Internet Appendix

Do Hedge Funds Provide Liquidity? Evidence From Their Trades

This Internet Appendix supplements the material in the paper with additional results and provides further details on our analysis. The plan of the Appendix is as follows. Appendix A outlines the procedure we use to identify hedge fund management companies in the Ancerno dataset. In Appendix B, as a validation of our matching procedure, we assess the extent to which the hedge fund trades in Ancerno capture variation in the quarterly holdings of the institutions that file the 13F form. We also show that the information on hedge funds' interim trading activity that emerges from Ancerno by far exceeds the snapshot one can gather from the quarterly filings. In Appendix C, we look at the characteristics of the hedge funds for which we have trades in Ancerno and that report to TASS. We show that the proportion of funds in Ancerno that fall in the quintiles of the distribution of TASS with respect to several characteristics, such as assets under management and flows, is rather evenly split. This means that hedge funds in Ancerno are representative of the hedge fund industry, as portrayed in TASS, across several dimensions. Appendix D shows that our main conclusions remain unaltered if we use weekly, instead of daily data. In Appendix E, we explore an additional way of controlling for stock type that consists of restricting the sample to stocks in the top market capitalization decile. Appendix F examines time variation in the volume of hedge fund trades. Appendix G looks at total returns to constrained and unconstrained funds to check whether constrained funds accept a loss in their trades in US stocks because they chase profitable opportunities in other asset classes. We do not find evidence in this direction. Finally, Appendix H replaces the trading cost measure that we use in the paper with those based on alternative price benchmarks. The results are unaltered. In the same Appendix, we examine the correlation of price impact measures of liquidity provision with those based on reversal strategies and find that these correlations are significant.

A Identification of hedge funds in Ancerno

We first describe the structure of Ancerno data and the specific identifiers used in our empirical analysis. Additional information on the variables contained in Ancerno can be found in the Appendix of Puckett and Yan (2011). Next, we detail the sources for hedge funds data that we use for the identification.

Ancerno obtains transaction data from its clients, which submit this information in "batches".

While Ancerno does not release the identity of the clients, a unique identifier (*clientcode*) is assigned to all trades belonging to a given client. A self-reported code (*clienttype*) is also provided that distinguishes clients among pension plan sponsors, money managers, and brokers.

In the data submitted to Ancerno, the clients specify the management company (i.e. the "manager") that is in charge of their funds. In some cases, the client corresponds to the manager, that is, the management company is submitting its own trading data through its Order Delivery System. Conversations with Ancerno representatives suggest that this is the case for many money managers. When client and manager differ, as is the case for example when the client is a pension plan sponsor, Ancerno typically receives the trade-data from their custodian bank. Although client names are not disclosed, manager names are released to us (variable *manager*). A unique identifier (*managercode*) allows us to group all trades that are being executed by the same company, even across clients. The manager name is the key variable for our identification of hedge fund management companies in Ancerno.

Ancerno assigns a number (*clientmgrcode*) to distinguish different positions a client may hold with the same manager. This is because the clients usually find it convenient when reporting to Ancerno to break down their relation to a manager into several categories. As an example, the combination of *clientcode* 12 and *clientmgrcode* 347324 is associated to *managercode* 316. This triple identifies a specific position that is managed by Pimco Advisors (*managercode* 316) on behalf of client "12", whose identity is unknown.[1] The same client may report other positions with the same manager that are marked by a different *clientmgrcode*. When manager and client coincide, these positions correspond most probably to different funds within the same family. However, because the client name is not revealed, we cannot assess when this is the case, nor have accurate information on the name of the individual fund that manages these positions. For this reason, we aggregate all trades at the management company level, which represents our unit of interest. This aggregation is suitable for hedge funds as the number of individual funds within each family is rather small. In line with this argument is the evidence that the average monthly number of different *clientcode-clientmgrcode* combinations per hedge fund manager is about 4 and equals 1 in one third of the months of the sample. In comparison, the same average calculated on non-hedge-fund managers in

[1] This example corresponds to an actual combination in Ancerno but is made just for illustrative purposes. In fact, Pimco Advisors does not enter our final dataset as it is not classified as a hedge fund.

the dataset is substantially higher at 49.

To identify hedge fund management companies in Ancerno, we manually match the list of manager names in Ancerno with two sources, following the procedure in Ben-David, Franzoni, and Moussawi (2012). The first source is a proprietary list of hedge fund managing firms that is compiled by Thomson Reuters based on 13F filing and is supplemented with ADV filings and industry listings. This list includes only institutions with investments above $100 million in qualified securities at the end of the year (mainly public equity, convertible bonds, and options) that are therefore required to file mandatory 13F reports to the SEC. By manual inspection of the company websites and by use of the ADV filings (see Ben-David, Franzoni, and Moussawi (2012)), these institutions only include "pure-play" hedge funds, that is, investment companies whose main line of operation is the hedge-fund business. This condition excludes some large institutions and investment banks that are present in Ancerno but that provide a wide range of other investment and asset management services. Further details on the filtering process can be found in Ben-David, Franzoni, and Moussawi (2012).

The second source for hedge funds names is the Lipper/TASS database. We use the last available tape that includes December 2010 data in the empirical analysis, while the identification exploits an early version of the file containing hedge fund management company names. In the matching, we look at both the "Graveyard" and "Live" databases. With respect to 13F filings, the set of hedge funds that are present in TASS is potentially larger as these are not restricted to having positions larger than $100 million. Moreover, information is available on a monthly basis, which leaves us with a sufficient number of observations for the cross-sectional analysis.

Of the 87 hedge fund management companies collectively identified using the two sources, 25 of them appear in both datasets, 22 appear only in 13F filings, and the remaining 40 are present only in TASS. Table A provides the distribution of the number of days on which the different companies report to Ancerno. The average fund is present in the dataset for 731 days (which is about 2.9 years, if we allow for 250 trading days in a year). The least represented hedge fund reports for just two days, while the most represented fund is there for about the entire twelve-year period. The median fund reports for about 1.7 years.

B Comparison to 13F filings

Focusing on the subset of Ancerno hedge-fund management companies that we match to the 13F filings, for each company-quarter, we compute the stock-level net trade. That is, if a given company within a given quarter buys 10,000 shares of IBM and then it sells 4,000 shares of IBM, the net trade in IBM for this fund-quarter is 6,000 shares. Then, using the 13F data for the same set of company-quarters, we compute the stock-level changes in holdings. Pooling all stock-quarter changes in holdings across all funds, we find that the correlation between the net changes in holdings from the two databases is 0.58. We consider this large number as rather reassuring on the validity of our matching procedure.

Even if the management companies in the two databases are correctly matched, and assuming that all the trades of a given manager are reported, the correlation between the changes in holdings in the 13F and the net trades in Ancerno can be less than perfect for two reasons. First, only a subset of the managers within a management company may be reporting to Ancerno. In such a case, we would be observing only the trades of a subset of the funds that operate under the umbrella of the management company. Second, some managers may report to Ancerno only within a subperiod during the quarter. That is, they could start reporting well after the beginning of the quarter, or they could disappear from the database before the end of the quarter. To control for this possibility, we recompute the correlation focusing on the institutions that report their trades to Ancerno at least in the first and in the last week of the quarter. For the subset of company-quarters that satisfy this condition, the correlation rises further to 0.60.

A different question concerns the amount of interim trading of hedge funds that is neglected by using the quarterly changes in holdings, such as those that are reported in the 13F filings. We infer this information from the comparison of the total company-level quarterly volume with the company-level net trades within a quarter. The first quantity results from the aggregation of the dollar trades in all stocks and accounts for the interim volume. For example, for a company that buys $20,000 of IBM and then sells $10,000 of IBM, and buys $40,000 of Apple and later on sells $50,000 of Apple, the total quarterly volume is $120,000. The second quantity results from aggregating at the fund level the stock-level net trades within the quarter; this measure replicates the net changes in holdings that can be inferred from the 13F filings. Sticking with the last example, the company-level net volume is \$20,000 (notice that when the stock-level net dollar trade is negative, we take its absolute value before aggregating at the company-level). For all company-quarters, Table A reports the distribution of the ratio of total volume to the net volume. We notice that on average total volume is about twice the net volume. This figure suggest that, for the average hedge fund management company, interim trading activity is likely to be largely understated if one only focuses on the net trades that result from the 13F filings. For the median company, the interim volume exceeds the net changes in holdings by about 25%. The distribution of this ratio is highly positively-skewed as a consequence of extreme right-tail observations (notice that the maximum for this ratio is about 670).[2]

C Comparison to TASS

For the subset of Ancerno institutions that we match to TASS, we can relate hedge funds' trading activity to hedge fund characteristics. The intersection of Ancerno and TASS yields a sample of 54 hedge fund management companies for which the period of TASS reporting overlaps with a period in which trades are also present in Ancerno, for a total of 2,267 company-month observations.[3]

From TASS, we construct the following set of variables that are aggregated across all funds belonging to the same family, thus conforming to the nature of our trade data. Returns, lockup period, redemption notice period, redemption frequency, amount of leverage in place (Leverage) are all calculated as asset-weighted averages of the corresponding individual funds' values. The AR(1) coefficient is then computed on the family-level returns. A fund' age is proxied by the number of months a management company has been reporting to TASS since 1994 (when the graveyard dataset becomes available). Following the literature standard, dollar flows in month t for a hedge fund family i are computed as $Flow_{i,t} = \sum_{j \in i}[AUM_{j,t} - R_{j,t}AUM_{j,t-1}]$, where $AUM_{j,t}$ represents asset under management for fund j within family i at the end of month t, and $R_{j,t}$ is its gross return on net asset value (NAV) between month $t-1$ and t. Relative flows are then calculated

[2] Jame (2012) computes a similar ratio and finds that interim activity amounts on average to a much smaller fraction of the quarterly changes in holdings. We believe that the difference in our results stems from our aggregation of the volume at the company-level, whereas Jame reports stock-level ratios. Reporting at the stock-level over-represents stocks that have negligible trading volume. In the company-level aggregation that we perform, these stocks have very little impact on the final ratio that we report.

[3] Notice that for the identification of hedge funds using TASS company names we do not impose the condition that TASS reporting overlaps with a period of reporting to Ancerno. This explains why, without this condition, the number of identified hedge fund management companies from TASS increases to 65.

as $Flow_{i,t} = \$Flow_{i,t}/AUM_{i,t-1}$, with $AUM_{i,t-1} = \sum_{j \in i} AUM_{j,t-1}$ denoting total assets for hedge fund i.

Panel A of Table C.1 displays summary statistics for the group of hedge funds in Ancerno that report to TASS, during the common period that is used in Tables 9 and 11. The average hedge fund has assets under management in the order of $221 million, with an annualized return of about 5.4% and an average positive flow of about 4.3% per annum. Funds are characterized by restrictions to redemptions in the form of lockup period (about 5 months on average), redemption period (37 days), and redemption frequency (about half-year). The average amount of leverage is about 80%, but the distribution is highly skewed with a maximum of 1600%. In our analysis, we winsorize the variable at the 99% to prevent exceptionally highly leveraged funds to exert undue influence. Finally, the average fund in Ancerno has been present in TASS for about seven years.

We next contrast the funds in Ancerno to the whole TASS universe. We do so by assigning all hedge funds in TASS to quintiles, separately for each month and characteristic. Next, we report in Panel B of Table C.1 the fraction of fund-month observations that belongs to each quintile. If the set of funds in Ancerno were a perfectly random sample from TASS, we would expect the percentage of funds falling in each quintile to be exactly 20%. As we can see, the distribution with respect to the AR(1) coefficient and flows lines up almost exactly with that in TASS, with observations in each quintile accounting for about 20% of the total. Hedge funds in Ancerno tend to be somewhat bigger and less performing in terms of returns compared to the whole TASS, although no quintile contains less than 13% of the observations. The distribution of age is, instead, strongly titled toward older funds.[4]

In Panel C, we show the distribution of the funds' investment styles. At the management company level, the style variables are constructed as the asset-weighted averages of fund-level style dummies. As an example, if a management company runs one fund classified as 'Long/Short Equity Hedge' that accounts for 70% of its AUM and an 'Equity Market Neutral' fund that accounts for the remaining 30%, we assign a value of 0.70 to the 'Long/Short Equity Hedge' style variable and a value of 0.30 to the 'Equity Market Neutral' variable for the same firm. As a result, the value of the

[4]We do not look at the remaining variables (redemption notice period and frequency, leverage, lockup period) because their distribution tends to cluster around some values, thus rendering quintile assignment impossible. As a matter of comparison, the leverage amount in TASS is lower than for our sample of funds at about 50%, but again with a large standard deviation of 118.60.

style variables may vary over time for a given company due to variation in the percentage of total AUM accounted for by the individual funds within the firm. In the table, we report the average across all months in the sample separately for the funds in Ancerno and for the TASS universe.

The large bulk (about 55%) of the funds that are matched to Ancerno are classified as 'Long/Short Equity Hedge'. The same category also stands out as the most relevant in the TASS universe, although with a much lower fraction of about 28%.[5] The second most represented category is 'Convertible Arbitrage', which accounts for 15.80% of the funds. Compared to TASS, funds in Ancerno are understandably titled toward styles that invest in equities, the sole exception being 'Fixed Income Arbitrage' (13.24%).[6] Therefore, it is not surprising that virtually no funds fall in the 'Fund of Funds' category (that accounts for about 23% of AUM in TASS) or in styles involving large use of derivatives such as 'Managed Futures' and 'Options Strategy'.

Finally, we address the concern that funds may contact Ancerno to monitor their costs precisely because they are experiencing a deterioration in their performance. We therefore look at the performance as recorded in TASS in the twelve months prior to the first month in which funds enter Ancerno, and in the twelve months after they stop appearing in Ancerno. Since the entry date changes across funds, and management companies differ in their risk exposure, we adjust fund returns by subtracting the equally-weighted average return to funds in the same style on a given month. The results are presented in Table C.2. Only two out of 24 months have a statistically significant average return, and there are no particular trends in performance in the months leading to the entry in Ancerno, nor in the months after they exit the sample.

D Weekly regressions

Our main results in the body of the paper are based on daily regressions. We focus on daily observations as the trade-level data allow us to track high-frequency changes in liquidity provision. On the other hand, our funding liquidity proxies are rather persistent and daily trading cost measures may be rather noisy. Therefore, whether lower frequency data allow a better identification of the effects we are after is ultimately an empirical question. We investigate this issue by estimating our

[5]This evidence is consistent with Lo (2007) who reports that the 'Long/Short Equity Hedge' style was the most numerous in TASS in virtually all years there considered.

[6]This presence is due to the fact that we aggregate styles at the management company level.

main regressions on weekly data where we average daily trading costs to a given manager within a given week. Results are presented in Table D. Panel A reports the estimates for the regression of equation (1) relating volume-weighted (left block) and equally-weighted (right block) trading costs to lagged funding liquidity variables, plus an autoregressive term. These estimate are similar in magnitude to those reported in Table 4 of the paper, which uses daily data. For example, the loading on the liquidity factor PC is virtually the same for volume-weighted costs (2.618 versus 2.616), and is around 2 for the equally-weighted series (1.943 versus 2.176). The statistical significance is also high, with all t-statistics exceeding the 1% critical value, but it is somewhat lower on average with respect to the figures in Table 4. This evidence suggests that using daily observations allows to capture some additional information that is averaged out at the weekly frequency. In Panel B of D, we present the estimates of equation (2) where we contrast hedge funds and other institutions liquidity provision. The results again confirm the claim that hedge funds' trading costs increase more sharply following periods of tight capital availability than those of other institutions. The coefficients have all the expected sign, and are strongly statistically significant.

E Controlling for stock type

As an alternative to including value-weighted controls for stock type, we also look at the predictability of trading costs for stocks with similar liquidity characteristics. That is, we re-estimate the model in equation (2) but restrict the sample to trades in stocks belonging to the top decile by market capitalization. The rationale for this test is that conditioning on stocks with a high level of liquidity filters out across-stock differences in liquidity. If our results are only driven by portfolio composition, we should not observe any predictable difference in the price impact faced by the two groups of investors when trading on equally liquid stocks.

The results in Table E show that much of the effect that we document in the paper also holds for trades in large stocks. Focusing on the interaction coefficients reported in the first row, the coefficient on the market is again negative and strongly significant and, at -1.611, it is larger than the -1.382 value in Table 4. The impact of VIX and TED spread is almost unchanged. Only in the case of LIBOR do we find a smaller and insignificant coefficient (the p-value is 0.11). The loading on the principal component PC is positive at 3.043 and largely significant, thus confirming the evidence that hedge funds trading costs are significantly more sensitive to funding liquidity than those experienced by other institutions, even controlling for stock type.

F Time-variation in volume

Hedge funds may incur in higher trading costs in bad times if they trade in larger sizes. This could happen, for example, if hedge funds were forced to unwind their positions through large orders in order to meet capital calls. This increased volume would negatively affect their trading performance, as large volumes are typically executed at worse prices. Table F reports the results for the regression of the daily log volume (left panel) and the daily log volume per trade (right panel) on the aggregate funding liquidity determinants, plus a lagged term.

Total volume is significantly related to LIBOR (with a negative sign) and to the TED spread (with a positive sign). The coefficient on LIBOR is large and strongly significant, and contradicts the story that higher total volume increases following adverse market conditions. Rather, it is consistent with the evidence in Anand, Irvine, Puckett, and Venkataraman (2013) that investors withdraw liquidity in periods of tight funding conditions by decreasing their stock market participation. Volume per trade is instead increasing in LIBOR and in market downturns, but decreases following periods of high VIX. The coefficients on VIX is the largest in absolute value. This probably explains why the combined effect of funding liquidity shocks, as captured by the principal component PC, is small but significantly negative. We conclude that increases in trading volume do not appear to be behind the observed rise in trading costs for hedge funds during times of tighter funding liquidity.

G Total returns and fund constraints

We find that the trade performance of constrained hedge funds worsens following tighter funding conditions. This evidence, however, may be consistent with an alternative explanation according to which constrained funds close their positions in U.S. equities at a loss (due to price pressure) to take advantage of profitable opportunities in other asset classes, which are not covered by Ancerno data. We investigate this possibility by looking at the monthly return from TASS which pertains to the whole portfolio of the fund, including assets other than U.S. equity. We compute the average return, separately for constrained and unconstrained funds, separately for months in ten deciles of the funding liquidity factor, PC. The first row of Table G reports the results for constrained funds. These funds experience severe losses during periods of high PC, with an average return of -2.59% and -3.89% in months where PC falls in the ninth and tenth decile, respectively. Unconstrained funds appear, in contrast, to be suffering smaller losses in correspondence to the same periods, with average returns (reported in the second row) of -1.58% and -2.40%, respectively. These differences are economically speaking large, although there is substantial time-series and cross-sectional variability.[7] Therefore, we conclude that constrained funds appear to be losing in periods of tight funding constraints at the overall portfolio level. This appears in contradiction with the conjecture that constrained funds voluntarily close down their positions in stocks to profit from opportunities in other markets.

H Alternative Measures of Liquidity Provision

Our analysis is based on trading costs obtained from comparing the execution price to the VWAP. However, analogous conclusions obtain when contrasting the trade execution price to either the price observed at the time the order was placed, or the opening price of the day on which the order was entered. Tables H.1 to H.4 contain estimates of the main Tables in the paper using these alternative benchmark prices. We see that hedge funds liquidity provision is sensitive to changes in funding liquidity (Table H.1), much more so than for other investors (Table H.2). The effect of a tightening in funding conditions is stronger for constrained funds (Table H.3), and is not a crisis-only phenomenon (Table H.4). In short, our findings are not driven by the particular choice of VWAP as benchmark price.

We also consider measures of liquidity provision other than price impact. As a first alternative, we focus on the dimension of liquidity provision that underlies reversal strategies, such as those in Lo and MacKinlay (1990) and Nagel (2012). To measure the extent to which hedge funds in Ancerno behave as liquidity providers, we compute the proximity of the actual hedge fund trades to the trades that are predicted by a reversal strategy. A reversal trade is defined as one that buys/sells a stock with a negative/positive market adjusted return over the prior K days (with

[7] Cumulating the 9th and 10th deciles, the difference between the average return to constrained and unconstrained funds is -1.11% with a t-statistic of -1.74.

$K = 1, 2, 3, 4, 5, 10$). Similarly to Nagel (2012), the weight $w^{rev}_{s,t}$ in each stock s according to the reversal strategy is:

$$w^{rev}_{s,t} = \frac{1}{K}\sum_{k=1}^{K}\left(\frac{-(R_{s,t-k:t-1} - \overline{R}_{t-k:t-1})}{1/2\sum_{s=1}^{N_t}|R_{s,t-k:t-1} - \overline{R}_{t-k:t-1}|}\right) \tag{1}$$

where N_t is the number of stocks traded on day t and upper bars denotes the cross-sectional average on a given day. This quantity represents the average portfolio weight across reversal strategies based on the cumulative excess return in the prior 1 to K days. We compare these weights to those that result from considering the actual volume ($Vol_{s,t}$) for each stock in Ancerno on day t:

$$w^{Anc}_{s,t} = \frac{Vol_{s,t} - \overline{Vol}_t}{1/2\sum_{s=1}^{N_t}|Vol_{s,t} - \overline{Vol}_t|} \tag{2}$$

The denominators in equations (1) and (2) ensure that the weights on the short side sum up to one as well as the weights on the long side, reflecting a self-financing strategy. We take a positive cross-sectional correlation between the two set of weights on a given day as evidence that hedge funds are acting as liquidity providers. This correlation, which we label ρ^{rev}, measures the correspondence in both sign and volume of actual trades to the prediction of a reversal strategy. If the price impact variable is inversely related to liquidity provision, we should find positive correlation between ρ^{rev} and the negative of the TC series.

The second alternative measure of liquidity provision is inspired by Anand, Irvine, Puckett, and Venkataraman (2013). The idea behind this variable is that if an institutional order i on day t is in the same direction as the daily return on that stock, it is considered as liquidity demanding, vice versa, orders with the opposite sign are liquidity providing. We denote the volume on the first type of orders as $Volume\_With_{i,t}$, while the volume of the second type of orders is $Volume\_Against_{j,t}$. Then, we compare the volume on the two types of orders to obtain a daily measure of trading style for the hedge fund sector as:

$$TS_t = \frac{\sum_i Volume\_With_{i,t} - \sum_j Volume\_Against_{j,t}}{\sum_i Volume\_With_{i,t} + \sum_j Volume\_Against_{j,t}} \tag{3}$$

A positive and large score on TS on a given day is taken as a signal that hedge funds' trading style is closer to liquidity demand on that day.[8]

[8]Note that while the reversal measure considers the return on the stock in the K days prior to the trade, the TS variable focuses on the return on the same day as the trade.

Panel A of Table H.5 reports correlations between $-TC$ and ρ^{rev}, aggregated at different frequencies and for different reversal horizons $K = \{1, 2, 3, 4, 5, 10\}$. It is reassuring that the correlations are positive and large, the highest being about 59% for the one-day horizon at the quarterly frequency. We infer that trades that appear to be liquidity providing on the dimension of price impact are likely to be so according to a reversal strategy criterion as well. Panel B compares the implicit trading cost TC to the trading style variable of Anand, Irvine, Puckett, and Venkataraman (2013). These authors show that institutions with a positive score on TS also rank high in terms of price impact. We confirm their results as we find a positive correlation, of about 30%, between TC and TS.

Perhaps even more telling than the correlations, Figure H plots the evolution of the alternative liquidity provision proxies alongside our TC measure, at the quarterly frequency. All variables have been normalized by their standard deviation to have comparable scale. The figure shows that the series display the same low frequency variation. In particular, there is a downward shift, consistent with increased liquidity provision, from the early sample towards the onset of the financial crisis. Then, the evidence suggests that liquidity demand by hedge funds was picking up again in correspondence with the financial crisis. At the end of the sample, in the last quarter 2010, the series are not yet back at their pre-crisis levels. One important remark concerns the observed long term decline of the series that ends with the financial crisis. If this trend was only affecting the measures that are based on price impact, one could interpret it as the mere effect of a long term decrease in trading costs. However, because this development affects the other two series as well, it reveals a deliberate shift towards liquidity provision by hedge funds. Overall, the message that emerges from Table H.5 and Figure H is that the price impact variable that we use in the analysis shares strong commonalities with other measures of liquidity provision and it is, therefore, a valid measure of liquidity provision.

Finally, Table H.6 exhibits estimates for the probit regression of the dummy variable indicating positive trading costs on the funding liquidity variables. Again, the interaction term for hedge funds has the expected sign, and is significant in all cases except LIBOR.

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Table A: Characteristics of hedge funds in Ancerno

This table reports the number of reporting days per management company and the ratio of total to net volume per quarter for the hedge funds companies that match to 13F filings. Sample period is January 1999 to December 2010.

	Obs	Mean	Std	Min	p25	p50	p75	Max
Reporting days per fund	87	731	806	2	120	428	1091	2967
Interim to total volume	1598	1.99	21.98	1.00	1.06	1.25	1.62	670.30

Table C.1: Comparison of hedge funds in TASS and Ancerno

Panel A reports the following statistics for the characteristics of hedge funds in Ancerno reporting to TASS: mean; standard deviation; minimum; 25th, 50th, and 75th percentiles; maximum. The characteristics are Redemption Notice Frequency (in days), Redemption Notice Period (in days), Lockup Period (in months), the amount of Leverage, the AR(1) coefficient in hedge fund returns, fund Age computed as the number of months the fund has reported to TASS, Assets Under Management (AUM), the monthly return, and percentage flows. Panel B displays the percentage of hedge funds in Ancerno falling in each quintile of the TASS universe. Panel C reports the AUM-weighted distribution of hedge fund styles in Ancerno and TASS.

Panel A: Summary statistics

Characteristic	Mean	Std	Min	p25	p50	p75	Max
Red. Not. Freq.	131.41	116.68	1.00	63.32	90	90	360
Red. Not. Per.	37.06	15.39	0	30	30	45	110.03
Lockup Per.	5.03	5.42	0	0	2.26	12	12
Leverage	79.72	238.14	0	0	0	110	1600
AR(1)	0.02	0.27	-0.90	-0.16	0.01	0.20	1.04
Age	81.75	38.36	14	54	76	103	192
AUM ($ million)	220.73	634.01	0.45	23.66	64.10	132.63	12024.80
Return	0.45%	4.65%	-14.23%	-1.35%	0.51%	2.19%	16.45%
Flows	0.36%	8.78%	-30.46%	-0.96%	0.04%	1.32%	63.37%

Panel B: Distribution with respect to TASS

Quintile	AUM	Return	Flows	AR(1)	Age
1	13%	26%	21%	21%	1%
2	18%	20%	22%	23%	8%
3	24%	16%	26%	20%	19%
4	30%	18%	19%	19%	28%
5	15%	20%	12%	17%	45%

Panel C: Distribution by style

Style	Ancerno	TASS
Convertible Arbitrage	15.80%	3.01%
Dedicated Short Bias	0.00%	0.14%
Emerging Markets	0.98%	3.62%
Equity Market Neutral	11.07%	5.21%
Event Driven	2.61%	10.10%
Fixed Income Arbitrage	13.24%	5.43%
Fund of Funds	0.67%	22.78%
Global Macro	0.04%	4.96%
Long Short Equity Hedge	54.80%	28.26%
Managed Futures	0.68%	5.46%
Multi Strategy	0.12%	8.00%
Options Strategy	0.00%	0.75%
Undefined	0.00%	2.28%

Table C.2: Hedge funds' returns before and after reporting to Ancerno

Style-adjusted average monthly returns (as recorded in TASS) across hedge fund companies that report to Ancerno in the twelve months prior to the first month in which they start reporting to Ancerno and in the twelve month after the last month in which they stop reporting to Ancerno.

	Months prior to entering Ancerno (month 0)											
	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Return	1.70%	-0.90%	1.40%	0.30%	-0.50%	-0.30%	1.30%	0.20%	-0.20%	1.00%	-0.10%	0.40%
	(2.69)	(-1.15)	(1.62)	(0.47)	(-0.70)	(-0.40)	(1.91)	(0.21)	(-0.19)	(1.41)	(-0.07)	(0.53)
	Months after exiting Ancerno (month 0)											
	+1	+2	+3	+4	+5	+6	+7	+8	+9	+10	+11	+12
Return	0.50%	-0.50%	-1.80%	-0.10%	-1.30%	-1.00%	-1.00%	-0.40%	-0.30%	0.00%	0.90%	1.20%
	(0.78)	(-0.80)	(-2.52)	(-0.15)	(-1.43)	(-0.94)	(-0.85)	(-0.31)	(-0.32)	(0.01)	(0.93)	(1.16)

Table D: Liquidity provision and funding liquidity, weekly results

Panel A reports OLS estimates of equation (3):

$$TC_{i,t+1} = a + bFundLiq_t + \phi TC_{i,t} + \epsilon_{i,t+1}$$

where $TC_{i,t+1}$ is the trading cost of hedge fund i in week $t+1$, and $FundLiq_t$ denotes alternatively R_M, VIX, TED, LIBOR, or PC measured in week t. Trading costs in a given week are computed as volume-weighted average in columns (1) to (5) and as equally-weighted average in columns (6) to (10).
Panel B reports OLS estimates of equation (5):

$$TC_{i,t+1} = a_1 + a_2 HF + b_1 FundLiq_t + b_2 HF \times FundLiq_t + \phi_1 TC_{i,t} + \phi_2 HF \times TC_{i,t} + \varepsilon_{i,t+1}$$

where $TC_{i,t+1}$ is the volume-weighted average trading cost of institution i in week $t+1$. HF equals 1 if the institution is a hedge fund and 0 otherwise. Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in Table 3. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. The estimates of the intercept and lag terms are omitted. The sample period is January 1999 to December 2010.

Panel A: Hedge funds

Dep. Var.:	Volume-weighted trading cost					Equally-weighted trading cost				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_M	-1.450					-1.277				
	(-3.50)					(-3.29)				
VIX		1.441					1.253			
		(3.38)					(3.14)			
TED			2.118					1.635		
			(4.65)					(3.86)		
LIBOR				3.269					2.853	
				(8.44)					(7.61)	
PC					2.616					2.176
					(6.38)					(5.69)
Obs.	14,517	14,549	14,549	14,549	14,517	14,517	14,549	14,549	14,549	14,517
R^2	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.06

Panel B: Hedge funds versus other investors

Dep. Var.: Volume-weighted trading cost

$FundLiq$:	R_M	VIX	TED	LIBOR	PC
	(1)	(2)	(3)	(4)	(5)
$HF \times FundLiq$	-1.152	1.593	2.722	1.933	2.839
	(-2.66)	(3.41)	(5.52)	(5.23)	(6.24)
$FundLiq$	-0.176	-0.159	-0.527	1.076	-0.198
	(-1.04)	(-0.84)	(-3.32)	(8.33)	(-1.12)
HF	5.571	5.519	5.701	5.616	5.663
	(14.66)	(14.68)	(15.07)	(15.02)	(15.14)
Obs.	184,645	184,937	184,937	184,937	184,645
R^2	0.03	0.03	0.03	0.03	0.03

Table E: Hedge funds' and other institutions liquidity provision and funding liquidity for large stocks

OLS estimates of equation (5):

$$TC_{i,t+1} = a_1 + a_2 HF + b_1 FundLiq_t + b_2 HF \times FundLiq_t + \phi_1 TC_{i,t} + \phi_2 HF \times TC_{i,t} + \varepsilon_{i,t+1}$$

where $TC_{i,t+1}$ is the volume-weighted average trading cost of institution i on day $t+1$ on stocks belonging to the top market capitalization decile. HF equals 1 if the institution is a hedge fund and 0 otherwise. Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in Table 3. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. The estimates of the intercept and lag terms are omitted. The sample period is January 1999 to December 2010.

Dep. Var.: Volume-weighted Trading Costs					
$FundLiq$:	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)
$HF \times FundLiq$	-1.611	2.745	2.273	0.587	3.043
	(-3.49)	(4.88)	(4.38)	(1.55)	(5.71)
$FundLiq$	0.088	-0.331	-0.341	0.265	-0.331
	(0.59)	(-2.35)	(-2.00)	(2.70)	(-1.94)
HF	6.336	6.184	6.383	6.327	6.306
	(16.40)	(16.46)	(16.41)	(16.31)	(16.49)
Obs.	415,521	415,521	415,521	415,521	415,521
R^2	0.01	0.01	0.01	0.01	0.01

Table F: Volume of hedge funds' trades and funding liquidity

OLS estimates of the model:

$$Vol_{i,t+1} = a + bFundLiq_t + \phi Vol_{i,t} + \epsilon_{i,t+1}$$

where Vol_i denotes alternatively log dollar volume of hedge fund i in Columns (1) to (5) and log dollar volume per trade of hedge fund i in Columns (6) to (10). Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in Table 3. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. The estimates of the intercept and lag term are omitted. The sample period is January 1999 to December 2010.

Dep. Var.:	Total log dollar volume					Total log dollar volume per trade				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_M	-0.001					0.003				
	(-0.14)					(0.59)				
VIX		-0.003					-0.040			
		(-0.44)					(-8.89)			
TED			0.019					0.003		
			(2.61)					(0.55)		
LIBOR				-0.045					0.039	
				(-6.08)					(8.38)	
PC					0.003					-0.016
					(0.48)					(-3.37)
Obs.	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211
R^2	0.56	0.56	0.56	0.56	0.56	0.48	0.48	0.48	0.48	0.48

Table G: Hedge funds' total returns and funding liquidity

Average return (as recorded in TASS) for constrained funds, unconstrained funds, and for their difference computed across all fund-month observations belonging to each decile of the distribution of the funding liquidity factor (PC). Hedge funds that are present in Ancerno, and at the same time report to TASS, are classified as constrained if they have positive leverage and a redemption notice period plus redemption frequency lower than 120 days (the median value in the sample). t-statistics are reported in parenthesis below the estimates. The sample period is January 1999 to December 2010.

	Deciles of PC									
	LOW=1	2	3	4	5	6	7	8	9	HIGH=10
Constrained HFs	2.87%	0.87%	1.14%	1.44%	-0.13%	1.13%	1.74%	-0.43%	-2.59%	-3.89%
	(8.88)	(2.82)	(3.55)	(3.26)	(-0.37)	(2.69)	(3.61)	(-1.03)	(-4.57)	(-4.88)
Unconstrained HFs	2.59%	1.74%	0.84%	0.75%	-0.27%	1.55%	1.79%	0.64%	-1.58%	-2.40%
	(6.83)	(9.37)	(2.99)	(2.64)	(-0.68)	(2.73)	(3.59)	(1.59)	(-2.77)	(-3.80)
Difference	0.29%	-0.86%	0.30%	0.69%	0.14%	-0.42%	-0.05%	-1.08%	-1.02%	-1.49%
	(0.56)	(-2.46)	(0.70)	(1.25)	(0.26)	(-0.60)	(-0.07)	(-1.67)	(-1.23)	(-1.47)

Table H.1: Hedge funds' liquidity provision and funding liquidity - alternative TC benchmarks

OLS estimates of equation (3):

$$TC_{i,t+1} = a + bFundLiq_t + \phi TC_{i,t} + \epsilon_{i,t+1}$$

where $TC_{i,t+1}$ is the trading cost of hedge fund i on day $t+1$, and $FundLiq_t$ denotes alternatively R_M, VIX, TED, LIBOR, or PC measured on day t. In Panel A, trading costs are computed using price at open as benchmark price, whereas Panel B uses price at placement. Within each panel, trading costs are computed as volume-weighted average across all trades in columns (1) to (5) and as equally-weighted average in columns (6) to (10). Within each specification, each column uses a different funding liquidity variable, $FundLiq$, which are defined as in Table 3. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. The estimates of the intercept and lag term are omitted. The sample period is January 1999 to December 2010.

Panel A: Trading Cost using Price at Open

	Volume-weighted					Equally-weighted				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_M	-5.082					-4.774				
	(-4.96)					(-5.24)				
VIX		5.777					5.330			
		(6.06)					(6.09)			
TED			2.127					1.998		
			(2.03)					(2.02)		
LIBOR				4.339					3.593	
				(5.26)					(4.82)	
PC					6.187					5.722
					(5.93)					(5.78)
Lag	0.171	0.171	0.172	0.171	0.170	0.213	0.213	0.214	0.213	0.213
	(28.20)	(28.20)	(28.36)	(28.25)	(28.19)	(34.08)	(34.05)	(34.21)	(34.12)	(34.06)
Obs.	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211
R^2	0.031	0.031	0.030	0.030	0.031	0.047	0.047	0.047	0.047	0.048

Panel B: Trading Cost using Price at Placement

	Volume-weighted					Equally-weighted				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_M	-4.886					-4.861				
	(-4.79)					(-5.39)				
VIX		4.699					4.278			
		(4.81)					(4.78)			
TED			2.580					2.645		
			(2.65)					(2.74)		
LIBOR				6.516					5.394	
				(8.02)					(7.37)	
PC					5.980					5.695
					(5.89)					(5.89)
Obs.	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211
R^2	0.032	0.032	0.031	0.032	0.032	0.048	0.048	0.047	0.048	0.048

Table H.2: Hedge funds' and other investors' liquidity provision and funding liquidity - alternative TC benchmarks

OLS estimates of equation:

$$TC_{i,t+1} = a_1 + a_2 HF + b_1 FundLiq_t + b_2 HF \times FundLiq_t + \phi_1 TC_{i,t} + \phi_2 HF \times TC_{i,t} + \epsilon_{i,t+1}$$

where $TC_{i,t+1}$ is the volume-weighted trading cost of institution i on day $t+1$. HF equals 1 if the institution is a hedge fund and 0 otherwise. In Panel A, trading costs are computed using price at open as benchmark price, whereas Panel B uses price at placement. Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in 3. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. The estimates of the intercept and lag terms are omitted. The sample period is January 1999 to December 2010.

Dep. Var.	Panel A: Price at Open					Panel B: Price at Placement				
$FunLiq$	R_M	VIX	TED	LIBOR	PC	R_M	VIX	TED	LIBOR	PC
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
$HF \times FundLiq$	-4.270	4.250	2.366	3.327	4.100	-3.905	2.815	2.380	5.292	3.583
	(-4.92)	(4.76)	(2.30)	(4.76)	(5.41)	(-4.73)	(3.32)	(2.60)	(7.98)	(5.10)
$FundLiq$	0.368	0.731	-0.695	-0.437	-0.111	0.273	1.044	-0.244	-0.354	0.201
	(1.24)	(2.32)	(-1.92)	(-1.82)	(-0.40)	(0.97)	(3.69)	(-0.72)	(-1.60)	(0.78)
HF	25.354	25.273	25.422	25.314	25.523	22.170	22.090	22.284	22.178	22.331
	(34.41)	(34.30)	(33.76)	(34.25)	(34.23)	(31.74)	(31.60)	(31.31)	(31.87)	(31.60)
Obs.	665,124	665,124	665,124	665,124	665,124	665,124	665,124	665,124	665,124	665,124
R^2	0.032	0.032	0.032	0.032	0.032	0.033	0.033	0.033	0.033	0.033

Table H.3: Liquidity provision, funding liquidity, and hedge funds' characteristics - alternative TC benchmarks

OLS estimates of equation (8):

$$TC_{i,t+1} = \alpha + \beta' FundLiq_t + \gamma' X_{i,m-1} + \eta' FundLiq_t \times X_{i,m-1} + \epsilon_{i,t+1}$$

where $TC_{i,t+1}$ is hedge fund i volume-weighted trading cost on day $t+1$. $X_{i,m}$ collects six cross-sectional characteristics. These are the amount of leverage in place ($Leverage$); minus the age of the fund ($Young$); the decile of the distribution of the first-order autocorrelation in returns ($Illiquid$); minus the year-to-date performance (Bad); a dummy variable ($LowRed$) that equals 1 if redemption notice period plus redemption frequency is lower than 120 days (the median in the sample); a dummy variable ($NoLock$) that equals 1 if lockup period is 0 and 0 otherwise. All cross-sectional controls are from the month preceding that of the trade (month $m-1$). In Panel A, trading costs are computed using price at open as benchmark price, whereas Panel B uses price at placement. Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in 3. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. All regressions include a lag, a intercept term, and style fixed effects (whose estimates are omitted). Bold face denotes estimates whose significance (at the 10% level) makes them consistent with Hypothesis 3 in the text. The sample period is January 1999 to December 2010.

	Dep. Var.: Volume-weighted trading cost									
	Panel A: Price at Open					Panel B: Price at Placement				
FundLiq	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)
Leverage×FundLiq	0.004	-0.034	**0.029**	**0.030**	0.001	0.005	-0.027	**0.032**	**0.022**	0.006
	(0.74)	(-5.70)	**(6.69)**	**(4.48)**	(0.32)	(0.95)	(-4.61)	**(7.38)**	**(3.36)**	(1.28)
Young×FundLiq	-2.219	**16.099**	0.674	-10.701	**13.721**	-1.586	**18.533**	1.119	-10.001	**14.622**
	(-0.76)	**(4.72)**	(0.15)	(-3.43)	**(3.93)**	(-0.55)	**(5.53)**	(0.26)	(-3.25)	**(4.25)**
Illiquid×FundLiq	-0.597	0.173	**1.168**	**1.755**	0.724	-0.552	0.607	**1.451**	**1.543**	1.007
	(-1.06)	(0.33)	**(2.14)**	**(3.30)**	(1.30)	(-0.99)	(1.18)	**(2.71)**	**(2.92)**	(1.85)
Bad×FundLiq	**-37.058**	**30.070**	-43.601	**21.164**	15.246	**-35.644**	**28.086**	-46.535	**17.497**	12.541
	(-3.08)	**(2.49)**	(-3.56)	**(1.65)**	(1.32)	**(-3.03)**	**(2.34)**	(-3.83)	**(1.37)**	(1.09)
LowRed×FundLiq	**9.565**	-6.405	**46.038**	**44.190**	**13.361**	**7.738**	-7.923	**48.625**	**49.278**	**15.313**
	(2.22)	(-1.44)	**(6.53)**	**(12.23)**	**(2.47)**	**(1.84)**	(-1.83)	**(6.83)**	**(13.67)**	**(2.86)**
NoLock×FundLiq	-2.598	-3.109	**-45.338**	**-20.220**	**-21.552**	-1.207	-1.679	**-44.475**	**-21.057**	**-21.695**
	(-0.64)	(-0.70)	**(-8.08)**	**(-5.63)**	**(-4.21)**	(-0.30)	(-0.39)	**(-7.87)**	**(-5.88)**	**(-4.28)**
Leverage	-0.087	-0.112	-0.085	-0.092	-0.092	-0.085	-0.104	-0.083	-0.085	-0.089
	(-15.46)	(-14.97)	(-14.54)	(-14.05)	(-15.99)	(-15.28)	(-14.35)	(-14.47)	(-13.28)	(-15.76)
Young	7.356	6.513	6.126	-6.016	9.387	5.522	4.818	4.131	-8.429	7.675
	(3.07)	(2.72)	(2.12)	(-2.11)	(3.70)	(2.32)	(2.04)	(1.44)	(-2.98)	(3.05)
Illiquid	-0.201	0.110	0.454	0.549	0.013	-0.294	0.058	0.413	0.430	-0.049
	(-0.42)	(0.22)	(0.93)	(1.13)	(0.03)	(-0.62)	(0.12)	(0.85)	(0.90)	(-0.10)
Bad	87.816	81.778	86.144	66.423	83.269	93.093	87.490	91.233	71.504	88.708
	(7.20)	(6.48)	(6.80)	(5.35)	(6.65)	(7.72)	(7.02)	(7.29)	(5.83)	(7.18)
LowRed	22.190	25.971	33.212	24.642	23.496	18.133	21.900	29.852	20.343	19.583
	(6.09)	(7.01)	(8.08)	(6.90)	(6.25)	(5.02)	(5.96)	(7.28)	(5.78)	(5.24)
NoLock	-4.219	-5.151	-11.556	-5.555	-6.467	-0.410	-1.562	-7.911	-2.021	-2.853
	(-1.22)	(-1.47)	(-3.18)	(-1.59)	(-1.83)	(-0.12)	(-0.45)	(-2.19)	(-0.59)	(-0.81)
FundLiq	-13.979	75.984	4.444	-52.722	67.718	-10.776	84.763	4.259	-49.252	69.684
	(-1.03)	(4.80)	(0.21)	(-3.54)	(4.10)	(-0.81)	(5.44)	(0.20)	(-3.36)	(4.29)
Obs.	26,670	26,659	26,659	26,659	26,659	26,670	26,659	26,659	26,659	26,659
R^2	0.04	0.04	0.04	0.05	0.04	0.03	0.04	0.04	0.05	0.04

Table H.4: Impact of 2007-2009 financial crisis - alternative TC benchmarks

OLS estimates of equation (3):

$$TC_{i,t+1} = a + bFundLiq_t + \phi TC_{i,t} + \epsilon_{i,t+1}$$

where $TC_{i,t+1}$ is the trading cost of hedge fund i on day $t+1$, and $FundLiq_t$ denotes alternatively R_M, VIX, TED, LIBOR, or PC measured on day t. The regression is estimated separately on the ex-crisis and crisis periods. The financial crisis period is defined as July 2007 to March 2009. Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in Table 3. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. In Panel A, trading costs are computed using price at open as benchmark price, whereas Panel B uses price at placement. All regressions include a lag term and an intercept (whose estimates are omitted). The whole sample period is January 1999 to December 2010.

Dep. Var.: Volume-weighted trading cost

Panel A: Price at Open

	Ex-crisis period					Crisis period				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
R_M	-1.027					-2.899				
	(-2.76)					(-3.61)				
VIX		1.995					1.887			
		(5.32)					(2.42)			
TED			5.325					2.244		
			(7.43)					(2.82)		
LIBOR				3.393					-0.083	
				(11.11)					(-0.06)	
PC					4.304					2.881
					(8.69)					(3.53)
Obs.	47,539	47,539	47,539	47,539	47,539	5,642	5,642	5,642	5,642	5,642
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Panel B: Price at Placement

	Ex-crisis period					Crisis period				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
R_M	-3.749					-8.495				
	(-3.29)					(-3.98)				
VIX		5.295					5.089			
		(4.63)					(2.58)			
TED			4.151					5.038		
			(2.10)					(2.60)		
LIBOR				6.813					1.579	
				(8.14)					(0.46)	
PC					9.109					7.609
					(6.43)					(3.68)
Obs.	47,539	47,539	47,539	47,539	47,539	5,642	5,642	5,642	5,642	5,642
R^2	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table H.5: Alternative measures of liquidity provision

This table relates the volume-weighted trading cost series based on VWAP with alternative measures of liquidity provision. Panel A displays minus the correlation with the measure of proximity to reversal strategies ρ^{rev}, based on returns in the prior K days. Panel B reports the correlation with the trading style measure proposed by Anand, Irvine, Puckett, and Venkataraman (2013) (AIPV). The correlations are computed for series aggregated at the Monthly and Quarterly frequencies. The sample period is January 1999 to December 2010.

Panel A: Reversal strategies

Horizon in days (K)	Monthly	Quarterly
1	0.443	0.589
2	0.429	0.553
3	0.416	0.532
4	0.407	0.513
5	0.406	0.508
10	0.413	0.506

Panel B: AIPV measure

	Monthly	Quarterly
Trading style	0.297	0.307

Table H.6: Hedge funds' and other institutions liquidity provision and funding liquidity, dummy indicator

Probit estimates of the model:

$$I_{i,t+1} = \Phi\left(a_1 + a_2 HF + b_1 FundLiq_t + b_2 HF \times FundLiq_t + \phi_1 I_{i,t} + \phi_2 HF \times I_{i,t}\right) + \epsilon_{i,t+1}$$

where $I_{i,t+1}$ equals 1 if the value-weighted trading cost for a given institution on day $t+1$ is positive and 0 otherwise. HF equals 1 if the institution is a hedge fund and 0 otherwise. Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in Table 3. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. The estimates of the intercept and lag terms are omitted. The sample period is January 1999 to December 2010.

	Dep. Var.: Liquidity provision dummy				
$FundLiq$:	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)
$HF \times FundLiq$	-0.011	0.015	0.013	0.001	0.018
	(-1.99)	(2.40)	(1.97)	(0.18)	(2.82)
$FundLiq$	0.010	-0.003	-0.014	0.006	-0.011
	(4.81)	(-1.63)	(-6.36)	(3.06)	(-5.25)
HF	0.173	0.173	0.173	0.173	0.174
	(20.40)	(20.41)	(20.34)	(20.43)	(20.42)
Obs.	671,240	671,240	671,240	671,240	671,240
Pseudo R^2	0.01	0.01	0.01	0.01	0.01

Figure H: Alternative measures of liquidity provision

Quarterly average series for three measures of liquidity provision on hedge funds trades. The first measure is aggregate volume-weighted trading costs that use as the volume-weighted average price (VWAP). Contrarian is defined as minus the correlation between hedge funds relative positions and those predicated by a reversal strategy (see Appendix H). Trading Style is the liquidity provision measure proposed by Anand, Irvine, Puckett, and Venkataraman (2013). The sample is the first quarter of 1999 to the last quarter of 2010.