies), clients (i.e., plan sponsors or money managers), and manager–client pairs (i.e., funds) in the ANcerno sample during the sample period 1999–2010. The second column of panel A reports the total number of management companies and funds in the TASS and Barclays sample from 1996 to 2013. Panel B reports the number of funds (or the number of management companies) that appear in the sample, averaged across each month in the year.

funds remain in the ANcerno sample (unreported). The average hedge fund remains in the sample for just over eight quarters, while funds at the 75th and 25th percentiles remain in the sample for 16 quarters and 3 quarters, respectively.

The Internet appendix provides additional details on the ANcerno database, with particular emphasis on database integrity. Specifically, the Internet appendix highlights that ANcerno does not suffer from backfill or survivorship bias (Fung and Hsieh 2000) or unreliable reported returns (Patton et al. 2015). In addition, in the Internet appendix, I explore the representativeness of the ANcerno sample by comparing ANcerno hedge funds to hedge funds that report to TASS and Barclays, as well as to hedge funds reporting quarterly holdings via Form 13F. I find that along most dimensions, ANcerno hedge funds are similar to the hedge funds reporting to TASS and Barclays and 13F-filing hedge funds. The most notable difference is that relative to 13F-filing hedge funds, ANcerno hedge funds are significantly larger in terms of total net assets and the number of stocks held in their portfolios.

2.2. Commercial Databases

I collect additional data on individual hedge funds by merging two commercial databases: TASS and Barclays. The union of these two databases contains monthly net-of-fee returns, monthly assets under management, and a single snapshot of a fund's organizational characteristics, including share restrictions, management fees, incentive fees, and investment styles. Following Titman and Tiu (2011), I impose a number of filters to minimize survivorship bias and backfill bias.

I first exclude fund-month observations prior to 1994. Prior to 1994, commercial databases only included surviving funds which generated a well-documented survivorship bias (see, e.g., Brown et al. 1999, Fung and Hsieh 2000). However, after 1994, commercial databases maintained a graveyard sample, which enables an analysis of both surviving and nonsurviving funds. In addition, in some tests, I assume the returns of the dropout funds are −100% in the last reporting month. This helps address the related concern that funds that stop reporting to commercial databases likely perform significantly worse after leaving the sample (Aiken et al. 2013, Agarwal et al. 2013).

I also employ several measures to mitigate backfill bias, which refers to a fund's tendency to backfill its historical returns when it first reports to commercial databases. As backfill bias tends to be particularly severe for small funds, I eliminate all funds with less than $30 million in assets under management. Specifically, if a fund starts with less than $30 million but later reaches $30 million in assets, it is included in the sample from the time at which the assets reach $30 million. It then remains in the sample as long as the fund exists, even if assets subsequently fall below the $30 million threshold. In addition, I eliminate the first 27 months from the history of each fund. Another source of backfill bias is caused by funds being late in reporting to databases. To minimize this bias, I exclude the last 8 months of the sample. The last month for which I have reported monthly returns is April of 2014. Accordingly, I end the sample in August of 2013.

Finally, the first two years of a fund's "clean" returns are used to estimate the fund's tendency to provide liquidity. Thus, my postestimate sample spans from January 1996 to August 2013. Table 1 provides summary statistics on the sample of hedge funds in the commercial databases. The final sample includes 3,913 funds and 1,920 fund families. Panel B shows that the hedge fund sample grows from 88 funds per month in 1996 to 1,639 funds in 2013.

3. Liquidity Provision and Equity Trading Returns—Evidence from Transaction Data

3.1. Defining and Measuring Liquidity Provision

I define liquidity provision as trading against price-pressure-induced mispricing.[7] This notion of liquidity provision is consistent with Franzoni and Plazzi (2015), who define liquidity providers as speculators who absorb temporary order imbalances and profit from the price pressure induced by liquidity-demanding trades. Examples of liquidity provision include buying stocks that institutional investors must sell quickly to meet investor redemptions (Coval and Stafford 2007) or selling stocks added to the S&P 500 index in the days surrounding index changes (Green and Jame 2011). Thus, liquidity providers are similar to the market makers in Grossman and Miller (1988). However, liquidity-providing hedge funds need not act like traditional market makers who tend to hold zero inventory at the end of the day. Instead, hedge funds may benefit from liquidity provision (either intentionally or unintentionally) as part of a more long-term strategy. For example, hedge funds that follow certain quantitative strategies, such as pairs trading, may indirectly benefit from liquidity provision (Kavajecz and Odders-White 2004, Engelberg et al. 2009). Alternatively, funds engaging in fundamental analysis may try to profit from liquidity provision by implementing limit orders or by waiting to submit buy (sell) market orders until stock prices are falling (rising). For example, Fred Fraenkel of Fairholme Hedge Funds describes his investment strategy as "deep-value investing where we do an enormous amount of work on a small number of names and buy them when they're exceedingly stressed and sell them when everybody wants them."[8]

Building off of this notion of liquidity provision, I consider two primary measures of liquidity provision. First, I identify liquidity-providing trades as contrarian trades—that is, buying stocks that are declining in price, and selling stocks that are rising in price.[9] This view of liquidity provision is consistent with Nagel (2012), who shows that the returns from reversal strategies that condition on returns over the prior one to five trading days closely track the returns earned by liquidity providers. Accordingly, for each stock, I compute a market-adjusted return over the past one day (*Mom1*) and past five days (*Mom5*), and then average the two returns (*Mom1&5*). I then define *LS* trades as purchases of stocks with low *Mom1&5* or sales of stocks with high *Mom1&5*. Similarly, *LD* trades are purchases of stocks with high *Mom1&5* or sales of stocks with low *Mom1&5*. In robustness tests, I also consider proxies for liquidity provision based solely on a stock's past one-day (*Mom1*), one-week (*Mom5*), or one-month (*Mom21*) return. All three variables are strongly positively correlated with *Mom1&5*, and all three yield qualitatively similar conclusions.

The second measure I consider is execution shortfall (*Shortfall*), defined 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. Trades with favorable prices relative to the price at the time of the placement (i.e., purchases with low execution shortfalls and sales with high execution shortfalls) are classified as liquidity-supplying trades.

For each fund-year, I compute a fund-level measure of liquidity provision. Specifically, I compute the principal-weighted average *Mom1&5* (*Shortfall*) of stocks purchased less the principal-weighted average *Mom1&5* (*Shortfall*) of stocks sold. At the fund level, the correlation between *Mom1&5* and *Shortfall* is 0.77, indicating that the two measures capture similar trading styles.

3.2. Characteristics of Liquidity-Supplying Funds

I begin by examining the characteristics of *LS* and *LD* funds. *LS* (*LD*) funds are defined as funds in the bottom (top) quintile of *Mom1&5*. For each fund-year, I compute the principal-weighted average characteristic of stocks purchased less the principal-weighted average characteristic of stocks sold. I consider the following characteristics: market capitalization (*Size*); the book-to-market ratio (*BM*); idiosyncratic volatility (*IVOL*); and the return on the stock in the prior day, week, and month (*Mom1*, *Mom5*, and *Mom21*, respectively). Each trading day, all stock characteristics are standardized to have mean 0 and variance 1. The appendix provides a more detailed description of the construction of the stock characteristics.

Panel A of Table 2 reports the average characteristics across all fund-days within the *LS*, *LN*, and *LD* portfolios. I also test whether the average value for *LS* funds is significantly different from the average value for *LD* funds. Significance is computed from standard errors clustered by management company and year. Not surprisingly, *LS* funds are significantly more contrarian as measured by *Mom1*, *Mom5*, and *Mom21*. *LS* funds also have significantly lower levels of *Mom1&5* in the year following the ranking period. Specifically, nearly 80% of the formation-period spread in *Mom1&5* persists in the year following the formation period. This suggests that a fund's tendency to engage in liquidity provision captures a dedicated trading strategy of the fund.

Panel B of Table 2 reports fund-level characteristics. For each fund-year, I compute the number of days the fund has appeared in the sample (*Age*), the average quarterly trading volume (*Volume*), the size of the fund's holdings constructed from its trading over the past 21 trading days (*Holdings Size1*), and the size of the holdings constructed over the entire sample

Table 2. Characteristics of Liquidity-Supplying Hedge Funds

	LS	*LN*	*LD*	*LS* − *LD*	*t*(*LS* − *LD*)
		Panel A: Stock characteristics of net purchases			
Fund-day obs.	40,333	127,933	41,325		
Mom1&5	−0.34	0.12	0.63	−0.97	(−15.11)
Mom1	−0.27	0.13	0.57	−0.84	(−14.94)
Mom5	−0.42	0.10	0.69	−1.11	(−14.96)
Mom21	−0.60	−0.01	0.60	−1.20	(−15.03)
Size	0.03	−0.05	−0.12	0.14	(4.09)
BM	−0.06	−0.01	0.05	−0.10	(−5.66)
IVOL	−0.01	0.05	0.06	−0.07	(−2.94)
Mom1&5 $(t+1)$	−0.23	0.11	0.52	−0.75	(−9.89)
		Panel B: Fund characteristics			
Age (days)	908.02	932.57	863.20	44.80	(0.63)
log(*Holdings Size1*)	15.22	15.90	15.99	−0.77	(−3.42)
log(*Holdings Size*)	18.00	18.42	18.18	−0.17	(−0.69)
log(*Volume*)	2.67	3.44	3.53	−0.86	(−3.65)
log(*Act./Implied*) * 100	9.50	14.38	16.48	−6.98	(−1.96)
Pct_Volume1	7.86	10.01	13.70	−5.84	(−5.64)
Money Manager	7.17	8.21	3.51	3.67	(0.81)
Com/Share	4.02	3.89	4.24	−0.22	(−0.49)
Shortfall	−0.37	0.30	1.18	−1.55	(−8.28)

Notes. This table compares the characteristics of *LS* and *LD* hedge funds. For each traded stock, I compute the market-adjusted return of the stock over the past one day (*Mom1*) and past five days (*Mom5*), and I average the two measures (*Mom1&5*). For each fund-year, I compute the principal-weighted average *Mom1&5* of stocks purchased less the principal-weighted average *Mom1&5* of the stocks sold. Funds in the bottom (top) quintile of *Mom1&5* are classified as *LS* (*LD*) funds. The remaining 60% of funds are classified as *LN*. Panel A reports the principal-weighted net purchases (i.e., buys − sells) of other stock characteristics during the year of the ranking period (or if labelled "$t+1$" in the year after the ranking period). I report the equally weighted average across all *LS, LN*, and *LD* hedge funds. I also report the difference between *LS* and *LD* funds. Panel B conducts a similar analysis for fund-level characteristics. All stock and fund characteristics are defined in the appendix. Reported in parentheses are *t*-statistics that are based on standard errors clustered by management company and year.

period (*Holdings Size*). I also compute the fraction of a fund's total holdings that are due to its trading over the past 21 trading days (*Pct_Volume1*) and a variable that measures the extent to which a fund engages in intraquarter trading (*Actual/Implied*). I also report summary statistics for the fraction of hedge funds entering the sample directly as money managers (*Money Manager*), the average commission per share (*Com/Share*), and the average shortfall (*Shortfall*). A more detailed description of each of the variables is provided in the appendix.

LS funds trade less as evidenced by their smaller *Holdings Size1* and *Volume*. Similarly, *LS* funds have longer holding periods, as measured by both *Actual/Implied* and *Pct_Volume1*. The relatively long holding periods of *LS* funds suggests that they are not acting like traditional markets, who tend to hold zero inventory at the end of the day. Instead, *LS* funds appear to provide liquidity as part of a more long-term strategy. For example, *LS* funds may be long-term investors who patiently execute trades. Alternatively, *LS* funds may trade against more long-lived mispricing.[10] Finally, *LS* funds have significantly lower *Shortfall*. The negative shortfall of *LS* funds suggests that they obtain better execution prices than their pretrade benchmarks, which is consistent with *LS* funds benefitting from liquidity provision.

3.3. Measuring Equity Trading Returns

I next examine whether a fund's tendency to supply liquidity is related to the returns it earns on its equity trades and holdings. I use transactions-based calendar-time portfolios to aggregate the trades of a fund.[11] Specifically, each time a fund buys a stock, I place the same number of shares in the calendar-time buy portfolio. The stock is placed in the portfolio on day 0 (the day of the purchase), and the position is held until (1) the fund reverses its position, (2) the fund drops out of ANcerno, or (3) the end of the holding period (whichever comes first).[12] If a buy trade offsets a preexisting sale (that occurred within the holding period), then the shares are removed from the sell portfolio. Thus, the buy portfolio reflects a fund's net-long position, based on its trades over the holding period. I perform an analogous procedure for sales.

I consider several holding periods. The first is to not assume any holding period. This is equivalent to computing the performance of hedge funds' equity holdings under the assumption that funds have no holdings prior to joining ANcerno. I label this performance metric as *EHR*. While *EHR* provides insight into whether hedge funds' equity holdings are informed, it has relatively low power for assessing hedge fund skill. For example, funds may continue to hold a position for non-performance-related reasons, such as transaction costs or capital gain taxes, which tends to push *EHR* toward zero. To offer more powerful tests of hedge fund skill, I also consider holding periods ranging from one month (*ETR1*) to one year (*ETR12*). The one-month holding period amounts to computing a fund's holdings based only on trades that were executed over the past 21 trading days. If hedge funds earn abnormal returns from trading against mispricing as a result of short-term price pressure, then focusing on positions initiated over the past month should yield more dramatic return differences.

Figure 1 reports the average *ETR* of the *buy* portfolio, the *sell* portfolio, and the *buy minus sell* portfolio over different holding periods. Specifically, I calculate the average *ETR* (e.g., *ETR1*, *EHR*) for each fund-day ($ETR_{f,t}$). I then compute the mean of $ETR_{f,t}$ across all funds in the sample on day $t(ETR_t)$. Finally, I compute the mean of ETR_t across the 3,019 trading days in the sample (*ETR*). Thus, *ETR1* reflects a time-series average of daily returns, expressed as a monthly return in percent. I compute standard errors from the time-series standard deviation of ETR_t.[13]

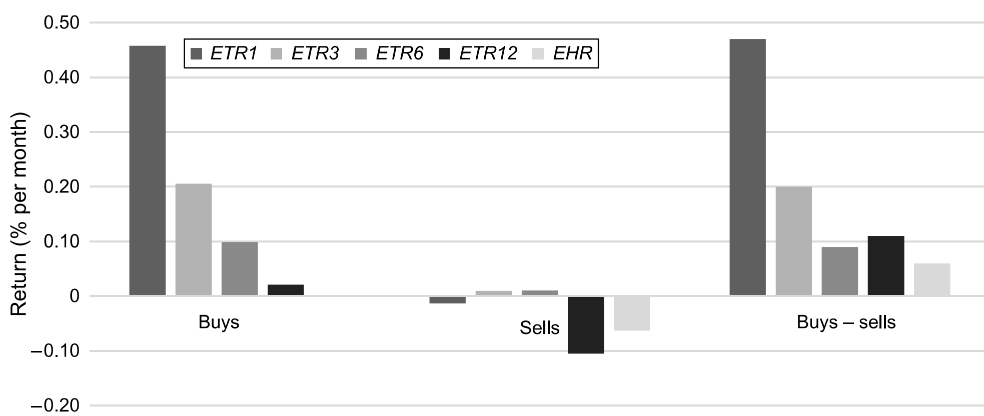
The construction of transactions-based calendar-time portfolios results in a time series of daily buy and sell portfolios. I compute the principal-weighted *ETR* of the buy (or sell) portfolio of fund f on day t as

$$R_{f,t} = \sum_{i=1}^{n} W_{i,t-1} R_{i,t}, \tag{1}$$

where $W_{i,t-1}$ is the weight of stock i in the portfolio of fund f. The weight of stock i is defined as the value of stock i scaled by the aggregate value of all positions in the portfolio. In computing the value of stock i, I distinguish between holdings due to trades made prior to day t and holdings due to trades made on day t. For trades made prior to day t, the value of stock i is computed as the number of shares held of stock i at the end of day $t-1$, multiplied by the closing price of stock i on day $t-1$. For trades made on day t, the value of stock i is computed as the number of shares traded of stock i on day t multiplied by the execution price. The variable $R_{i,t}$ is a measure of the return of stock i on day t. For trades made prior to day t, $R_{i,t}$ is the benchmark-adjusted return of stock i on day t. For trades made on day t, $R_{i,t}$ is computed as the closing price on day t divided by the execution price. This approach yields a time series of daily returns. I convert the daily returns to monthly returns by multiplying the daily return estimate by 21.

I follow Daniel, Grinblatt, Titman, and Wermers (hereafter DGTW) (Daniel et al. 1997) and Wermers (2004) in computing benchmark-adjusted returns. Specifically, excess returns are measured relative to the DGTW 125 size, industry-adjusted book-to-market, and momentum benchmarks.[14] I use DGTW-adjusted returns as the benchmark for two reasons. First, characteristic matching allows for benchmarks that explain more of the realized variation in returns than those based on factor loadings and thus have greater power to detect abnormal performance (Daniel et al. 1997). Second, it allows for greater comparability to the large literature that reports DGTW-adjusted returns as a

Figure 1. The Average Equity Trading Returns of Hedge Funds



Notes. *ETR* is computed using transactions-based calendar-time portfolios. Each time a fund buys a stock, I place the same number of shares in the calendar-time buy portfolio. The stocks are placed in the portfolio on day 0 (the day of the purchase), and day 0 returns are based on the reported execution price. The position is then held until (1) the fund reverses its position, (2) the fund drops out of the ANcerno sample, or (3) the end of the holding period (whichever comes first). If a buy trade offsets a preexisting sale (that occurred within the holding period), then the shares are removed from the sell portfolio. I report the results for holding periods of one month (*ETR1*) through 12 months (*ETR12*). I also report the results that assume no holding period, which is equivalent to computing a fund's equity holdings under the assumption that the fund had no holdings prior to joining ANcerno (*EHR*). I perform an analogous procedure for sales. I compute the principal-weighted return on the buy and sell portfolios, as well as the difference between the buy and sell portfolios. I report DGTW-adjusted returns, computed as 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. For each trading day in the sample, I first compute the equal-weighted average *ETR* across all funds in the sample. I then report the time-series average of *ETR*, expressed as monthly returns, in percent. The sample includes 3,019 trading days from 1999 to 2010.

measure of fund skill based on a fund's holdings or transactions.[15] In the Internet appendix, I also compute *ETR* using several different return benchmarks and find qualitatively similar results.

Two additional clarifications are in order in interpreting *ETR*. First, ANcerno does not provide any information on management or incentive fees; thus, *ETR* is gross of any fund expenses. As such, the analysis explores whether hedge funds earn abnormal returns on their equity holdings but does not offer any insight into what fraction of the abnormal returns are captured by the manager in the form of higher fees. Second, I report results gross of trading commissions. This allows for a more direct comparison to the literature that measures returns using quarterly holdings. In the Internet appendix, I find that my main conclusions are unchanged if I estimate returns net of trading commissions.

It is clear that the *ETR* of hedge funds is most evident over shorter horizons. In particular, hedge funds' *ETR1* of the *buy minus sell* portfolio is 0.47% per month, which is highly significant ($t = 4.34$). The *ETR* generally falls as the holding period increases, and the *EHR* of the average hedge fund is 0.06% per month, which is statistically insignificant. Thus, the average hedge fund has significant short-term trading skill, but their holdings do not outperform. Transaction costs (e.g., trading commissions) and other constraints (limited profitable investment ideas, taxes, etc.) likely limit hedge funds' ability to fully take advantage of their short-term trading skill.

3.4. Liquidity Provision and Equity Trading Returns

I now turn to my central research question of whether a fund's tendency to supply liquidity can help identify funds with superior equity trading returns. Table 3 presents the results of 2,767 daily cross-sectional (i.e., Fama–MacBeth) regressions where the dependent variable is a fund's *ETR1*. In Specification 1, the only independent variables are *LD*, *LN*, and *LS*, dummy variables for whether the fund is classified as liquidity-demanding, liquidity-neutral, and liquidity-supplying, respectively, as defined in Table 2. I exclude the intercept from the regression, so the estimates reflect the average *ETR1* of each portfolio. The results indicate that *LS* funds generate a statistically significant *ETR1* of 1.13% per month in the year following the formation period, while *LD* funds earn a statistically insignificant 0.06% per month. The last row confirms that the difference between the two estimates is statistically significant.

Specification 2 augments Specification 1 by including a number of control variables. The controls include the stock and fund characteristics reported in Table 2. However, I omit some variables because of high correlations. First, since *Mom1&5* is highly correlated with the other momentum variables and price impact, I exclude the *Mom1*, *Mom5*, *Mom21*, and *Shortfall* variables. I also drop log(*Volume*) because of its strong correlation with log(*Holdings Size1*), and I drop *Pct_Volume1* since I separately include its numerator, log(*Holdings Size1*), and denominator, log(*Holdings Size*). I also control for a fund's *ETR1* in the prior year (*Past ETR1*). I standardize all continuous control variables to have mean 0 and variance 1 on each day, and log(*Holdings Size1*), log(*Holdings Size*), and log(*Actual/Implied*) are standardized separately by institution type (i.e., plan sponsor versus money manager). I winsorize values that are more than three standard deviations from the mean.

Specification 2 reports the results after including the control variables. I find that *Past ETR1* is significantly positive, which suggests that funds exhibit persistence in their short-term trading skill.[16] I also find a negative and marginally significant coefficient on log(*Holdings Size1*), which is consistent with *ETR1* being subject to capacity constraints. Importantly, including the controls has relatively little impact on the estimated *ETR1* of *LS* funds (1.08%) and *LD* funds (−0.08%).

Specification 3 of Table 3 replaces the *LD*, *LN*, and *LS* dummies with *Mom1&5*, a continuous measure of a fund's tendency to demand liquidity. The results indicate that a one-standard-deviation increase in *Mom1&5* is associated with a 0.45%-per-month decline in *ETR1*. Specification 4 replaces *Mom1&5* with *Shortfall*. A one-standard-deviation increase in *Shortfall* is associated with a 0.43% per-month decline in *ETR1*, suggesting that both *Mom1&5* and *Shortfall* yield similar conclusions. Finally, Specification 5 includes both *Mom1&5* and *Shortfall*. Both variables remain negative, but the coefficients and statistical significance are reduced. This is not surprising, given the strong correlation between the two variables ($\rho = 0.77$).

Table 4 repeats the analysis of Table 3, but now the dependent variable is *EHR* instead of *ETR1*. I also replace *Past ETR1* with *Past EHR*. The main results from Table 4 are qualitatively similar to those of Table 3. In particular, *LS* funds earn significant *EHR* in the year following the formation period, while *LD* funds do not (Specification 2), and *Mom1&5* negatively forecasts *EHR* (Specification 3). Specification 4 indicates that the relationship between *EHR* and *Shortfall* is only marginally significant ($p = 0.10$), and Specification 5 shows that *Mom1&5* is a better predictor of *EHR* than *Shortfall*. One possible explanation for this finding is that *Mom1&5*, which considers returns over the past five trading days, does a better job of capturing longer-term liquidity provision strategies (e.g., trading against mispricing that has accrued because of demand shocks over several days).[17]

While the results from Tables 3 and 4 are qualitatively similar, the magnitudes do differ. For example, a comparison of Specification 3 in Tables 3 and 4 indicates

Table 3. Liquidity Provision and *ETR1*

	Spec. 1	Spec. 2	Spec. 3	Spec. 4	Spec. 5
Intercept			0.50	0.45	0.46
			(3.65)	(3.33)	(3.33)
Liquidity demand dummy (*LD*)	0.06	−0.08			
	(0.21)	(−0.28)			
Liquidity neutral dummy (*LN*)	0.47	0.45			
	(3.27)	(2.81)			
Liquidity supply dummy (*LS*)	1.13	1.08			
	(4.17)	(3.76)			
Mom1&5			−0.45		−0.25
			(−2.73)		(−1.07)
Shortfall				−0.43	−0.28
				(−2.77)	(−1.26)
Size		0.26	0.25	0.24	0.25
		(1.35)	(1.30)	(1.27)	(1.28)
BM		0.16	0.17	0.16	0.18
		(1.02)	(1.04)	(0.96)	(1.08)
IVOL		0.13	0.19	0.12	(0.15)
		(0.70)	(1.04)	(0.62)	(0.77)
Com/Share		−0.06	−0.07	−0.01	0.02
		(−0.47)	(−0.57)	(−0.10)	(0.13)
log(*Actual/Implied*)		0.19	0.25	0.27	0.28
		(1.52)	(1.96)	(2.08)	(2.15)
log(*Holdings Size1*)		−0.59	−0.60	−0.57	−0.49
		(−1.73)	(−1.76)	(−1.68)	(−1.43)
log(*Holdings Size*)		0.44	0.46	0.38	0.36
		(1.43)	(1.49)	(1.25)	(1.18)
log(*Age*)		−0.01	0.01	0.08	0.05
		(−0.11)	(0.06)	(0.88)	(0.55)
Past ETR1		0.10	0.08	0.10	0.11
		(1.99)	(1.64)	(2.05)	(2.10)
Money Manager		−0.31	−0.34	−0.33	−0.38
		(−1.24)	(−1.35)	(−1.33)	(−1.51)
Average obs. (per day)	71	71	71	71	71
Number of days	2,767	2,767	2,767	2,767	2,767
Average R^2 (%)	8.60	28.48	24.62	24.37	28.88
LS − *LD*	1.07	1.16			
	(2.68)	(2.66)			

Notes. This table reports the estimates from 2,767 daily Fama–MacBeth regression from January 2000 to December 2010. The dependent variable is the *ETR1* of a hedge fund (as defined in Section 3.3). All of the independent variables are defined in the appendix and are computed in the year prior to computing *ETR1*. All continuous variables are standardized to have mean 0 and variance 1 on each trading day. The variables log(*Holdings Size1*), log(*Holdings Size*), and log(*Actual/Implied*) are standardized separately for plan sponsors and money managers; *t*-statistics, based on standard errors computed from the time-series standard deviation, are reported in parentheses.

that a one-standard-deviation increase in *Mom1&5* is associated with a 0.45%-per-month reduction in *ETR1* versus a 0.16% per-month reduction in *EHR*. The stronger magnitudes associated with *ETR1* are not surprising since (1) the profits from with liquidity provision are concentrated over short holding periods, and (2) for the average *LS* hedge fund, less than 10% of its holdings are due to positions formed in the past month. These findings point the possibility that the *EHR* of *LS* funds with shorter holding periods should be particularly strong. To explore this possibility, in untabulated analysis, I estimate Specification 3 separately for funds in the top versus bottom half of *Pct_Volume1*. I find that the coefficient on *Mom1&5* is −0.31% ($t = -3.21$) for funds in the top half of *Pct_Volume1*, compared with −0.06% ($t = -0.62$) for funds in the bottom half of *Pct_Volume1*. This suggests that the superior *EHR* of *LS* funds is concentrated among funds with shorter holding periods.

In the Internet appendix, I confirm that the main findings from Tables 3 and 4 are robust to a variety of methodological choices. Specifically, I show that my

Table 4. Liquidity Provision and *EHR*

	Spec. 1	Spec. 2	Spec. 3	Spec. 4	Spec. 5
Intercept			0.13	0.12	0.12
			(2.28)	(2.10)	(2.16)
Liquidity demand dummy (*LD*)	−0.12	−0.05			
	(−0.85)	(−0.38)			
Liquidity neutral dummy (*LN*)	0.06	0.10			
	(1.31)	(1.87)			
Liquidity supply dummy (*LS*)	0.25	0.36			
	(1.80)	(2.70)			
Mom1&5			−0.16		−0.23
			(−2.39)		(−2.62)
Shortfall				−0.11	0.05
				(−1.63)	(0.56)
Size		−0.07	−0.06	−0.05	−0.08
		(−1.10)	(−0.91)	(−0.83)	(−1.18)
BM		−0.04	0.01	0.00	0.01
		(−0.78)	(0.14)	(0.04)	(0.20)
IVOL		0.05	0.05	0.02	(0.03)
		(0.67)	(0.73)	(0.34)	(0.45)
Com/Share		0.05	0.05	0.06	0.09
		(0.93)	(0.87)	(1.01)	(1.54)
log(*Actual/Implied*)		0.10	0.09	0.09	0.08
		(1.55)	(1.47)	(1.50)	(1.39)
log(*Holdings Size1*)		−0.08	−0.06	−0.03	−0.02
		(−0.69)	(−0.45)	(−0.24)	(−0.16)
log(*Holdings Size*)		0.03	0.02	−0.03	−0.01
		(0.22)	(0.13)	(−0.30)	(−0.11)
log(*Age*)		0.02	0.01	0.02	0.01
		(0.52)	(0.26)	(0.55)	(0.34)
Past EHR		0.05	0.04	0.05	0.06
		(0.77)	(0.63)	(0.89)	(0.92)
Money Manager		−0.22	−0.24	−0.22	−0.27
		(−2.08)	(−2.21)	(−1.99)	(−2.46)
Average obs. (per day)	76	76	76	76	76
Number of days	2,767	2,767	2,767	2,767	2,767
Average R^2 (%)	9.06	29.92	26.48	26.58	28.62
LS − *LD*	0.37	0.41			
	(1.71)	(2.11)			

Notes. This table reports the estimates from 2,767 daily Fama–MacBeth regression from January 2000 to December 2010. The dependent variable is the *EHR* of a hedge fund (as defined in Section 3.3). All independent variables are defined in the appendix and are computed in the year prior to computing *EHR*. All continuous variables are standardized to have mean 0 and variance 1 on each trading day. The variables log(*Holdings Size1*), log(*Holdings Size*), and log(*Actual/Implied*) are standardized separately for plan sponsors and money managers; *t*-statistics, based on standard errors computed from the time-series standard deviation, are reported in parentheses.

main results are robust to alternative proxies for liquidity provision including *Mom1*, *Mom5*, and *Mom21*, and alternative return measures including returns net of commissions, raw returns, hedge fund index alphas, and five-factor alphas. The results are also similar after excluding the small sample of hedge funds that directly subscribe to ANcerno (i.e., money managers), including hedge fund management companies that are less likely to have an all-equity focus, excluding the financial crisis period (i.e., July through December of 2008), or estimating results using panel regressions with standard errors clustered by both management company and time. Finally, I correct for "look-ahead" bias due to fund attrition within the ANcerno sample (ter Horst et al. 2001, Baquero et al. 2005) and continue to find very similar results.

4. Why Do Liquidity-Supplying Hedge Funds Exhibit Superior Equity Trading Returns?

4.1. Mechanical Short-Term Reversal Strategies

The superior performance of *LS* funds may simply reflect their greater exposure to short-term reversal strategies, which tend to earn abnormal returns (see, e.g., Jegadeesh 1990, Lehmann 1990, Nagel 2012). If short-term reversal strategies account for the superior *ETR* of *LS* funds, then (1) liquidity-supplying trades should earn higher returns than liquidity-demanding trades, and (2) within a given trade style (i.e., liquidity-supplying versus liquidity-demanding), there should be little difference in the *ETR* of *LS* and *LD* funds. I test these conditions by partitioning trades into three groups: liquidity-supplying, liquidity-demanding, and liquidity-neutral. I define purchases of stock in the bottom third of *Mom1&5* or sales of stock in the top third of *Mom1&5* (based on NYSE breakpoints) as *LS* trades. *LD* trades are defined analogously. Finally, purchases and sales of stocks in the middle third of *Mom1&5* are defined as *LN* trades.

Panel A of Table 5 reports the average *ETR1* across all hedge funds in their *LD*, *LN*, and *LS* trades, and panel B reports the results separately for *LS*, *LN*, and *LD* funds. Two clear patterns emerge. First, across all hedge funds, the average *ETR1* is insignificant in *LD* trades but is significantly positive in *LS* trades. This finding is consistent with short-term reversal strategies yielding abnormal returns. Since *LS* funds place more weight on *LS* trades, this finding also suggests that *LS* funds' greater exposure to short-term reversal strategies contributes to their superior *ETR1*. Second, across all trade types, the *ETR1* of *LS* funds is greater than the *ETR1* of *LD* funds (although the difference is not significant for *LS* trades). This suggests that the higher *ETR1* of *LS* funds does not stem entirely form short-term reversal strategies.

Table 5. *ETR1* by Trade Type

	LS trades	*LN* trades	*LD* trades
	Panel A: All hedge funds		
All funds	1.22	0.47	−0.06
	(5.78)	(3.18)	(−0.28)
	[62]	[61]	[64]
	Panel B: Sorts by fund trading style		
LD funds	1.27	0.06	−0.58
	(3.23)	(0.15)	(−1.60)
	[12]	[12]	[13]
LN funds	1.05	0.38	−0.04
	(4.41)	(2.21)	(−0.16)
	[38]	[38]	[40]
LS funds	1.73	1.21	0.49
	(4.65)	(3.83)	(1.27)
	[12]	[11]	[11]
LS − *LD* funds	0.46	1.15	1.07
	(0.91)	(2.35)	(2.10)

Notes. This table reports the average *ETR1* of hedge funds partitioned by trade type. The three trade types are *LS* trades, *LN* trades, and *LD* trades. I define *LS* trades as purchased of stocks in the bottom third of *Mom1&5* and sales of stocks in the top third of *Mom1&5*. Similarly, *LD* trades are purchases of stocks in the top third of *Mom1&5* and sales of stocks in the bottom third of *Mom1&5*. All other trades are defined as liquidity-neutral (*LN* trades). *Mom1&5* is defined as the average market-adjusted return on the stock in the prior one and five trading days. Panel A reports the results across all hedge funds, and panel B reports the results for *LS*, *LN*, and *LD* funds, as defined in Table 2. Reported in parentheses are t-statistics that are based on standard errors computed from the time-series standard deviation. I also report the number of ANcerno hedge funds that appear in the portfolio, averaged across all trading days in the sample. The sample includes 2,767 trading days from 2000 to 2010.

To obtain a better sense of the relative importance of exposure to short-term reversals strategies, I adopt an approach similar to Wermers (2000) and decompose the *ETR1* across all trades ($ETR1_{\mathrm{ALL}}$) into three components: characteristic selectivity (*CS*), characteristic timing (*CT*), and average style (*AS*). First, I compute the $ETR1_{\mathrm{ALL}}$ of the buy (or sell) portfolio for f fund on day t as

$$ETR1_{\mathrm{ALL},\,ft} = W_{LS,\,ft}(R_{LS,\,ft}) + W_{LN,\,ft}(R_{LN,\,ft}) + W_{LD,\,ft}(R_{LD,ft}). \tag{2}$$

The variable $W_{LS,\,ft}$ is the weight of *LS* holdings in the portfolio of fund f on day t, defined as the size of the holdings that stem from *LS* trades scaled by the aggregate value of all positions in the portfolio; $R_{LS,\,ft}$ is the *ETR1* associated with the *LS* holdings of fund f on day t. The second and third terms present analogous components for *LN* and *LD* holdings, respectively. Thus, $ETR1_{\mathrm{ALL}}$ is the principal-weighted *ETR* across the three trade types.[18]

I measure the characteristic selectivity of the buy (or sell) portfolio of fund f on day t as

$$CS_{ft} = W_{LS,\,ft}(R_{LS,\,ft} - \bar{R}_{LS,\,t}) + W_{LN,\,ft}(R_{LN,\,ft} - \bar{R}_{LN,\,t}) + W_{LD,\,ft}(R_{LD,\,ft} - \bar{R}_{LD,\,t}). \tag{3}$$

The variables $W_{LS,\,ft}$ and $R_{LS,\,ft}$ are defined as in Equation (2), and $\bar{R}_{LS,\,t}$ is the (equally weighted) average of $R_{LS,\,t}$ across all funds on day t. Thus, $R_{LS,\,ft} - \bar{R}_{LS,\,t}$ captures fund f's *ETR1* on *LS* trades in excess of the average hedge fund's *ETR1* on *LS* trades. The second and third terms present analogous components for *LN* and *LD* holdings, respectively.

The *CS* measure does not capture a fund's ability to time trading styles. For example, a fund that engages in greater amounts of liquidity provision during periods of low funding liquidity will generate a higher *ETR1* than funds that supply liquidity during periods of high funding liquidity. To measure a fund's *ETR1* that stems from tilting their trading toward a style when the returns to that style are higher, I compute the characteristic timing (*CT*) measure of fund f on day t as follows:

$$\begin{aligned} CT_{ft} = {} & (W_{LS,\,ft}\bar{R}_{LS,\,t} - \bar{W}_{LS,\,f}\bar{R}_{LS}) \\ & + (W_{LN,\,ft}\bar{R}_{LN,\,t} - \bar{W}_{LN,\,f}\bar{R}_{LN}) \\ & + (W_{LD,\,ft}\bar{R}_{LD,\,t} - \bar{W}_{LD,\,f}\bar{R}_{LD}). \end{aligned} \tag{4}$$

Table 6. Decomposing *ETR1* Stock Picking, Style Timing, and Average Style

	$ETR1_{ALL}$	*CS*	*CT*	*AS*
LD funds	0.05	−0.30	0.01	0.34
	(0.19)	(−1.37)	(0.09)	(3.26)
	[14]	[14]	[14]	[14]
LN funds	0.46	−0.05	0.03	0.48
	(3.23)	(−0.54)	(0.28)	(3.91)
	[44]	[44]	[44]	[44]
LS funds	1.19	0.51	0.06	0.62
	(4.40)	(2.24)	(0.50)	(4.75)
	[13]	[13]	[13]	[13]
LS − *LD*	1.14	0.81	0.05	0.27
	(2.89)	(2.22)	(0.62)	(4.22)

Notes. This table decomposes the *ETR1*($ETR1_{ALL}$) of *LS*, *LN*, and *LD* funds. *LS*, *LN*, and *LD* funds are defined as in Table 2. I decompose *ETR1* into three components: *CS*, *CT*, and *AS*. *CS* is a measure of the stock-picking ability of a fund relative to other hedge funds making a trade in the same trade style (i.e., *LS*, *LN*, or *LD* trades as defined in Table 5). *CT* measures a fund's ability, relative to other hedge funds, to time styles. Finally, *AS* captures a fund's tendency to overweight styles that are associated with more profitable trades. Additional details of the decomposition are available in Section 4.1. Reported in parentheses are *t*-statistics. For the *CS* and *CT* measures, standard errors are computed from the time-series standard deviation. For *AS*, standard errors are computed from time-series estimates after clustering by year. In brackets, I also report the number of hedge funds that appear in the portfolio, averaged across all trading days in the sample. The sample includes 2,767 trading days from 2000 to 2010.

The variables $W_{LS,ft}$ and $\bar{R}_{LS,t}$ are defined as in Equations (2) and (3). We denote by $\bar{W}_{LS,f}$ the average weight of liquidity-supplying holdings in the portfolio of fund f across all days in the calendar year for which day t belongs,[19] and $\bar{R}_{LS}$ is the average $\bar{R}_{LS,t}$ across all days in the calendar year. Thus, $(W_{LS,ft}\bar{R}_{LS,t} - \bar{W}_{LS,f}\bar{R}_{LS})$ captures the return premium from placing greater weight in *LS* trades when the returns to *LS* trades are greater. The last two terms present analogous components for *LN* and *LD* holdings, respectively.

Finally, to measure the *ETR1* earned by a fund as a result of the fund's tendency to engage in a greater amount of short-term reversal trades, I compute the average style (*AS*) component of a fund's *ETR1*. I compute the *AS* for fund f on day t as

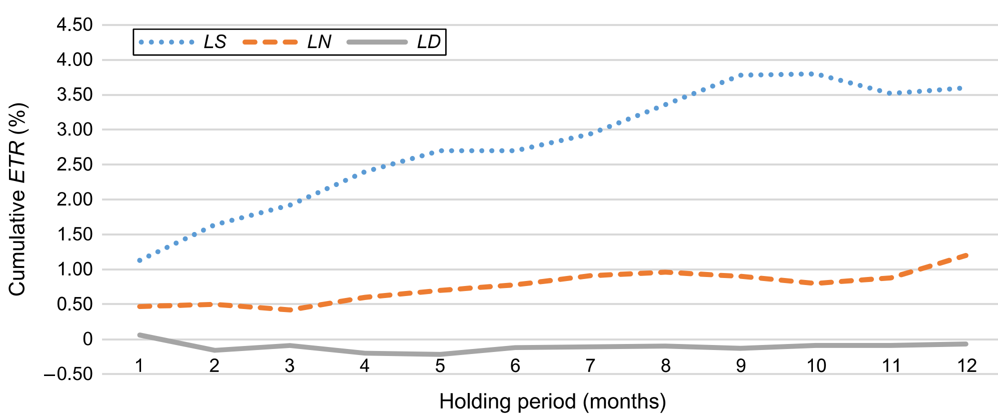
$$AS_{ft} = \bar{W}_{LS,f}\bar{R}_{LS} + \bar{W}_{LN,f}\bar{R}_{LN} + \bar{W}_{LD,f}\bar{R}_{LD}, \tag{5}$$

where all variables are defined as in Equations (2)–(4). Thus, the *AS* measure provides an estimate of a fund's *ETR1* that stems from placing greater weight on trading styles that earn higher average *ETR1*.[20]

Table 6 reports the average $ETR1_{ALL}$ of the buy minus sell portfolios and its decomposition into the *CS*, *CT*, and *AS* components. The decomposition indicates that 24% (0.27/1.14) of the superior $ETR1_{ALL}$ of *LS* funds stems from the *AS* component. This suggests that placing greater weight on the more profitable *LS* trades (i.e., exposure to short-term reversal strategies) contributes significantly to *LS* funds' superior *ETR1*. Additionally, the CS component accounts for roughly 70% (0.81/1.14) of *LS* funds' superior *ETR1*, which suggests that *LS* funds have superior stock-picking ability even after controlling for the style of the trade. Finally, there is no evidence that *LS* funds have a comparative advantage in characteristic timing.

The results above suggest that differences in exposure to short-term reversal strategies account for roughly 24% of the superior *ETR1* of *LS* funds. The impact of reversal strategies on *LS* funds' *EHR* is likely to be substantially smaller. The profits from short-term reversal strategies tend to persist for only one month (Jegadeesh 1990). However, the superior *EHR* of *LS* funds, coupled with their relatively long holding periods, suggests that their trades outperform over longer holding periods. To provide more direct evidence, Figure 2 plots the cumulative abnormal returns of *LS*, *LN*, and *LD* funds for holding periods ranging from 1 month to 12 months.

Figure 2. (Color online) Cumulative *ETR* for Different Holding Periods



Notes. This figure plots the cumulative *ETR* of *LS*, *LN*, and *LD* funds for holding periods ranging from 1 month to 12 months. *LS*, *LN*, and *LD* funds are defined as in Table 2. Cumulative *ETR* is the average *ETR*, as described in Figure 1, multiplied by the holding period (in months). The sample includes 2,767 trading days from 2000 to 2010.

While *LS* funds' outperformance is largest in the first month (1.13%), the cumulative *ETR* grows to 3.60% over a 12-month holding period. Thus, the abnormal returns of roughly 2.5% that accrue from months 2 through 12 cannot be explained by mechanical reversal strategies. Instead, the findings suggests that liquidity-supplying funds often benefit from trading against more long-lived mispricing.

4.2. Liquidity Provision Skill—Evidence from Forced vs. Voluntary Mutual Fund Trading

The evidence from the previous section suggests that short-term reversal strategies cannot explain the majority of *LS* funds' superior *ETR1* and *EHR*. Instead, the findings point to the possibility that *LS* funds benefit from more skillful forms of liquidity provision. In particular, *LS* funds may exhibit skill in distinguishing between uninformed versus informed demand shocks.

A test of liquidity provision skill requires identifying stocks that are mispriced because of large uninformed demand shocks. One such example is stocks that experience selling (buying) pressure as a result of mutual fund outflows (inflows). Coval and Stafford (2007) highlight that strategies that take the opposing side of fire sales (fire purchases) earn substantial abnormal returns for up to 18 months after the event quarter. Furthermore, the profits from the strategy cannot be fully captured by simply sorting on past returns.[21]

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*:

$$Pressure_{i,t} = \begin{pmatrix} \sum_f \max(0, \Delta Holdings_{f,i,t}) \mid flow_{f,t} > P90 \\ -\sum_f \max(0, -\Delta Holdings_{f,i,t}) \mid flow_{f,t} < P10 \end{pmatrix} \cdot (AvgVolume_{i,t-12:t-6})^{-1} \quad (6)$$

I define fire sale (fire purchase) stocks as stocks in the bottom (top) quintile of *pressure*. I limit the sample to fire sale or fire purchase stocks. For each fund-quarter with at least five trades, 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 separately. I also report the results across all trades and for *LS*, *LN*, and *LD* trades (as classified using *Mom1&5*). Standard errors are clustered by management company and quarter.

Panel A of Table 7 presents the results. Not surprisingly, *LS* trades are significantly more likely to trade against *pressure* than *LD* trades. However, the classification is somewhat noisy, with roughly 50.8% of *LS* trades trading against *pressure* versus 47.9% for *LD* trades. Similarly, across all trades types, *LS* funds are significantly more likely to trade against *pressure* than *LD* funds (53.2% versus 46.0%). More interestingly, within a given trade type, *LS* funds continue to be more likely to trade against pressure than *LD* funds. For example, among *LD* trades, 44.7% of *LD* funds trade against *pressure* compared with 51.1% for *LS* funds, and the difference is statistically significant. In other words, even after controlling for differences in exposure to short-term reversal strategies, *LS* funds continue to be more likely to benefit from liquidity provision.

As a second test, I examine hedge fund trading around voluntary trading by mutual funds. I define voluntary trading as

$$Voluntary_{i,t} = \begin{pmatrix} \sum_f \max(0, \Delta Holdings_{f,i,t}) \mid flow_{f,t} < 0 \\ -\sum_f \max(0, -\Delta Holdings_{f,i,t}) \mid flow_{f,t} > 0 \end{pmatrix} \cdot (AvgVolume_{i,t-12:t-6})^{-1}. \quad (7)$$

In other words, I define purchases by funds experiencing outflows (i.e., flow < 0) and sales by funds experiencing inflows (i.e., flow > 0) as voluntary trades. I define voluntary buys (voluntary sells) as stocks in the top (bottom) quintile of *voluntary*. This measure is related to Alexander et al. (2007), who find that purchases (sales) by fund managers receiving outflows (inflows) tend to be informed.[22] Thus, *LS* funds would typically benefit from avoiding trading against *voluntary* trades.

Panel B of Table 7 reports results analogous to panel A after replacing *pressure* with *voluntary.* Across all funds, *LS* trades are significantly less likely to trade against *voluntary* than *LD* trades.[23] Similarly, across all trades, *LS* funds are significantly less likely to trade against *voluntary* than *LD* funds. Furthermore, within a given trade type, *LS* funds remain significantly less likely to trade against *voluntary* than *LD* funds. Collectively, the results from Table 7 suggest that *LS* funds exhibit liquidity provision skill. Specifically, among stocks with similar past returns, *LS* funds overweight stocks experiencing uninformed demand shocks and underweight stocks experiencing informed demand shocks.

4.3. Equity Trading Returns Around Information Events

The results from Table 7 suggest that *LS* funds are able to skillfully distinguish between uninformed and informed trading. If the prior results reflect a more systematic pattern in which *LS* funds are generally

Table 7. Liquidity Provision Around Forced vs. Voluntary Mutual Fund Trading

	All trades	*LS* trades	*LN* trades	*LD* trades	*LS* trades − *LD* trades
	Panel A: Forced mutual fund trading				
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%
	[1,967]	[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 funds − *LD* funds	7.24%	8.30%	4.70%	6.41%	
	(5.00)	(5.58)	(2.32)	(3.53)	
	Panel B: Voluntary mutual fund trading				
All funds	46.68%	44.81%	46.53%	48.85%	−4.04%
	[3,531]	[3,289]	[3,171]	[3,290]	(−3.76)
LD funds	49.25%	46.44%	47.97%	51.53%	−5.10%
	[700]	[641]	[626]	[678]	(−3.49)
LN funds	46.87%	45.35%	46.54%	48.77%	−3.42%
	[2,139]	[1,992]	[1,940]	[2,041]	(−2.92)
LS funds	43.48%	41.57%	45.01%	45.96%	−4.39%
	[692]	[656]	[605]	[571]	(−2.19)
LS funds − *LD* funds	−5.78%	−4.87%	−2.96%	−5.58%	
	(−4.40)	(−3.09)	(−1.74)	(−3.33)	

Notes. Panel A reports the percentage of hedge funds' trades that provide liquidity to stocks experiencing extreme selling or extreme buying pressure due to forced mutual fund 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) separately. I also report the results across all trades as well as for *LS*, *LN*, and *LD* trades (as defined in Table 5). Panel B reports analogous results for voluntary mutual fund trading. Specifically, for each stock-quarter, I compute *Voluntary* defined as the fraction of average volume due to voluntary trading. Voluntary purchases (sales) are defined as purchases (sales) by funds experiencing outflows (inflows). Stocks in the bottom (top) quintile of *voluntary* are classified as voluntary sale (voluntary purchase) stocks. Reported in parentheses are *t*-statistics that are based on standard errors clustered by manager and quarter. The number of fund-quarter observations are reported in brackets.

skilled at interpreting and processing public information, then the superior *ETR1* of *LS* funds may be amplified immediately after major information events (see, e.g., Kim and Verecchia 1994, Krinsky and Lee 1996). To explore this possibility, I split hedge fund trading into *postevent*, *preevent*, and *nonevent* trades. I define *postevent* trades as trades that occur on the day of an earnings announcement (as reported in the Institutional Brokers' Estimate System (I/B/E/S)) or news story (collected from the *Wall Street Journal*).[24] I focus exclusively on the event-day, as Huang et al. (2013) find that institutions trade on the news tone only on the release day. I also explore whether *LS* funds are skilled at anticipating major information releases by examining preevent trades, defined as trades that occur in the three days prior to an earnings announcements or news story. All other trades are defined as *nonevent* trades. I compute the *ETR1* of *LS*, *LN*, and *LD* funds for *postevent*, *preevent*, and *nonevent* trades. If a fund does not have any *postevent* (*preevent*) holdings, I omit the fund when calculating *postevent* (*preevent*) *ETR1*.

Table 8 reports that *LS* funds' *postevent* trades earn an *ETR1* of 2.14%. This estimate is highly significant and is roughly 80% larger than their *ETR1* in *nonevent* trades. Unfortunately, the sample of postevent trading is too small to further decompose the *ETR* of *LS* funds based on the trade style (i.e., liquidity-supplying versus liquidity-demanding). Regardless, the evidence is consistent with *LS* funds exhibiting superior skill in processing public information—a skill that is likely critical in minimizing the adverse-selection risk associated with liquidity provision strategies.

4.4. Funding Constraints and the Superior Equity Trading Returns of Liquidity-Supplying Funds

I next examine whether the superior *ETR* of *LS* funds varies with funding conditions. There are at least two reasons to believe that *LS* funds will perform particularly well during periods of more limited funding liquidity. First, the profits associated with liquidity provision increase substantially during periods of market turmoil (Nagel 2012).

Table 8. *ETR1* Around Information Events

	Nonevent trades	*Preevent* trades	*Postevent* trades
LD funds	0.07	0.46	0.31
	(0.25)	(0.80)	(0.52)
	[14]	[8]	[7]
LN funds	0.35	0.81	0.88
	(2.38)	(2.74)	(2.75)
	[43]	[30]	[25]
LS funds	1.20	1.34	2.14
	(4.36)	(2.40)	(3.05)
	[13]	[7]	[6]
LS − *LD*	1.13	0.88	1.83
	(2.70)	(1.10)	(1.93)

Notes. This table splits hedge funds' trades into three groups: *nonevent*, *preevent*, and *postevent*. *Postevent* trades are trades that occur on the day of an earnings announcement or new story, and *preevent* trades are trades that occur in the three day prior to an earnings announcement or news story. All other trades are classified as *nonevent* trades. This table reports the *ETR1* of *LD*, *LN*, and *LS* funds (as defined in Table 2) for each trade type. Reported in parentheses are t-statistics that are based on standard errors computed from the time-series standard deviation. I also report the number of funds that appear in the portfolio, averaged across all trading days in the sample.

Second, a fund's tendency to provide liquidity can serve as a signal of a fund's financing constraints. Liquidity provision strategies, while generally profitable, are not riskless. Stocks that experience large uninformed demand shocks can experience significantly worse mispricing before prices revert to fundamental value (see, e.g., DeLong et al. 1990, Shleifer and Vishny 1997). As a result, hedge funds that experience margin calls or investor redemptions could be forced to liquidate positions at losses. Thus, a fund's willingness to provide liquidity may signal that the fund is less financially constrained. Consistent with this view, Franzoni and Plazzi (2015) find that hedge funds with greater share restrictions, lower leverage, and more liquid assets are more likely to provide liquidity during periods of market turmoil. However several other factors can contribute to a fund's financial constraints, many of which are difficult to empirically measure. Examples include connections with prime brokers, the stability and sophistication of the investor base, personal relationship with large investors, and the risk aversion of the fund manager. Thus, a fund's tendency to provide liquidity may be a useful way of aggregating both observable and unobservable measures of financial constraints. If *LS* funds benefit from looser funding constraints, then their superior performance should be amplified during periods of lower funding liquidity when differences in funding constraints are more binding.

Table 9 examines how the performance of *LS* and *LD* funds varies with the VIX, a common measure of funding constraints (Nagel 2012). Specifically, I repeat Specifications 1 and 3 of Tables 3 and 4 but split the sample based on whether the VIX is above or below its median value over the 2000–2010 sample period. In the interest of brevity, I only report the coefficients on the *LS* and *LD* dummies or the *Mom1&5* variable. Specification 1 indicates that *LS* funds earn an *ETR1* of 1.81% when the VIX is above its median while *LD* funds underperform by −0.05%. Similarly, Specifications 2 and 4 show that when the VIX is above its median, a one-standard-deviation increase in *Mom1&5* is associated with a statistically significant −0.71% per-month decline in *ETR1* and a −0.25% decline in *EHR*.

Table 9. Liquidity Provision and Returns—High vs. Low VIX

	High VIX				Low VIX			
	ETR1 Spec. 1	*ETR1* Spec. 2	*EHR* Spec. 3	*EHR* Spec. 4	*ETR1* Spec. 5	*ETR1* Spec. 6	*EHR* Spec. 7	*EHR* Spec. 8
LD funds	−0.05		−0.21		0.15		−0.04	
	(−0.10)		(−0.82)		(0.58)		(−0.28)	
LS funds	1.81		0.48		0.45		0.03	
	(3.87)		(1.91)		(1.65)		(0.23)	
Mom1&5		−0.71		−0.25		−0.05		−0.06
		(−2.64)		(−2.09)		(−0.27)		(−0.86)
Controls	None	Spec. 3—Table 3	None	Spec. 3—Table 4	None	Spec. 3—Table 3	None	Spec. 3—Table 4
Avg. obs.	63	63	67	67	81	81	86	86
LS − *LD*	1.86		0.68		0.30		0.07	
	(2.69)		(1.74)		(0.73)		(0.34)	

Notes. This table reports hedge funds' *ETR1* and *EHR* but now splits the sample based on whether the VIX index is above or below its median value over the 2000–2010 sample period. Specifications 1 and 3 repeat Specification 1 of Tables 3 and 4, respectively, for the 1,378 days for which the VIX is above its median. Specifications 5 and 7 present analogous results for the 1,389 days for the VIX is below its median. Specifications 2 and 4 (6 and 8) repeat Specification 3 of Tables 3 and 4, respectively, when the VIX is above (below) its median. Reported in parentheses are t-statistics.

By contrast, Specifications 5–8 indicate that the difference in the *ETR1* or *EHR* of *LS* and *LD* funds is economically small and statistically insignificant when the VIX is below its median. In untabulated analysis, I confirm that the results are similar if I replace the VIX Index with the TED Spread (the three-month Eurodollar deposit rate minus the three-month Treasury Bill rate), another proxy for funding constraints (see, e.g., Garleanu and Perdersen 2011). I also find similar results after excluding the second half of 2008, which suggests that the above patterns are not simply a consequence of the 2008 financial crisis.

As noted earlier, part of the superior performance of *LS* funds during periods of low funding liquidity may stem from the fact that short-term reversal strategies are more profitable during such periods (Nagel 2012). To explore the importance of mechanical reversal strategies, I repeat the performance decomposition of Table 6 but now partition the sample based on whether the VIX is above or below the median. Panel A of Table 10 shows that when the VIX is above its median, both the *CS* and *AS* components contribute to the *LS* funds' superior *ETR1*, with the *CS* component accounting for about 70% of the relative outperformance (1.35/1.93). Thus, the majority of the superior *ETR1* of *LS* funds during periods of tighter funding constraints cannot be explained by short-term reversal strategies. Panel B indicates that *LS* funds do not exhibit superior stock picking relative to *LD* funds when the VIX is below its median value. This suggests that *LS* funds' liquidity provision skill is concentrated during periods of tighter funding constraints, when there are fewer funds competing for liquidity provision profits (Franzoni and Plazzi 2015). Overall, the results from Tables 9 and 10 are consistent with *LS* funds have less binding financing constraints, which allows them to more profitably trade against mispricing during periods of market turmoil.

Table 10. Decomposing *ETR1*: Stock Picking, Style Timing, and Average Style—High vs. Low VIX

	$ETR1_{ALL}$	*CS*	*CT*	*AS*
Panel A: Decomposing *ETR1*—High VIX				
LD funds	−0.05	−0.51	0.02	0.44
	(−0.12)	(0.09)	(0.02)	(2.96)
	[13]	[13]	[13]	[13]
LN funds	0.47	−0.24	0.10	0.62
	(1.91)	(0.51)	(0.10)	(3.64)
	[38]	[38]	[38]	[38]
LS funds	1.87	0.85	0.23	0.80
	(4.05)	(1.20)	(0.23)	(4.87)
	[11]	[11]	[11]	[11]
LS − *LD* funds	1.93	1.35	0.22	0.36
	(2.97)	(2.48)	(0.77)	(5.73)
Panel B: Decomposing *ETR1*—Low VIX				
LD funds	0.15	−0.10	0.00	0.25
	(0.58)	(0.01)	(0.00)	(3.35)
	[16]	[16]	[16]	[16]
LN funds	0.44	0.14	−0.04	0.34
	(3.15)	(−0.35)	(−0.04)	(4.59)
	[49]	[49]	[49]	[49]
LS funds	0.50	0.18	−0.12	0.44
	(1.82)	(−1.07)	(−0.12)	(5.19)
	[15]	[15]	[15]	[15]
LS − *LD* funds	0.35	0.28	−0.12	0.19
	(0.92)	(0.85)	(−0.74)	(2.86)

Notes. This table repeats the performance decomposition of Table 6 but now partitions the sample based on whether the VIX is above or below its median value over the 2000–2010 sample period. Reported in parentheses are *t*-statistics. For the *CS* and *CT* measures, standard errors are computed from the time-series standard deviation. For *AS*, standard errors are computed from time-series estimates after clustering by year. In brackets, I also report the number of hedge funds that appear in the portfolio, averaged across all trading days in the sample. The sample in panel A (panel B) includes 1,378 (1,389) trading days over the 2000–2010 sample period.

5. Liquidity Provision and Hedge Funds Returns—Evidence from Commercial Databases

5.1. Measuring Liquidity Provision from Realized Returns

The evidence from transaction data suggests that *LS* funds earn significantly higher returns on their equity trades and holdings than *LD* funds. However, transaction data suffer from a few limitations. First, since transaction data do not include a fund's holdings, nonequity trades, or expenses (i.e., management and incentive fees), *ETR* computed from transaction data may differ significantly from the realized returns that accrue to investors. Second, the ANcerno sample is relatively small and may not be representative of the broader hedge fund industry. Finally, prospective investors generally do not have access to ANcerno data and thus cannot identify *LS* funds using transaction-based measures of liquidity provision. To alleviate the above concerns, in this section, I use the realized returns of hedge funds reporting to two commercial databases, TASS and Barclays, to reexamine the relationship between liquidity provision and fund performance.[25]

I begin by sorting hedge funds into quintiles based on their tendency to supply liquidity. Since I no longer observe a fund's transactions, I measure a fund's tendency to provide liquidity as the fund's beta with respect to the returns to liquidity provision (*RLP*) factor constructed in Jylhä et al. (2014). The factor is the return to a contrarian zero-investment long-short trading strategy that buys stocks with positive expected weekly excess returns, as forecasted based on past daily returns over the prior month, and sells short stocks with negative expected returns.[26] I focus on *RLP* because it closely reflects the short-term reversal strategy that characterizes *LS* hedge funds in the ANcerno sample, and because Jylhä et al. (2014) find that many hedge funds have significant exposure to this factor.

I estimate a fund's sensitivity to the liquidity provision factor (β_{RLP}) using the following time-series regression:

$$R_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + \varepsilon_{i,t}, \tag{8}$$

where $R_{i,t}$ is the net-of-fee excess return of hedge fund i in month t, α_i is the abnormal performance of hedge fund i over the regression time period, $\beta_{i,k}$ is the factor loading of hedge fund i on factor k during the regression period, $F_{k,t}$ is the return for factor k in month t, and $\varepsilon_{i,t}$ is the error term. The regression includes nine factors. The first factor, and the variable of primary interest, is the returns to liquidity provision (*RLP*) factor. To ensure that the loading on *RLP* is distinct from other common hedge fund strategies, I also include the Fung and Hsieh (2004) seven factors. These factors are the S&P 500 return minus the risk free rate (*SNPMRF*); the Wilshire small cap minus large cap return (*SCMLC*); the change in the constant maturity yield of the 10-year Treasury (*BD*10*RET*); the change in the spread of Moody's Baa minus the 10-year Treasury (*BAAMTSY*); and the returns on primitive trend-following strategies for bonds (*PTFSBD*), currencies (*PTFSFX*), and commodities (*PTFSCOM*). I also control for hedge funds' exposure to unexpected marketwide liquidity shocks by including the Sadka (2006) liquidity risk factor (*SADKALIQ*). I estimate regression (8) each year over rolling two-year windows and exclude funds that do not have a complete time series of 24 monthly observations.

I begin by examining the extent to which a fund's β_{RLP} is consistent with *Mom1&5*. 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. As β_{RLP} is measured over a two-year window, I also average the *Mom1&5* over a two-year window. I then merge the ANcerno data with hedge funds in the commercial databases at the management company level. The overlapping sample includes 84 fund-year observations. I find that the correlation between β_{RLP} and *Mom1&5* is −0.36. Since ANcerno primarily captures equity-focused funds, it may be more appropriate to compare the measures for only equity-focused funds in commercial databases (58 fund-year observations). For this subsample, I find a correlation of −0.52. Both correlations are highly significant, indicating that β_{RLP} is a reasonable proxy for a fund's tendency to provide liquidity.

5.2. Characteristics of Liquidity-Supplying Funds in TASS and Barclays

For each year from 1996 to 2013, I compute the fund's first-order serial correlation of returns (*Asset Illiquidity*) and the fund's market beta (β_{SP500}) and adjusted R-squared (*Fund* R^2) estimated from regression (8). I also collect the number of months since the fund first entered the sample (*Age*) and the fund's assets under management (*AUM*). Finally, I collect several time-invariant fund characteristics including *Management Fee*, *Incentive Fee*, the sum of notice and redemption period (*Restrictions*), the minimum required investment (*Minimum Investment*), and dummy variables for whether the fund uses leverage (*Leverage*) or has a high watermark (*High Watermark*). I winsorize all continuous fund characteristics at the 1st and 99th percentiles and convert β_{SP500} to a quintile ranking. To reduce skewness, I also use log transformations for *Minimum Investment*, *Age*, and *AUM*.

Each year, I sort funds into quintiles based on β_{RLP}, estimated from regression (8) over the past two years. I define a fund as *LS* if its β_{RLP} is in the top 20%, and I define a fund as *LD* if its β_{RLP} is in the bottom 20%. The remaining 60% of funds are classified as *LN*. Table 11 reports summary statistics for *LS*, *LN*, and *LD* funds. *LS* funds have higher minimum investments and somewhat higher share restrictions. Aragon (2007) finds that both variables are associated with higher returns because they attract more patient capital, which allows the funds to invest in more illiquid assets. The fact that both variables are also associated with a fund's tendency to provide liquidity suggests another possible channel through which more stable funding can improve performance.

LS funds have more incentivized contracts as evidenced from their higher incentive fees and increased likelihood of having a high-watermark provision. *LS* funds also tend to have lower adjusted R^2, suggesting that they are more likely to hedge systematic risk. Interestingly, incentive fees, high-watermark provision, and a lower R^2have all been shown to predict superior performance (see Ackermann et al. 1999, Agarwal et al. 2009, and Titman and Tiu 2011, respectively). Finally, *LS* funds tend to have lower market betas. This is consistent with recent evidence that the profits from liquidity provision are particularly large during periods of market turmoil (Nagel 2012).

5.3. Liquidity Provision and Realized Returns—Univariate Evidence

I now examine whether funds that tend to supply liquidity outperform in subsequent periods. Specifically, at the beginning of year t, I sort funds into quintiles based on their β_{RLP} estimated over the past two years.

Table 11. Characteristics of Liquidity-Supplying Hedge Funds in TASS and Barclays

	LS	*LN*	*LD*	*LS* − *LD*	*t*(*LS* − *LD*)
Fund-month obs.	38,333	115,177	38,439		
log(*AUM*)	18.31	18.74	18.44	−0.13	(−3.07)
log(*Age*)	4.66	4.65	4.66	0.00	(0.35)
Management Fee	1.46	1.37	1.52	−0.05	(−3.06)
Incentive Fee	17.83	13.19	16.54	1.28	(6.68)
High Watermark	0.82	0.73	0.79	0.03	(2.96)
Leverage	0.59	0.44	0.54	0.04	(2.98)
log(*Minimum investment*)	12.92	12.89	12.70	0.23	(4.80)
Restrictions	118.33	133.94	113.31	5.01	(1.77)
Fund R^2	0.35	0.40	0.39	−0.05	(−5.67)
β_{SP500} *Rank*	2.17	1.78	2.51	−0.34	(−8.64)
Asset Illiquidity	0.03	0.07	0.03	0.00	(0.26)

Notes. This table presents descriptive statistics for the sample of hedge funds reporting to TASS and Barclays. Funds are sorted into groups based on their tendency to supply liquidity. I measure a fund's tendency to provide liquidity as the fund's beta with respect to a liquidity provision factor (β_{RLP}). The variable 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 et al. (2014). Funds are classified as *LS* if their β_{RLP} is in the top 20% and *LD* if their β_{RLP} is in the bottom 20%. All other funds are classified as *LN*. For each group of funds, I report the averages of several fund characteristics. The definitions of fund characteristics are described in the appendix. The fourth column reports the difference in the characteristics between *LS* and *LD* funds. The fifth column tests whether the difference in the fourth column is significantly different from zero. The *t*-statistics, reported in parentheses, are based on standard errors clustered by fund and month.

I then examine the average performance of the portfolio of funds each month in year *t*. I repeat this procedure each year, resulting in 212 estimates of monthly returns, from January 1996 to August 2013.

Table 12 reports the average portfolio returns. Standard errors are computed from the time series using a Newey–West (1987) adjustment with six lags. In the first column, the performance measure is excess return,

Table 12. Realized Returns and Liquidity Provision—Univariate Evidence

	Excess return Spec. 1	Delisting-adjusted excess return Spec. 2	Sharpe ratio (annualized) Spec. 3	Eight-factor alpha Spec. 4	Style-adjusted return Spec. 5	Excess return: high VIX Spec. 6	Excess return: low VIX Spec. 7
1 (*LD* funds)	0.35	−0.72	0.52	0.13	−0.06	0.05	0.62
	(1.49)	(−2.47)	(2.82)	(0.98)	(−0.80)	(0.12)	(2.84)
2	0.30	−0.68	0.83	0.13	−0.09	0.11	0.46
	(1.91)	(−3.08)	(4.14)	(1.54)	(−2.50)	(0.46)	(3.72)
3	0.32	−0.58	1.25	0.20	−0.05	0.16	0.46
	(2.37)	(−2.81)	(5.95)	(3.08)	(−1.16)	(0.75)	(4.57)
4	0.44	−0.45	1.18	0.30	0.03	0.35	0.52
	(3.09)	(−2.18)	(6.03)	(4.32)	(1.00)	(1.58)	(5.03)
5 (*LS* funds)	0.66	−0.30	0.82	0.52	0.17	0.70	0.63
	(3.83)	(−1.25)	(5.96)	(5.09)	(2.77)	(2.57)	(4.17)
LS − *LD*	0.31	0.42	0.30	0.39	0.23	0.66	0.01
	(2.33)	(2.61)	(2.85)	(3.26)	(2.15)	(3.12)	(0.06)

Notes. At the beginning of each year from 1996 to 2013, I rank hedge funds reporting to TASS and Barclays into quintiles based on the fund's tendency to supply liquidity. I measure a fund's tendency to provide liquidity as the fund's beta with respect to a liquidity provision factor (β_{RLP}). The variable 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 et al. (2014). Quintile 1 consists of funds with the lowest β_{RLP} (i.e., liquidity-demanding funds), and quintile 5 consists of funds with the highest β_{RLP} (i.e., liquidity-supplying funds). I hold the portfolio for one year and calculate equally weighted returns. Monthly mean returns (in percent) and Newey and West (1987) *t*-statistics (in parentheses) are reported for each quintile. The first through the fifth columns report the results for five different performance metrics. Excess returns are net-of-fee returns less the risk-free rate. Delisting-adjusted returns are excess returns with the added assumption that funds that delist earn −100% for their last monthly return. The Sharpe ratio is the excess return scaled by the standard deviation of excess returns during the calendar year. The eight-factor alpha is the alpha from the Fung and Hsieh (2004) seven-factor model augmented to include the Sadka (2006) liquidity-risk factor. The style-adjusted return is the return of the fund less the average returns of all funds in the same style. Additional details on style classification are in the appendix. Specification 6 reports excess returns for the 98 months where the VIX index is above its median breakpoint, as defined in Table 9. Specification 7 reports analogous results for the 114 months where the VIX index is below its median breakpoint. The full sample spans 212 months from January 1996 to August 2013. In the average month, each quintile consists of roughly 185 funds.

defined as the net-of-fee realized return less the risk-free rate. The results indicate that *LD* funds earn a statistically insignificant excess return of 0.35% per month, while the corresponding estimate for *LS* funds is a highly significant 0.66% per month. Furthermore, the return difference between the two portfolios, 0.31%, is also significant. The second column reports the results using delisting-adjusted excess returns. Specifically, if a fund drops out of the sample, I replace its last reported return with a return of −100%. This approach is excessively harsh since many funds that delist do not completely liquidate. Nevertheless, comparing delisted-adjusted returns with returns that are completely unadjusted provides a useful upper and lower bound of the potential impact of a delisting bias. The results indicate that accounting for delisting bias increases the spread between *LS* and *LD* funds to 0.42% per month. This suggests that differences in survival rates are unlikely to account for *LS* funds' relative outperformance.

To better control for risk differences across funds, the third column examines Sharpe ratios, defined as the ratio between the average monthly excess return and the standard deviation of excess returns over the calendar year. I require a fund to have 12 monthly returns, and I winsorize Sharpe ratios at the 1st and 99th percentiles. I also annualize Sharpe ratios by multiplying by the square root of 12. *LN* funds tend to earn the highest Sharpe ratios. This may reflect the fact that funds with less concentrated portfolios, and thus less idiosyncratic risk, are less likely to have extreme betas with respect to the liquidity provision factor. Nevertheless, I continue to find that *LS* funds earn significantly higher Sharpe ratios relative to *LD* funds.

In the fourth column, I report alphas from the Fung and Hsieh (2004) seven-factor model augmented to include the Sadka (2006) liquidity-risk factor (hereafter referred to as the eight-factor alpha). The alphas are estimated from one time-series regression of the excess returns of the portfolio on the factor returns. The results indicate that *LS* funds outperform *LD* funds by a statistically significant 0.39%. Since hedge fund returns often exhibit serial correlation, I also consider a smoothing-adjusted alpha that includes the eight factors used in the fourth column, plus a lag of each of the eight factors, and find very similar results (unreported).

The fifth column reports style-adjusted returns, defined as the return of the fund less the average return of all funds in the same style. I merge the different self-reported styles in TASS and Barclays into nine styles: *CTAs*, *Emerging Markets*, *Equity Focused*, *Event Driven*, *Fund of Funds*, *Global Macro*, *Multistrategy*, *Relative Value*, and *Sector*.[27] To the extent that peers within each style have similar liquidity levels and take similar risk, style-adjusted returns help control for serial correlation and option-like features in returns (Jagannathan et al. 2010). Style-adjusted returns are also more appropriate for investors seeking to identify outperforming funds within a given style. The results again indicate that *LS* funds earn significant style-adjusted returns while *LD* funds do not, and the difference between the two estimates is statistically significant.

The sixth and seventh columns report the excess returns of hedge funds during periods where the VIX index is above and below its median breakpoint (as defined in Table 9), respectively. Consistent with the findings from transaction data, I find that the superior performance of *LS* funds is concentrated during periods of more limited funding liquidity. In particular, when the VIX is above its median value, *LS* funds outperform *LD* funds by a statistically significant 0.66% per month. By contrast, there is virtually no difference in performance when the VIX index is below its median value.

5.4. Liquidity Provision and Realized Returns—Regression Evidence

I next examine whether a fund's tendency to supply liquidity can predict returns after controlling for a number of existing determinants of hedge fund performance. Specifically, I estimate 212 monthly cross-sectional (i.e., Fama–MacBeth) regressions of fund performance on a fund's tendency to supply liquidity and control variables. I consider two measures of fund performance: excess returns and Sharpe ratios.[28] The primary variable of interest is β_{RLP} *Rank*, which is the quintile ranking of β_{RLP}. I use the quintile ranking of β_{RLP} because of the significant measurement error associated with estimating fund-level betas. Nevertheless, in untabulated analysis, I find very similar results using the estimated β_{RLP}, winsorized at the 1st and 99th percentiles.

The control variables include all of the fund characteristics reported in Table 11. To control for performance persistence, I also include the fund's past Sharpe ratio. I include the Sharpe ratio, rather than the excess return, to account for the fact that excess returns that are more precisely estimated are better predictors of future performance (e.g., Kosowski et al. 2007, Jagannathan et al. 2010). All continuous variables are standardized, and all regressions include style fixed effects. Thus, tests examine whether liquidity provision helps identify outperforming funds within a given style. Excluding style fixed effects yields similar results (unreported).

Specifications 1 and 2 of Table 13 report the results using excess returns and Sharpe ratios, respectively. The coefficients on the control variables are largely consistent with existing literature. For example, past Sharpe ratios are correlated with future performance

Table 13. Realized Returns and Liquidity Provision—Regression Evidence

	Fama–MacBeth regressions		Panel regressions	
	Excess ret. [1]	Sharpe ratio [2]	Excess ret. [3]	Sharpe ratio [4]
β_{RLP} *Rank*	0.05	0.06	0.07	0.06
	(2.31)	(3.63)	(3.16)	(3.93)
Sharpe Ratio	0.05	0.49	0.06	0.43
	(1.61)	(11.89)	(2.02)	(9.28)
log(*AUM*)	−0.02	0.04	−0.01	0.06
	(−1.27)	(1.56)	(−0.83)	(2.92)
log(*Age*)	−0.03	−0.03	−0.02	−0.03
	(−2.52)	(−2.77)	(−2.10)	(−1.89)
Management Fee	0.03	−0.04	0.02	−0.03
	(1.81)	(−2.68)	(1.34)	(−1.65)
Incentive Fee	−0.01	−0.04	−0.02	−0.04
	(−0.34)	(−2.42)	(−1.18)	(−2.27)
High Watermark	0.05	0.07	0.02	0.04
	(2.21)	(3.29)	(1.69)	(2.67)
Leverage dummy	0.03	0.06	0.04	0.03
	(1.19)	(2.22)	(1.39)	(0.98)
log(*Minimum Investment*)	0.06	0.06	0.05	0.07
	(2.75)	(2.75)	(3.24)	(3.97)
Restrictions	0.03	0.08	0.03	0.10
	(1.59)	(3.80)	(1.37)	(4.02)
Fund R^2	0.01	0.05	0.04	0.09
	(0.22)	(1.72)	(1.79)	(2.68)
β_{SP500}*Rank*	0.07	−0.07	0.05	−0.06
	(1.31)	(−2.65)	(1.09)	(−2.38)
Asset Illiquidity	0.04	0.23	0.12	0.36
	(0.34)	(2.04)	(1.27)	(3.77)
Fixed effects	Style	Style	Time × Style	Time × Style
Average obs./Obs.	905	904	191,911	191,724
Average within R^2/Within R^2 (%)	12.79	14.57	0.18	3.07

Notes. This table reports results from regressions of excess returns or Sharpe ratios on a fund's tendency to supply liquidity and control variables. I measure a fund's tendency to provide liquidity as the fund's beta with respect to a liquidity provision factor (β_{RLP}). The variable 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 et al. (2014). I convert β_{RLP} to a quintile ranking (β_{RLP} *Rank*). 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 and West (1987) 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.

(Jagannathan et al. 2010); older funds underperform (Aggarwal and Jorion 2010); funds with greater investment flexibility, as measured by share restrictions and minimum investments, outperform (Aragon 2007); and funds with stronger incentives, as measured by high watermark provisions, also outperform (Agarwal et al. 2009).[29] Importantly, a fund's tendency to supply liquidity remains incrementally useful in predicting future performance. Specifically, a one-quintile increase in β_{RLP} *Rank* is associated with a 0.05% per-month increase in excess returns and a 0.06 increase in annualized Sharpe ratios. Specifications 3 and 4 repeat the analysis using panel regressions with style-time fixed effects, and standard errors clustered by both fund and time. The estimates from the panel regression are very similar.

Table 14 repeats Specifications 3 and 4 of Table 13 for each of the nine hedge funds styles separately. In the interest of brevity, I only report the coefficient on β_{RLP} *Rank*. I find that β_{RLP} *Rank* is significant in five of the nine styles: *Equity Focused*, *Fund of Funds*, *Multistrategy*, *Relative Value*, and *Sector*, while β_{RLP} *Rank* is positive but insignificant in the remaining four styles (*CTAs*, *Emerging Markets*, *Event Driven*, and *Global Macro*). The significant relation among *Equity Focused* funds is consistent with the ANcerno data that focus exclusively on equity trading. The significant relation among *Fund of Funds* is reassuring, since many of the biases associated with hedge fund returns are likely to be less severe for funds of funds (Fung and Hsieh 2000). Collectively, the evidence from Tables 12–14 suggest that β_{RLP} *Rank* is a useful predictor of fund performance.[30]

Table 14. Realized Returns and Liquidity Provision by Hedge Fund Style

	Excess return		Sharpe ratio	
	Obs.	Coeff.	Obs.	Coeff.
1. All styles	191,911	0.07	191,724	0.06
		(3.16)		(3.93)
2. *CTAs*	7,620	0.03	7,615	0.03
		(0.63)		(0.95)
3. *Emerging Markets*	16,205	0.11	16,173	0.02
		(1.73)		(0.92)
4. *Equity Focused*	53,248	0.07	53,207	0.05
		(2.67)		(3.18)
5. *Event Driven*	18,133	0.00	18,119	0.02
		(0.04)		(0.72)
6. *Fund of Funds*	57,860	0.06	57,805	0.05
		(2.62)		(1.93)
7. *Global Macro*	6,527	0.02	6,519	0.02
		(0.56)		(0.77)
8. *Multistrategy*	8,419	0.09	8,415	0.14
		(2.04)		(3.81)
9. *Relative Value*	13,501	0.09	13,477	0.14
		(3.14)		(3.72)
10. *Sector*	10,398	0.14	10,394	0.11
		(3.15)		(3.32)

Notes. This table reports results from regressions of excess returns or Sharpe ratios on a fund's tendency to supply liquidity and control variables. I measure a fund's tendency to provide liquidity as the fund's beta with respect to a liquidity provision factor (β_{RLP}). The variable 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 et al. (2014). I convert β_{RLP} to a quintile ranking (β_{RLP} *Rank*). The regression includes the same control variables as reported in Table 13 but reports only the coefficient on β_{RLP} *Rank*. Estimates are based on panel regressions with t-statistics (in parentheses) computed from standard errors clustered by fund and month. Row 1 reports the results across all hedge fund styles. Rows 2–10 repeat the analysis for nine hedge fund styles. Additional details on style classifications are in the appendix. The sample includes funds that report to TASS and Barclays and spans from January 1996 to August 2013.

6. Conclusion

This paper offers a first look at whether liquidity-supplying funds earn superior returns. Using transaction-level data, I show that funds that engage in greater amounts of short-term contrarian trading (i.e., liquidity provision) earn significantly higher returns on their equity trades and holdings. The superior returns are not simply a consequence of mechanical reversal strategies but instead largely reflects liquidity provision skill. For example, holding past returns constant, liquidity-supplying funds are more likely to trade against stocks heavily traded by constrained mutual funds and less likely to trade against stocks experience heavy trading pressure from unconstrained funds. The outperformance of liquidity-supplying funds is also concentrated during periods of limited funding liquidity, which suggests that a fund's tendency to provide liquidity is a useful proxy for the fund's financing constraints.

While the transaction data used in this study provide a unique opportunity to better understand the mechanisms through which liquidity-supplying hedge funds outperform, the data are not without their limitations. In particular, the transaction data rely on a relatively small sample of hedge funds and offer a noisy proxy for the realized returns that accrue to investors. I address these concerns by conducting out-of-sample tests using the net-of-fee realized returns of nearly 4,000 hedge funds reporting to TASS and Barclays. I confirm that funds that tend to follow liquidity provision strategies, as measured by a fund's beta with respect to a liquidity provision factor, earn significantly higher excess returns and Sharpe ratios. The superior performance of liquidity-supplying funds holds after controlling for a number of factors known to explain hedge fund performance, including share restrictions, minimum investments, high watermarks, asset illiquidity, and past performance. Overall, the findings suggest that a fund's tendency to provide liquidity offers incrementally valuable information to investors seeking to identify better-performing funds.

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Appendix. Variable Definitions

Stock Characteristics

Note that all stocks 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.
- *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 30 divided by market capitalization on December 31 of the same fiscal year. Estimated for the fiscal year prior to the year of the trade.
- *IVOL*: the square root of the mean squared residual from an annual regression of a firm's daily returns on the return on the market (value-weighted CRSP index). Computed in the year prior to the year of the trade.

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). A more detailed definition is provided in Section 3.3.
- *EHR*: equity holding returns; the DGTW-adjusted returns on a fund's long holdings less the DGTW-adjusted returns on the funds 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). A more detailed definition is provided in Section 3.3.
- *Age*: the total number of days the fund first reported to ANcerno.
- *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 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.
  - 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. *Actual/Implied* would thus be 1.31 ($170,000/$130,000).
- *Pct_Volume1*: *Holdings Size1*/*Holdings Size*. This measure is computed for all fund-days in which the fund has been in the ANcerno sample for at least one year.
  - Suppose a fund purchased 200 shares of Microsoft on January 30, sold 100 shares of Microsoft on June 30, and sold 50 shares of Apple on July 27. If the price of Apple on July 30 is $100 and the price of Microsoft is $50, then the total value of the fund's long holdings is $500 ((200 − 100) × 50), and the total value of its short holdings is $500 (50 × 100), resulting in total holdings value (i.e., *Holdings Size*) of $1000. As the positions in Microsoft were established more than 21 trading days ago, the total value of the fund's holdings due to trades in the prior month is $500 (i.e., *Holdings Size1*). This would result in a *Pct_Volume1* of 50% ($500/$1000).
- *Plan Sponsor*: a dummy variable equal to 1 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 0 for hedge funds that enter the sample because they directly hire ANcerno (i.e., *Money Manager*).
- *Money Manager*: a dummy variable equal to 1 if the hedge fund directly subscribes to ANcerno. This value is set to 0 for hedge funds that enter the sample because they manager money on behalf of a plan sponsor who subscribes to ANcerno (i.e., *Plan Sponsor*).
- *Com/Share*: the dollar volume paid in commissions scaled by total share volume traded (reported in cents).
- *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. For each fund-year, I compute a fund-level measure of *Shortfall as* the principal-weighted average *Shortfall* of stocks purchased less the principal-weighted average *Shortfall* of stocks sold.

Fund Characteristics Obtained from TASS and Barclays Data

- *Excess Return*: the fund's net-of-fee monthly return less the risk-free rate.
- *Delisting-Adjusted Excess Return*: excess returns with the added assumption that funds that delist earn −100% for their last monthly return.
- *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 percentiles.
- *Eight-Factor Alpha*: The alpha of a portfolio estimated from one-time series regression (from January 1996 to August 2013) of the portfolio's excess return on the Fung and Hsieh (2004) seven factors plus the Sadka (2006) liquidity-risk factor.
- *Smoothing-Adjusted Alpha*: The alpha of a portfolio estimated from one time-series regression (from January 1996 to August 2013) of the portfolio's excess return on the Fung and Hsieh (2004) seven factors plus the Sadka (2006) liquidity-risk factor, and the lagged monthly return of the each of the eight factors.
- *Style-Adjusted Return*: the return of the fund less the average return of all funds in the same style.
- β_{RLP}: a fund's beta with respect to the liquidity provision factor of Jylhä et al. (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 Watermark*: a dummy variable that equals 1 if the fund has a high-watermark provision.
- *Leverage*: a dummy variable equal to 1 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 et al. (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 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 of Jylhä et al. (2014) over two-year rolling windows.
- *Asset Illiquidity*: the first-order serial correlation of a fund's returns.
- *Hedge Fund Styles*: Specific strategies listed in TASS and Barclays are mapped into the following nine broad hedge fund styles:[31]
  - *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
  - *Multistrategy*: balanced (stocks and bonds), multiadvisor, multistrategy, 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.

Endnotes

[1] See http://www.barclayhedge.com/research/indices/ghs/mum/HF_Money_Under_Management.html (accessed February 7, 2014).

[2] Nagel (2012) constructs a model that shows that the returns from contrarian (or reversal) strategies closely track the returns earned by liquidity providers. Studies that relate liquidity provision to contrarian trading over a one-day, one-week, and one-month horizon include Khandani and Lo (2011), Lehmann (1990), and Jegadeesh (1990), respectively.

[3] The sample ends in 2010 because later vintages do not include manager identifiers. Other papers that use ANcerno include Anand et al. (2012, 2013), Green et al. (2014), Jegadeesh and Tang (2010), Puckett and Yan (2011), and Franzoni and Plazzi (2015).

[4] ANcerno provides an additional variable, *Clientmgrcode*, which does vary within a client–manager pair. However, discussions with ANcerno representatives indicate that different *Clientmgrcodes* within a client–manager pair generally do not reflect different fund products. For example, if a plan sponsor hires Alliance Bernstein and reports the fund as "Alliance Bernstein" in one period and "Alliance Bern" in another period, ANcerno will assign two different *Clientmgrcodes.*For this reason, ANcerno provides a separate reference file that maps different *Clientmgrcodes*into one consistent manager code.

[5] Equity funds include equity long-only, equity long-bias, equity long/short, and equity market-neutral.

[6] Funds that average less than five equity trades per quarter could be equity focused and just have very low turnover. Dropping such funds is still useful since the performance of these funds is likely to be heavily influenced by the funds' holdings prior to joining ANcerno (which are not observable), rather than their trading. In the Internet appendix, I confirm that my main results are robust to including nonequity funds in the sample.

[7] Note that profits from liquidity provision are conceptually (and empirically) different from profits from liquidity risk. Profits from liquidity risk reflect the excess return from holding stocks that are exposed to aggregate shocks in the level of liquidity (Sadka 2010), while profits from liquidity provision reflect the returns from providing immediacy (Grossman and Miller 1988). Empirically, the returns from liquidity risk and liquidity provision are negatively correlated (Jylhä et al. 2014). For example, during the 2008 financial crisis, the returns on stocks with high liquidity risk declined (Sadka 2010), while the returns to liquidity provision increased (Nagel 2012).

[8] Quoted in *FINalternatives* (2014).

[9] This measure focuses on liquidity provision within equities and thus abstracts from the potentially important role of liquidity provision across asset classes (e.g., moving from cash to equities during the recent financial crisis).

[10] For example, Coval and Stafford (2007) highlight that mutual fund flow-induced price pressure takes 18 months to fully reverse, and Froot and Dabora (1999) show that strategies that attempt to take advantage of price differentials on "Siamese Twin" stocks can take several years to fully correct. More generally, Frankel and Lee (1998) show that mispricing, as estimated from a discounted residual income model, can forecast future returns for horizons of at least three years, and Kokkonen and Suominen (2015) provide evidence that hedge funds help correct this mispricing.

[11] Seasholes and Zhu (2010) emphasize the benefits of calendar-time portfolios relative to other approaches.

[12] In a few cases, managers appear to exit and reenter ANcerno. In cases where a fund does not make any trades in ANcerno for more than two consecutive quarters, I assume that the fund has left ANcerno. If the fund later appears, I compute holdings as if it were a new fund.

[13] I find that *ETR* does not exhibit significant serial correlation. For example, the first-order autocorrelation of *ETR1* and *EHR* for hedge funds is −0.02 ($t = -1.07$) and −0.03 ($t = -1.47$). Thus, computing standard errors from the time-series standard deviation should lead to unbiased standard errors (Petersen 2009). In unreported tests, I also compute the standard errors using a Newey–West adjustment with six lags and find virtually identical standard errors.

[14] I thank Russ Wermers for providing the benchmark classifications. The DGTW benchmarks are available at http://alex2.umd.edu/wermers/ftpsite/Dgtw/coverpage.htm (accessed June 3, 2013).

[15] Examples of such papers include Daniel et al. (1997), Wermers (2000), Chen et al. (2000), Alexander et al. (2007), Griffin and Xu (2009), and Puckett and Yan (2011).

[16] Persistence in *ETR1* is stronger before controlling for a fund's tendency to demand or supply liquidity. Specifically, after omitting the *LD*, *LN*, and *LS* dummies, the coefficient on *Past ETR1* increases to 0.15 ($t = 3.08$).

[17] Consistent with this view, in the Internet appendix, I find that *Mom1&5* classification is more strongly correlated with providing liquidity to fire sale and fire purchase stocks (as defined in Coval and Stafford 2007) than *Shortfall*.

[18] $ETR1_{\mathrm{ALL}}$ differs slightly from the *ETR1* computed in Figure 1 because offsetting trades that occur across different trading styles no longer counteract each other. For example, if a fund made an *LS* purchase of 100 shares of IBM on January 5 and an *LD* sale of 100 shares of IBM on January 10, the computation of *ETR1* on January 11 would not include any holdings of IBM while the computation of $ETR1_{\mathrm{ALL}}$ would include holdings of 100 shares of IBM in both the *LS* buy and the *LD* sell portfolio. The correlation between $ETR1_{\mathrm{ALL}}$ and *ETR1* across fund-days is 99.23%, indicating that this distinction is not significant.

[19] Note that this approach uses forward-looking information. Given that the objective of this analysis is to simply understand the source of the superior *ETR1*, the use of forward-looking information is not problematic.

[20] The *AS* measure has no within-fund variation during a trading year. Thus, in computing the standard errors for the *AS* measure, I cluster by year. I continue using Fama–MacBeth standard errors for the *CS* and *CT* components.

[21] For example, a mechanical short-term reversal strategy would not distinguish between stock prices falling because mutual funds are voluntarily selling for informational reasons versus forced selling to meet investor redemptions. Similarly, some stocks experiencing flow-induced selling pressure will have announced strong positive fundamental news. Such stocks might have positive returns (i.e., a high *Mom1&5*) but could be underpriced because of selling pressure.

[22] Consistent with Alexander et al. (2007), in untabulated analysis, I find that *voluntary* is positively associated with future returns.

[23] The contrarian nature of voluntary trades is likely a consequence of fund flows chasing performance. Voluntary sales are, by definition, made by funds experiencing inflows. Funds experiencing inflows are likely to have recent good performance, resulting in voluntary sales being more contrarian. Similar reasoning holds for voluntary purchases.

[24] Following Engelberg (2008) and Bradshaw et al. (2014), I use Factiva's Intelligent Indexing to match firms and news and require the firm's name to appear at least once in the article to ensure the accuracy of the matching. Following Tetlock (2011), I exclude news articles with fewer than 50 words.

[25] A third data source that could be used to evaluate the performance of hedge funds is 13F stockholdings (see, e.g., Griffin and Xu 2009). In the Internet appendix, I find that inferences based on 13F data are consistent with the findings from transaction data and commercial databases.

[26] I thank Petri Jylhä, Kalle Rinne, and Matti Suominen for sharing data on the liquidity provision factor. More details on the construction of the factor can be found in Suominen and Rinne (2011) and Jylhä et al. (2014).

[27] The appendix provides more details about the style classifications.

[28] Using delisted-adjusted returns instead of excess returns yields slightly stronger results.

[29] One exception is that *Fund* R^2 is positively associated with performance, which is inconsistent with the evidence in Titman and Tiu (2011). When I limit the sample to the 1996–2005 period analyzed in Titman and Tiu (2011), I also find a negative relationship. However, this pattern reverses in the post-2005 period.

[30] In the Internet appendix, I present evidence that funds with higher β_{RLP} *Rank* do experience modestly higher net flows after controlling for a number of known determinants of hedge funds flows. This points to the possibility that some investors already recognize the superior performance associated with *LS* funds.

[31] If a more narrow strategy (e.g., emerging markets – Eastern Europe/CIS) is clearly a subset of a broader strategy (e.g., emerging markets), I list only the broader strategy.

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