Do Hedge Funds Provide Liquidity? Evidence From Their Trades

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ABSTRACT

The paper provides significant evidence of limits of arbitrage in the hedge fund sector. Using unique data on institutional transactions, we show that the price impact of hedge fund trades increases when aggregate conditions deteriorate. The finding is consistent with arbitrageurs' withdrawal from liquidity provision following a tightening in funding liquidity. Compared to other institutions, hedge funds display the largest sensitivity of trading costs to aggregate conditions. We pin down this effect to a subset of hedge funds that are more exposed to funding constraints because of their leverage, lack of share restrictions, asset illiquidity, low reputational capital, and trading style. Value-based trading strategies demand liquidity in bad times, whereas momentum strategies provide liquidity. Lastly, a decrease in hedge fund trading intensity predicts a widening of the bid-ask spread at the stock-level, while other institutions' trading activity does not seem to matter for market liquidity.

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1 Introduction

In the literature that relates market liquidity to investors' funding conditions (e.g. Brunnermeier and Pedersen (2009)), a liquidity provider is the ultimate holder of an underpriced asset and short-seller of an overpriced one. Hedge funds are the main candidates to play this role as they closely resemble the 'speculators' in these models in terms of both trading strategies and reliance on external finance. Consistent with this notion of liquidity provision, the typical hedge fund strategies provide an anchor for mispriced securities by making portfolio decisions conditional on perceived misvaluations. In this regard, hedge funds are different from the traditional market makers (e.g. the specialists or, more recently, the high-frequency traders), which tend to hold zero inventories at the end of the day. This paper focuses on this dimension of liquidity provision and studies empirically the dependence of hedge funds' stock trades on funding conditions.[1]

While there is evidence that hedge funds profit from liquidity provision, (e.g., Aragon (2007), Sadka (2010), Jylha, Rinne, and Suominen (2012)), other studies point out limits to this ability. A large body of theoretical literature posits arbitrageurs' dependence on external finance which, at times of market stress, becomes unreliable.[2] Some recent empirical evidence confirms that hedge fund performance is related to funding conditions (Teo (2011)) and that hedge funds' withdrawal from the market impacts stock liquidity (Aragon and Strahan (2012)). Given the importance of liquidity provision for the smooth functioning of financial markets, it is crucial to understand how hedge funds respond to a deterioration in aggregate conditions. Knowledge of the interplay between funding conditions and liquidity provision is also key to identify hedge funds' role in spreading systemic risk (Boyson, Stahel, and Stulz (2010), Billio, Getmansky, Lo, and Pelizzon (2012)).

Prior work uses quarterly portfolio holdings to infer the trading behavior of hedge funds in equity markets during the last financial crisis (Ben-David, Franzoni, and Moussawi (2012)). However, liquidity provision is inherently a trade-level concept relating to how patiently a trade is executed. Quarterly changes in portfolio holdings, therefore, cannot distinguish between long-term portfolio reallocations and short-term variations in liquidity supply. The latter can be examined more

[1] The same notion of liquidity provision is used in a recent paper by Anand et al. (2013), who also draw on institutional trading data. These authors describe a tri-party market with liquidity demanders, intermediaries (i.e. specialists or high-frequency traders), and long-term liquidity suppliers. Like us, these authors interpret the buy-side institutions as the long-term suppliers of liquidity.

[2] A brief selection of theoretical papers that model limits of arbitrage includes Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Gromb and Vayanos (2010), Gromb and Vayanos (2012).

appropriately by means of the trade-level data that we use in this study. Anand, Irvine, Puckett, and Venkataraman (2013), like us, draw on institutional trading data to infer market participation of institutional investors. We depart from their analysis mainly in our focus on the cross-sectional dimension within the institutional sector. We contrast the behavior of hedge funds, whose trading strategies are very sensitive to external funding, to that of other institutions (mutual funds and pension funds), which are less dependent on changes in funding conditions due to a limited reliance on leverage. Also, within the hedge fund sector, we study how the impact of funding variables on liquidity provision interacts with fund level measures of financial constraints, such as: leverage, redemption restrictions, asset illiquidity, and reputational capital. Lastly, while prior studies mostly focus on the financial crisis, we show that the dependence of hedge funds' liquidity provision on funding constraints holds in 'normal' times as well.

Our data set contains trade-level observations for over eight hundred different institutions (hedge funds, mutual funds, pension funds, and other money managers) during the January 1999 to December 2010 period. The data source is Abel Noser Solutions (aka 'Ancerno'), a company specialized in consulting services to institutional investors for trading costs analysis.[3] Ancerno provides researchers with data on the trading activity of its clients' portfolio managers, under the agreement that the names of the client institutions are not disclosed. However, the name of the institution that manages the client's portfolio is provided. This information allows us to identify eighty-seven distinct hedge fund management companies.[4] These firms appear to be highly representative of the overall industry along several dimensions. In particular, we provide evidence that the hedge funds in our sample are not statistically different from the other funds in TASS in terms of the exposure to the main explanatory variables of this study.

The notion of liquidity that we state at the beginning guides our identification of liquidity provision/demand in the data. We expect liquidity demanders to trade impatiently and, consequently, to have a positive price impact. The opposite is true for liquidity suppliers. As in Puckett and

[3]Other recent studies using Ancerno data are Chemmanur, He, and Hu (2009), Puckett and Yan (2011), Chemmanur, Hu, and Huang (2010), Anand, Irvine, Puckett, and Venkataraman (2013), Anand, Irvine, Puckett, and Venkataraman (2012).

[4]In more detail, we identify hedge fund management companies by manually matching the managers in Ancerno with a list of hedge fund management companies in the 13F mandatory filings and the Lipper/TASS database. The list of hedge funds in the 13F filings is the same that is used in Ben-David, Franzoni, and Moussawi (2012) and Ben-David, Franzoni, Landier, and Moussawi (2012). The institutions that report to both Ancerno and 13F are hedge-fund management companies as opposed to the individual funds. For consistency, we aggregate the fund-level observations in TASS at the management company level. When we use the wording 'hedge funds', we broadly refer to the firms that belong to this asset class rather than to the specific funds within a management company.

Yan (2011), we compute price impact as the percentage difference between the execution price and the volume-weighted average price (VWAP) for the same stock during the day, and express this difference as a fraction of the VWAP. Our choice of benchmark is immaterial for our conclusions, as the results hold also when we compute price impact using the Price at Market Open, as in Anand, Irvine, Puckett, and Venkataraman (2013), or the Price at Order Placement, as in Anand, Irvine, Puckett, and Venkataraman (2012). We also consider proxies for liquidity provision based on reversal strategies (Lo and MacKinlay (1990) and Nagel (2012)) and trading style (Anand, Irvine, Puckett, and Venkataraman (2013)). These alternative measures correlate strongly with price impact, which is reassuring about the identification strategy.

Our analysis is organized around three hypotheses that formulate the predictions of the limits of arbitrage theories. First, in the times series, we conjecture and test that hedge funds' liquidity provision depends on aggregate funding conditions. Second, we contrast hedge funds to the other institutions in our data, as in a difference-in-differences approach. If hedge funds trading costs are driven by funding constraints, rather than by a generalized increase in the price of liquidity in bad times, we expect this effect to persist also when benchmarking to other institutions. We motivate this conjecture by arguing that hedge funds' funding needs are more sensitive to financial conditions than those of other institutions. Third, we explore the heterogeneity within the hedge fund sector. The prediction is that hedge funds are not equally exposed to funding liquidity. Rather, the sensitivity to funding conditions depends on firm-level determinants that are related to the availability and reliability of funding.

The results are easily summarized. In the time series, we find that liquidity provision deteriorates when funding conditions tighten. There is substantial variation in hedge funds' implicit trading costs over the sample period. Starting in 2002, trading costs declined unambiguously until the first semester of 2007. In this period, hedge funds' liquidity provision appears to be at its highest. Then, price impact starts to increase towards the end of 2007, in correspondence with the Quant Meltdown (Khandani and Lo (2011)). In the first semester of 2009, our measure unambiguously suggests that hedge funds drastically increased their liquidity consumption. Liquidity demand became less pronounced from the second semester of 2009 through the end of 2010. Consistent with Brunnermeier and Nagel (2004), who show that hedge funds rode the Internet Bubble and then switched to contrarian positions shortly before the downturn, we also observe an increase in trading costs in the year 2000, which is then reversed in the 2001-2002 period. In a regression framework, we find that hedge funds' price impact increases following a drop in the stock market and increases in the VIX, the TED Spread, and the LIBOR and we show that the relation holds outside of the financial crisis as well. These variables are proxies for funding liquidity, either through the value of collateral (related to the return on the stock market), the tightness of margins (related to the VIX), or the cost of leverage (measured by the TED Spread and the LIBOR).[5] Thus, the evidence is consistent with a role for limits of arbitrage in hedge funds' liquidity provision.

In the comparison with other institutions, hedge funds appear to be significantly more exposed to changes in funding liquidity. While other institutions also experience an increase in trading costs during the financial crisis, the price impact of their trades is only about 50% of that for hedge funds in 2009Q1. The regression analysis suggests that there is no systematic relation between the trading costs of other institutions and most of the funding liquidity proxies. This is not a result of the fact that hedge funds trade in more illiquid stocks, as it holds also when controlling for stock- and trade-level characteristics. Using the other institutions as a control group allows us to infer that the increase in hedge funds' trading costs results from their reduced liquidity provision in bad times, rather than from a generalized surge in trading costs for all investors.

The analysis of the heterogeneity within the hedge fund sector gives further confirmation of the conjecture that limits of arbitrage theories describe hedge fund behavior. We find that the exposure of price impact to aggregate funding conditions is significant larger for funds with higher leverage, more illiquid assets, lower reputational capital (as measured by fund age and past performance), and lower restrictions to investors' redemptions. These characteristics are related to hedge funds' ability to retain capital in bad times. As such, they are proxies for funding constraints. Furthermore, only the funds that are classified as constrained by having positive leverage and low redemption restrictions, display a relation between their trading costs and the aggregate funding liquidity proxies. This result gives an important qualification to our previous findings. The statement that hedge funds are more constrained than other institutions in their ability to provide liquidity in bad times has to be confined to the subset of hedge funds with trading styles that magnify their exposure to limits of arbitrage.

[5] These macro variables are used as proxies for funding liquidity in, for example, Hameed, Kang, and Viswanathan (2010), Boyson, Stahel, and Stulz (2010), Garleanu and Pedersen (2011), and Nagel (2012).

As a further validation of the limits of arbitrage conjecture, we show that, when funding conditions deteriorate, the trades of more constrained funds are less profitable over the next five-day horizon. This can happen if hedge funds respond to a tightening in funding liquidity by giving up to profitable trading strategies or by aggressively seeking liquidity in the market. In either case, this result suggests that binding constraints force hedge funds to deviate from their optimal trading strategies.

Another dimension of the cross-sectional heterogeneity in the hedge fund sector that we explore is related to hedge funds' trading styles. For a hedge fund, its trading strategy is the ultimate determinant of the availability of funding liquidity. For example, different trading strategies require different levels of leverage to be profitable. A fund whose trading strategy requires higher leverage may be obliged to forced liquidations in bad times. We focus on three popular trading styles in the equity space: short-term reversal, momentum, and value. We study the hedge funds' behavior in terms of liquidity provision based on each of these dimensions, both unconditionally and as a function of aggregate conditions. We find that momentum and reversal strategies provide liquidity in bad times, while value strategies extract liquidity when funding conditions deteriorate. Given that value stocks are to a large extent low-beta stocks, the latter finding seems consistent with the arguments in Frazzini and Pedersen (2013) that arbitrageurs' use leverage to exploit the high expected returns of low-beta/value stocks. This leverage makes a betting-against-beta strategy harder to hold on to in bad times and obliges the funds to forced liquidations, which have large price impact and raise the trading costs.

To conclude, we study to what extent hedge funds' trading matters for market liquidity. Our data give us a unique opportunity to address this question. We regress market liquidity on hedge-fund trading intensity at the stock level controlling for stock characteristic and aggregate conditions. Our analysis shows that an increase in hedge fund trading in a given stock reduces the bid-ask spread in the following week. The trading intensity of other institutions, instead, does not seem to matter for market liquidity. Using direct evidence on hedge fund trading intensity at the stock level, this finding complements the results in Aragon and Strahan (2012) that hedge fund market participation affects stock liquidity.

Our paper relates to different strands of the literature. Some recent papers explore trading activity of institutional investors using Ancerno data. Most closely related to our work, Anand, Irvine, Puckett, and Venkataraman (2013) contrast the trading behavior and liquidity provision of Ancerno institutions in calm times and during the 2007-2009 financial crisis. They study the implications of institutional trades for stock price resiliency. Relative to their work, our contribution is to investigate differences in liquidity provision between hedge funds and other institutions. We also identify heterogeneity in liquidity provision within the hedge fund sector as a function of limits of arbitrage. Puckett and Yan (2011) show that the intra-quarter trading activity of institutional investors that is concealed by quarterly filings generates persistent and significant abnormal returns. They also find that the most skilled funds experience higher trading costs and, therefore, demand liquidity in their trades. Our evidence lines up well with their findings in that hedge funds are among the institutions with higher interim activity and are found to be on average liquidity demanders. Lipson and Puckett (2010) find that the institutions in Ancerno are on aggregate net buyers during extreme market declines, but this does not come at the cost of negative ex-post returns. We complement their work by documenting that funding liquidity shocks have a negative impact on the short-term performance of the most constrained funds. In the hedge fund literature, Sadka (2010) identifies a liquidity risk premium in hedge fund average returns. Our results possibly provide the microstructure evidence on the dependence of hedge fund returns on liquidity risk. Closely related to our paper, Teo (2011) shows that the performance of hedge funds with low restrictions to redemptions is most impacted by redemptions when aggregate conditions deteriorate. Our incremental contribution relative to this work is to show that limits of arbitrage impact performance by restraining hedge funds' ability to provide liquidity. Patton and Ramadorai (2012) uncover high-frequency variation in hedge fund risk loadings. They use the daily series of financial variables that are similar to our measures of aggregate conditions. Our results suggest that there is heterogeneity in hedge funds' exposures to aggregate conditions as a function of fund-level financial constraints. Jylha, Rinne, and Suominen (2012) regress hedge fund returns on a measure of the returns from providing immediacy and show that liquidity provision depends on, for example, restrictions to redemptions. We find consistent evidence by measuring liquidity provision directly at the trade level. Also related, Gantchev and Jotikasthira (2012) use Ancerno data to show that hedge funds are active in providing liquidity to the market for corporate control when other institutions are selling their stakes. Finally, with respect to the theoretical literature, our results are consistent with the claim that arbitrageurs' liquidity provision is subject to time-varying financial constraints (e.g., Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009)).

The paper is organized as follows. Section 2 describes the structure of our trade-level dataset and the identification of hedge funds. Section 3 presents our measure of liquidity provision and examines the time-series dynamics of trading costs contrasting hedge funds to other institutions. Section 4 contains the fund level analysis that relates liquidity provision and performance to cross-sectional fund characteristics. Section 5 studies hedge fund liquidity provision as a function of different trading strategies. Section 6 relates stock-level liquidity to hedge fund trading intensity. Section 7 summarizes the robustness analysis which is then reported in the Internet Appendix. Finally, Section 8 offers concluding remarks.

2 Data source and descriptive statistics

We begin with a description of the institutional trading data that is used in this study. Section 2.1 discusses the data source and the information available for each trade. Section 2.2 describes the procedure to identify hedge funds. Section 2.3 provides summary statistics for the key variables in the dataset. Finally, Section 2.4 addresses the potential concern of a sample selection bias.

2.1 Institutional trading data

Our data on institutional trades span the January 1, 1999 to December 31, 2010 sample period. The data provider is Abel Noser Solutions, formerly Ancerno Ltd. (we retain the shorter name of 'Ancerno'). Ancerno provides consulting services for transaction cost analysis to institutional investors and makes these data available for academic research with a delay of three quarters under the agreement that the names of the client institutions are not made public.[6] An advantage of Ancerno data is that they contain a complete and detailed record of a manager's trading history since the manager started reporting to Ancerno. While institutions voluntarily report to Ancerno, the fact that clients submit this information to obtain objective evaluations of their trading costs, and not to advertise their performance, suggests that self-reporting should not bias the data. Indeed, the characteristics of stocks traded and held by Ancerno institutions and the return performance of

[6]Prior studies that use Ancerno data to investigate the behavior of institutional investors include Chemmanur, He, and Hu (2009), Goldstein et al. (2009), Chemmanur, Hu, and Huang (2010), Goldstein, Irvine, and Puckett (2011), Puckett and Yan (2011), Anand, Irvine, Puckett, and Venkataraman (2013), and Anand, Irvine, Puckett, and Venkataraman (2012).

the trades have been found to be comparable to those in 13F mandatory filings (Puckett and Yan (2011), Anand, Irvine, Puckett, and Venkataraman (2012)). Another appealing feature of Ancerno is the absence of survivorship biases in that it also includes institutions that were reporting in the past but at some point terminated their relationship with Ancerno. Finally, the dataset is devoid of backfill bias, as Ancerno reports only the trades that are dated from the start of the client relationship.

The data are organized on different layers. The lowest-level observational unit is the individual trade. Information at the trade-level includes key variables such as: the transaction date and time (at the minute precision); the execution price; the prevailing price when the trade was placed on the market; the number of shares that are traded; the side (buy or sell); the stock CUSIP. Ancerno argues that among the sell trades they are also reporting short sales, which are especially relevant for hedge funds. We cannot, however, separate regular sales from short sales. At the upper level, the trade belongs to a daily broker release which is also called a "ticket". At the daily ticket level, we use the following variables: the volume-weighted average price of all trades in the market for a given stock (VWAP); the opening price for the traded stock. In the top layer, trades are part of a unique order, which can span several days. Ancerno provides us with two variables (*lognumber* and *oNumber*) whose combination helps grouping trades belonging to the same order. We double-check the accuracy of these identifiers using the algorithm proposed by Anand, Irvine, Puckett, and Venkataraman (2012), and opt for the latter whenever there is discrepancy between the two procedures. At the order level, among other information, we use: the date/time of order placement; the date/time of the last trade in the order; the market price for the stock at the time of order decision and placement.[7] Depending on the analysis, we make use of variables from different layers of the data.

2.2 Identification of hedge fund management companies

Ancerno obtains the data from either pension funds or money managers. In case the client is a pension fund, the trades can originate from multiple money managers. Client names are always

[7] In the early part of the sample, there are concerns about the reliability of time stamps. For example, until 2002, 78% of orders appear to have placement time at open (9:30 am) and last execution time at close (4:00 pm), while this fraction is just 17% for the entire sample. From conversations with Ancerno, it turns out that the time stamps for these orders may be inaccurate. Excluding these observations from the empirical analysis on execution time does not alter our conclusions.

anonymized. However, the names of the companies that are managing the clients' portfolios are given. This piece of information allows us to identify hedge funds among the different management companies.

An identifier denotes the trades originating from the same management company (the variable *managercode*). Also, corresponding to the company identifier, we are given the name of the management company to which the trade pertains (the variable *manager*). This variable is crucial for our identification of hedge funds. We identify hedge funds among Ancerno managers by matching the names of the management companies with two sources. The first source is a list of hedge funds that is based on quarterly 13F mandatory filings. This source is also used in Ben-David, Franzoni, and Moussawi (2012) and is based on the combination of a Thomson Reuters proprietary list of hedge funds, ADV filings, and industry listings. The second source is the Lipper/TASS Hedge Fund Database, which contains hedge-fund-level information at the monthly frequency. In the identification process, we make sure to select exclusively "pure-play" hedge fund management companies, that is, institutions whose core business is managing hedge funds. This is done by applying the same criteria as in Brunnermeier and Nagel (2004) and by manual verification. In the Internet Appendix, we provide further discussion of the structure of the Ancerno dataset and details on the matching procedure with these two institutional data sources.

Ancerno does not provide reliable information on the identity of the individual fund that is executing the trade within a fund management company. For this reason, we work on trades aggregated at the hedge fund management company level. Compared to other institutional investors, such as mutual funds, aggregation at the management company level tends to be less of a concern for hedge funds as the number of funds per company is rather small - in the order of two on average - and the returns of funds within the same company tend to be highly correlated (Ben-David, Franzoni, Landier, and Moussawi (2012)). When there is no possibility of confusion, we will refer to hedge fund management companies simply as to hedge funds. In the end, the matching procedure allows us to identify 87 distinct hedge fund management companies that are present in Ancerno at various times throughout the sample.[8]

[8]In a recent paper, Jame (2012) also uses Ancerno to identify hedge funds following a procedure that resembles our own. He ends up with a sample of 74 hedge fund management companies, which is somewhat smaller than our sample, possibly because we also use the management company names in TASS for the identification. Based on the reported summary statistics, our sample is fairly comparable to his set of hedge funds.

As a validation of our matching procedure, in the Internet Appendix, we assess the extent to which the hedge fund trades in Ancerno relate to the trades that can be inferred from 13F filings. We find that the trades in the Ancerno dataset capture a fair amount of variation in the quarterly holdings of the institutions that file the 13F form.

2.3 Sample selection and summary statistics

Following Keim and Madhavan (1997), we filter the data to reduce the impact of outliers and potentially corrupt entries. In detail, we drop transactions with an execution price lower than $1 and greater than $1,000. We also eliminate trades from orders with an execution time, computed as the difference between the time of first placement and last execution of the order, greater than one month. Together, these filters reduce our initial sample by less than 3%. The resultant sample consists of nearly 6.4 million of transactions in U.S. equity.

Panel A of Table 1 contains summary statistics for a number of daily series that are constructed from the final dataset. The first row reports the number of hedge fund management companies that are reporting on a given day. This number is on average 21, and ranges from a minimum of 10 to a maximum of 34 managers. These managers are responsible for an average of 2,214 daily transactions (second row), or 736 orders (third row), which implies an average of about three trades per order. The distribution of the number of trades and orders per day is however highly skewed, with a maximum of 17,308 and 11,525 respectively. The average and median execution time (fourth row) is about 1 day, and ranges between 0.069 (about 27 minutes) and a maximum of about 7 days.[9] The last four rows in the panel provide information on dollar volume. The average daily volume is about $350 million, with a maximum of $2.5 billion recorded on May 6, 2010. Volume per trade is on average $229 thousand, and varies between $24 thousand and about $1 million. Finally, we look at whether volume per trade differs across buy and sell trades. Interestingly, the volume per sell trades tends to be larger than the volume per buy trade (averages of $240 thousand versus $226 thousand, respectively). Hence, hedge funds appear to be less concerned about reducing the price impact of their trades when it comes to sell trades, possibly reflecting the urgency of fire sales. This is consistent with Keim and Madhavan (1995) who find that institutions tend to split more

[9]These figures are about half to one day smaller than those reported in Keim and Madhavan (1995) for other institutional investors over the 1991-1993 period. The differences may be due to the fact that our hedge funds are not directly comparable to their sample of institutions, and also to the overall decline in execution time over the 2000s.

buy trades than sell trades.

In Panel B of Table 1, similar statistics are displayed for all non-hedge-fund institutions that report to Ancerno. These institutions include mutual funds, pension plans, and other financial institutions that do not classify as “pure-play” hedge funds. The large bulk of these other institutions consists of mutual funds. There are on average 248 non-hedge-fund managers per day during our sample period. The number of trades and aggregate trading volume are, therefore, much larger than for hedge funds. However, the volume per trade appears directly comparable and varies in a similar range as for hedge funds. This implies that differences in trading costs between the two groups are not mechanically due to systematically different trade sizes.

2.4 Is the sample representative?

Next, we tackle the important question of whether our sample of hedge funds suffers from a selection bias. If the companies in our data are selected on the basis of characteristics that correlate with the explanatory variable of interest (funding liquidity), the inference that we make cannot be generalized to the entire hedge fund sector. For example, one may legitimately conjecture that the institutions that turn to Abel Noser Solutions for consulting services are those with lower trading skill. As such, they may be more likely to suffer when aggregate funding conditions deteriorate.

Our first reply to this concern is that the hedge funds that we study are managers for Ancerno's clients. As such, they are not choosing to use Ancerno's consulting services. Rather, it is the Ancerno clients (e.g. pension funds) that ask the hedge funds to report their trades. This fact, in our view, goes a long way in addressing the issue of self-selection.

Second, we provide statistical evidence that further spells the concern of a self-selected sample. In particular, if the sample is selected, we should observe a difference in loadings on the explanatory variables between funds in the sample and the other funds in TASS. Our explanatory variables measure funding liquidity and are explained in more detail in Section 3. For the present purposes, it is sufficient to test whether the impact of these variables on the returns of the Ancerno hedge funds is stronger than for the hedge funds that are in TASS, but not in Ancerno.

We test for this selection bias by running fund-level regressions of returns on the Fung and Hsieh (2001) risk factors plus each of the explanatory variables of interest (i.e. the funding liquidity factors), using the fund monthly returns available in TASS in the 1999-2010 period. To ease the economic interpretation of the differences across variables, the liquidity factors have been standardized to mean zero and variance unity. In Panel A of Table 2, we report the average sensitivities for the funds in TASS that report to Ancerno and for all other funds in TASS, as well as the p-value for the null hypothesis that their difference is zero. For the exposure to the market (R_M), TED spread, and funding liquidity factor (PC) we find no significant difference in the exposure between the two groups. Just in the case in LIBOR do we observe a higher sensitivity of Ancerno funds to funding shocks. For LIBOR (p-value 0.011) and VIX (p-value 0.053) we find that funds in Ancerno are actually on average less affected by funding condition shocks. The difference are, however, economically rather small as they imply that a two standard deviation increase in either VIX or LIBOR would lead to an expected difference of about 12.4bps and 25bps, respectively, between the two groups returns. We also consider the possibility that the sample size is negatively affecting the power of our test. This would be of special concern if the distribution of loadings for the Ancerno funds were much larger than that of the other funds in TASS. We therefore also report the cross-sectional standard deviation of the loadings (std) in the second row, and the p-value for the null hypothesis that the variance of funds in Ancerno is larger than those in TASS. Only in the case of the exposure to the market do we find that the distribution of Ancerno loadings is significantly wider (at 1.186%) than that of the other funds in TASS (Std of 0.895%).

To provide a visual impression of the distribution of these factor loadings, we plot in Figure 1 the kernel densities of the risk loadings to each of the five funding liquidity variables. The solid line denotes all other TASS funds, while the dotted line is for the funds in Ancerno. As we can see, the similarity between the two distributions is substantial. In particular, the sensitivities of Ancerno funds appears to be neither significantly skewed toward higher sensitivities nor to be sampled from the tails of the population of TASS funds. This further validates the evidence from our previous statistical tests that the sample of Ancerno funds is not pre-selected.

We also examine whether the number and risk profile of funds varies systematically over time thus biasing our inference. To that end, Panel B of Table 2 presents the results of regressing the number of funds in the database (row labeled '# funds') on the funding liquidity variables. As we can see, no predictable patterns are observed as all coefficients are largely insignificant. In the second row, we repeat the regression but replace the dependent variable with the average risk loading with respect to each funding variable across the funds that are reporting to TASS in a given month. This conditional analysis amounts to asking whether funds that are present in Ancerno are systematically different (in terms of their exposure to funding conditions) in periods of tighter or looser capital constraints. The results, reported in the row labeled 'loading', clearly demonstrate that this is not the case.

As a final investigation of the sample representativeness, we contrast the characteristics of funds in Ancerno versus TASS. Specifically, we look at the distribution of: monthly returns; percentage flows; the AR(1) coefficient of returns based on 1-year rolling windows, as a measure of asset illiquidity; age, as proxied by the logarithm of the number of months in which the fund appears in TASS; the amount of Leverage in place; and logarithm of assets under management, AUM. Panel C of Table 2 reports the average value of the characteristic for the two groups of 'TASS' and 'Ancerno' funds, as well as the p-value for their difference. We note that the differences in average returns, flows, asset illiquidity, and leverage are largely statistically insignificant. They are also economically quite small. Just in the case of Age and AUM do we see significant differences, with funds in Ancerno being generally older and bigger.[10] If anything, the fact that funds in Ancerno tend to be more mature should make it harder to detect the impact of limits of arbitrage, as these funds may arguably be more unconstrained than otherwise younger funds.

Overall, our analysis shows that the hedge funds in Ancerno do not load on funding liquidity more strongly than other funds in TASS, nor that the number and characteristics of reporting funds differs significantly over time and with respect to TASS. Hence, we are inclined to conclude that our sample is representative of the hedge fund universe as far as the exposure to funding liquidity is concerned.

3 Time-series variation in liquidity provision

3.1 Measuring liquidity provision

Our analysis is inspired by the literature on the limits of arbitrage (Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Gromb and Vayanos (2010), Gromb and Vayanos (2012)). In this literature, liquidity provision is modeled as speculators' ability to absorb temporary order imbalances and to smooth price fluctuations (see, e.g., Brunner-

[10]These two characteristics tend to be, as expected, highly correlated.

meier and Pedersen (2009)). The speculator in these models profits from the price pressure which is induced by a liquidity demanding trade. Our goal is to provide the empirical counterpart to this theoretical concept.

The standard approach in the empirical market microstructure literature is to identify liquidity provision with limit orders and liquidity demand with market order. This strategy is not feasible in our context, as we do not observe the order type. To overcome this limitation of the data, we follow prior literature that works with institutional trades (Keim and Madhavan (1997), Puckett and Yan (2011), Anand, Irvine, Puckett, and Venkataraman (2013)) and capture liquidity provision via a measure of price impact. Price impact is related to the impatience of trading. A liquidity providing trade typically leans against the main order flow. If it is a buy trade it is likely located in out-of-favor stocks, whereas, if it is a sell trade, it makes stocks available that the majority of investors are trying to buy. For this reason, liquidity-providing trades are expected to have limited or negative price impact.

In computing price impact, we need to define the benchmark price to which the transaction price is compared. Lacking the observation of the bid-ask quote prevailing at the time of the trade, we rely on the volume-weighted average of trading prices for the same stock during the day in which the transaction occurred (VWAP). This measure is originally proposed by Berkowitz, Logue, and Noser (1988), and used more recently by Puckett and Yan (2011) who, like us, draw on the Ancerno data. Adopting this benchmark amounts to asking how well the trader did relative to the average transaction during the same day.[11]

We construct hedge fund-level trading costs as the dollar volume-weighted (TC^{VW}) or equally-weighted (TC^{EW}) average trading cost with respect to the VWAP across all trades within a given day. The volume-weighted daily trading cost on day t for manager i is computed aggregating across all trades j:

$$TC_{i,t}^{VW} = \sum_j \frac{\$Vol_j}{\sum_j \$Vol_j} \left(\frac{P_j - VWAP_j}{VWAP_j} \right) \times Side_j \tag{1}$$

and the equally-weighted daily trading cost is:

$$TC_{i,t}^{EW} = \sum_j \frac{1}{N_t} \left(\frac{P_j - VWAP_j}{VWAP_j} \right) \times Side_j \tag{2}$$

[11] See Hu (2009) for an analysis of the properties of price-impact measures based on the VWAP.

where *Side* equals 1 for a buy and -1 for a sell trade. Analogous measures are computed separately for buy (subscript b) and sell (subscript s) trades.

Of course our choice of benchmark, as well as the strategy to use price impact as a measure of liquidity provision, are to some extent discretional. To reassure the reader, in the Internet Appendix, we show that the benchmark is immaterial for our conclusions, as the results can be replicated computing price impact using the Price at Market Open, as in Anand, Irvine, Puckett, and Venkataraman (2013), or the Price at Order Placement, as in Anand, Irvine, Puckett, and Venkataraman (2012). In the Internet Appendix, we also consider proxies for liquidity provision based on reversal strategies (Lo and MacKinlay (1990) and Nagel (2012)) and trading style (Anand, Irvine, Puckett, and Venkataraman (2013)). These alternative measures correlate strongly with our main proxy for liquidity provision, which is reassuring about the identification strategy.

3.2 Overview of trading costs

Panel A of Table 3 contains summary statistics for trading costs expressed in basis points (bps) pooling all fund-day observations. Over the sample, the average volume-weighted trading cost is about 8bps with a standard deviation of 66bps. Much of this variability, however, is due to observations in the tail of the distribution, as demonstrated by the relatively small interquartile range (about 45bps). Equally weighted trading costs are lower on average at 4bps. This difference suggests that large trades denote liquidity demand on average. Each of the two variables is characterized by a modest degree of time-series persistence, with first-order autocorrelations of about 0.10.

In order to offer a low-frequency view on the evolution of hedge funds trading costs, we display in Figure 2 the aggregate volume-weighted (top plot, black bars) and equally-weighted (bottom plot, black bars) series averaged over the quarter. Several considerations are in order. Trading costs show a substantial increase from about 0.20% at the beginning of the sample to a high of 1% in the early 2001, a period that is characterized by the rise and burst of the Internet bubble. This finding resonates with the results in Brunnermeier and Nagel (2004) who argue that hedge funds were taking strong bets on overvalued technological stocks during this period and then partly reversed their position during the subsequent downturn. In our series, trading costs start decreasing from the 2001 peak and remain at their lowest levels until mid-September of 2007, when they start increasing again to reach late 2001 levels. Interestingly, the equally-weighted series remains negative for the vast majority of the 2005 to late 2008 period, suggesting that during the last crisis some hedge funds were providing liquidity to the market while others were engaging in massive liquidations of their positions. This evidence lines up with the findings in Ben-David, Franzoni, and Moussawi (2012).

A question that we address in our subsequent analysis is whether hedge funds are different from other institutions in their liquidity provision. As a preview, we construct analogous trading costs series using the trades of all non-hedge-fund institutions that report to Ancerno. Looking at Panel B of Table 3, it is immediately apparent that the average trading costs for these investors are much lower than those of hedge funds on both a volume-weighted basis (1bp versus 8bps) and an equally-weighted basis (-3.4bps versus 4.3bps). The time-series behavior of the trading costs experienced by the two groups is also markedly different. In Figure 2, the white bars display the quarterly average for the volume-weighted (top plot) and equally-weighted (bottom plot) series of trading costs to other investors in Ancerno. These series appear to be much less sensitive to aggregate conditions than those for hedge funds. For example, trading costs in the down market of mid-2000 to mid-2001, which was characterized by relatively high interest rates, have similar magnitude to those observed in the boom market mid-2004 to mid-2005, with much cheaper access to credit.

3.3 Hedge funds' liquidity provision and funding liquidity

The upshot of the limit of arbitrage theories is that the agency relationship between the fund managers and their capital providers can divert arbitrageurs' actions from pursuing profitable trading opportunity. As a result, mispricing persists and market liquidity decreases.

Due to the leeway in their trading strategies, hedge funds play the role of prototypical arbitrageurs. These institutions, however, need to raise and maintain their capital in order to be able to trade. Thus, hedge funds are constrained in their actions by the need to retain and attract investors. In addition, hedge funds make intensive use of leverage in the form of borrowed capital, short selling, and derivative positions. This fact exposes them to a close scrutiny by their brokers and trading counterparties. These actors stand ready to call for additional margins in case of increased risk of the hedge funds' positions, a surge in the cost of capital, and a drop in the value of the collateral that is posted by hedge funds. These considerations suggest that limits-of-arbitrage theories may well describe hedge fund behavior. If this is the case, we should observe a decrease in hedge fund liquidity provision following a decrease in funding liquidity, which is defined as the availability of trading capital (Brunnermeier and Pedersen (2009)).

We test this conjecture by first studying the trading behavior of our sample of hedge funds in the U.S. equity market. In doing that, we face the challenge of identifying truly exogenous variation in hedge funds' funding liquidity. Fund flows are certainly related to the availability of trading capital. However, they are hardly exogenous as investors react to a rational anticipation of future performance, which in turn is related to hedge funds' liquidity provision. Thus, we choose to measure funding liquidity using financial variables that proxy for the prevailing funding conditions. Our assumption is that the evolution of these variables does not depend on hedge funds' liquidity provision in the future. Under this assumption, changes in aggregate conditions can be used as exogenous sources of variation in funding liquidity.

Based on the findings in Hameed, Kang, and Viswanathan (2010) that liquidity supply by financial intermediaries is positively related to market performance, we test whether the hedge fund sector decreases liquidity provision following a decline in the stock market. These authors' implicit assumption is that the financial intermediation sector has a positive net position in stocks. Thus, losses in the stock market entail a deterioration of liquidity providers' capital. In the context of hedge funds, this assumption seems to apply as well. For example, Fung and Hsieh (2004) show that the average hedge fund has a positive beta on the S&P 500. Even some of the funds in the self-declared market-neutral style, appear to have a significant exposure to the market factor (Patton (2009)).

The extent to which hedge funds can lever up their positions affects their ability to correct mispricing and provide liquidity. Patton and Ramadorai (2012) show that hedge funds' risk exposures are significantly related to the TED spread (the three-month LIBOR minus the three-month T-bill rate). To explain their finding they refer to Garleanu and Pedersen (2011), who argue that the interest rate difference between collateralized and uncollateralized loans (or Treasury securities) captures arbitrageurs' shadow costs of funding. Thus, we also use the TED spread to proxy for systematic time-series variation in funding liquidity. Moreover, the leverage available to hedge funds varies with the costs of borrowing. Thus, we use the LIBOR to proxy for the level of interest rates.

Finally, Brunnermeier and Pedersen (2009) argue that the margins imposed by brokers to arbitrageurs depend on the volatility of asset prices. In their paper, brokers set margins according to Value-at-Risk models, for which volatility is the main input. Because we want to focus on aggregate variables, we use the VIX to measure the impact of volatility on liquidity provision by the hedge fund sector through the margin requirements channel.

To summarize, we formulate and test empirically the following

Hypothesis 1: Hedge funds' liquidity provision in the stock market is positively related to aggregate measures of funding liquidity. In particular, liquidity provision depends:

· *Positively on the past performance of the market*
· *Negatively on the TED spread*
· *Negatively on the LIBOR*
· *Negatively on the VIX.*

Panel C of Table 3 reports summary statistics for the four financial variables in Hypothesis 1. At the daily frequency, these variables are quite persistent, but they experience substantial variation during the prolonged period we consider.[12] In addition, we also use the first principal component of these four variables, which we label PC and we refer to it as to the funding liquidity factor. From the correlation matrix, we notice that PC is strongly negatively related to the market return and positively to VIX and TED, and has a small positive correlation with LIBOR.

We test Hypothesis 1 by means of the following linear regression model:

$$TC_{i,t+1} = a + bFundLiq_t + \phi TC_{i,t} + \epsilon_{i,t+1} \tag{3}$$

where $TC_{i,t+1}$ is hedge fund i trading cost on day $t+1$, and $FundLiq_t$ denotes alternatively one of the five funding liquidity determinants (R_M, VIX, TED, LIBOR, or PC) measured on day t. We include lagged trading costs to account for the small persistence in this series that is observed in Table 3. To ease the discussion, here and throughout our subsequent regressions, we express trading costs in basis points and standardize the variables in $FundLiq_t$, so that the coefficient b represents the expected change in trading costs (in bps) following a one standard deviation increase

[12]For example, the VIX ranges from a minimum of 0.10 in November, 2006 to a maximum of about 0.81 in October, 2008. Similarly, the LIBOR rate varies from 0.2% throughout 2010 to as high as 6.9% in the mid-2000.

in $FundLiq_t$. The model is estimated by pooling all fund-day observations over the full 1999-2010 sample.[13]

The left-hand-side block of Panel A of Table 4 presents the estimates for b when trading costs are volume-weighted. The five different specifications for $FundLiq_t$ are reported in columns (1) to (5), respectively. Below the estimates, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. In the first specification, we relate liquidity provision to R_M. The coefficient on R_M is found to be negative at -1.515, and statistically significant at the 1% level. Hence, a one-standard deviation negative shock to stock market valuations is associated with weaker liquidity provision by hedge funds whose trading costs increase on average by about 1.5 basis points. In column (2), we look at the relation between liquidity provision and the VIX. The coefficient is positive at 1.750, with an associated t-statistic of 4.79. A slightly stronger effect is found for the TED spread, with a coefficient of 1.925 and a t-statistic of 5.12, and especially for LIBOR whose effect is largest at 3.220, or 3.2 basis points. Given the unconditional mean of trading costs of about 8 basis points (Table 3), these effects appear, economically speaking, quite large. Finally, the loading on the funding liquidity factor PC is positive at 2.618, and highly statistically significant.

In the right-hand-side block of the panel, the same analysis is repeated for equally-weighted trading costs. Similarly to the volume-weighted results, all coefficients are significant and have the expected sign: they are negative for R_M, and positive for the other four variables. However, the economic impact of the variables is generally weaker. We impute this reduction in significance to the fact that the equally-weighted measure dampens the impact of large trades, which are mostly relevant to measure liquidity demand.

In Panel B of Table 4, we look at the results for volume-weighted trading costs when these are separately calculated for buy and sell trades. Owing to their ability to take short positions, which are part of the sell trades reported to Ancerno, hedge funds are in the position of taking advantage of both upturns and downturns. Thus, it is interesting to examine whether time-variation in liquidity provision characterizes differently the two sides of the market. The statistical significance of the funding liquidity determinants characterizes both buys and sells, but the coefficients for sell-side

[13] As a robustness check, Internet Appendix D shows that the main findings hold also when using data aggregated at the weekly frequency.

trading costs are substantially larger in absolute value for all variables but TED. The difference is particularly large for R_M (-0.830 versus -1.727) and for the VIX (1.162 versus 2.771).

Next, we investigate the extent to which our results are affected by the 2007-2009 financial crisis. This is a legitimate concern due to the large variations experienced by the funding liquidity variables during that period. To that end, we repeat our analysis separately for the crisis and ex-crisis period. Following Anand, Irvine, Puckett, and Venkataraman (2013), we define the crisis period as spanning the January 2007 to May 2009 sample. Table 5 reports the estimates of equation (3) in the two samples. Regardless of the sample considered, all coefficients have the expected sign and their magnitude and significance is comparable to the estimates appearing in Panel A of Table 4.[14] These findings lend support to the view that time-variation in hedge funds' liquidity provision represents a pervasive behavior, and not a crisis-only phenomenon.

In order to measure the impact of the funding liquidity variables on liquidity provision it is essential to keep 'order difficulty' fixed. That is, it is possible that a deterioration of aggregate conditions determines also a shift in the characteristics of hedge fund trades that drives up trading costs, without an actual change in the attitude towards liquidity provision. Here, we address changes in order difficulty that are observable at the trade level. In the next subsection, we develop an approach to control for aggregate changes in order difficulty that affect all traders. We modify equation (3) to include appropriate controls for order characteristics that allow us to keep the observable order characteristics fixed:

$$TC_{i,t+1} = a + bFundLiq_t + \delta' Z_{i,t} + \varepsilon_{i,t+1} \tag{4}$$

where the vector $Z_{i,t}$ collects the following variables, which are partly inspired by prior literature (e.g. Anand, Irvine, Puckett, and Venkataraman (2012)): *Buy*, a dummy that equals 1 for buy trades, and 0 otherwise; *Lagged Return*, the stock return in the prior day; *NYSE*, a dummy that equals 1 for stocks listed at the NYSE, and 0 otherwise; *Inverse Price*, the inverse of day-t stock price; *Relative Volume*, the ratio between the number of shares traded to the average volume of the stock in the prior 30 days; *Amihud*, the Amihud illiquidity ratio; *Size* and *Book-to-Market*, the stock

[14] The effect of R_M is somewhat stronger in the crisis period, while that of VIX is comparable at about 1.9. In contrast, the coefficient on TED is more than twice as large in the ex-crisis period, while LIBOR is insignificant in the 2007-2009 sample. Finally, the loading on the principal component PC is a large 4.304 in the ex-crisis period compared to a 2.881 figure in the crisis sample.

market capitalization and book-to-market deciles. All variables are computed as volume-weighted averages at the fund-day-side level. These controls ensure that our inference is not driven by the fact that hedge funds trade different volumes or in stocks with different degrees of liquidity.

The estimates of equation (5) are reported in Panel A of Table 6. They do not modify our conclusions as the slopes on the funding liquidity variables are not substantially impacted by the inclusion of trade-level characteristics. The signs of the control variables line up with the findings of prior literature and conform to expectations. Overall, the results support the prediction in Hypothesis 1 that periods characterized by tighter funding constraints in the form of a reduction in the value of collateral, a surge in aggregate uncertainty or in risk premia as captured by the VIX, and costlier access to credit are accompanied by a decrease in hedge funds' ability to provide liquidity.

3.4 Hedge funds vs. other institutions

Our empirical approach to capture liquidity provision consists of measuring the price impact of hedge fund trades. Price impact, however, is not only related to the net demand of liquidity in a trade, but also to the cost of liquidity in the market. Put simply, the same liquidity-motivated buy order of 10,000 shares of IBM could have different price impacts in different market conditions. Likely, when aggregate conditions deteriorate, the price of liquidity is higher. These considerations highlight an important empirical challenge in identifying variations in liquidity provision as a function of aggregate funding liquidity. The component of price impact due to arbitrageurs' withdrawal from liquidity provision, which we wish to identify, is subject to the confounding effect from the increase in the cost of liquidity in bad times.

To separate out the liquidity-provision effect, we benchmark hedge fund trading costs to those experienced by other investors in comparable market conditions, as in a difference-in-differences approach. Besides hedge funds, our data cover other institutional investors, mutual funds and pension funds, which we use to control for market-wide variation in the cost of liquidity. The rationale for our strategy is that the aggregate increase in trading costs is filtered out when comparing hedge funds to other institutions.

For this set of investors to serve as a valid control group, however, it has to be the case that their liquidity provision is subject to changes in funding conditions to a smaller extent than for hedge funds. This seems to be a fair assumption. For example, mutual funds make only limited use of leverage, if at all, which makes them less exposed to changes in borrowing conditions and volatility. Also, the convexity of the flow-performance relation (Chevalier and Ellison (1997), Sirri and Tufano (2002)) implies that mutual fund flows are relatively less sensitive to poor past performance than hedge fund flows, for which the flow-performance relation has been found to be linear (Li, Zhang, and Zhao (2011)) or even concave (Ding, Getmansky, Liang, and Wermers (2009)). Related to this point, the hedge funds' institutional clientele is likely to react more quickly to changing performance than the retail investors in mutual funds because of a more structured investment process and risk management considerations. Supporting these arguments, Ben-David, Franzoni, and Moussawi (2012) show that during the recent crisis hedge funds engaged in more important portfolio liquidations than mutual funds, and link this different behavior to the more significant outflows from the hedge fund sector, the leverage, and the institutional clientele of hedge funds.

Thus, the need to benchmark hedge funds' trading costs to those of other institutions brings us to formulate the following

Hypothesis 2: Capital availability for hedge funds is more subject to aggregate conditions than for other institutions (mutual funds and pension funds). As a result, the sensitivity of hedge funds' liquidity provision to funding liquidity is stronger than for other institutional investors.

To test Hypothesis 2, we estimate the interacted model:

$$TC_{i,t+1} = a + b_1 FundLiq_t + b_2 HF \times FundLiq_t + \delta' Z_{i,t} + \varepsilon_{i,t+1} \tag{5}$$

where HF is a dummy variable that equals 1 if institution i is a hedge fund, and 0 otherwise. The coefficient b_1 measures the expected impact of a one-standard deviation increase in $FundLiq_t$ on the trading costs of investors that are not hedge funds. The loading on the interaction term, b_2, captures instead the additional effect of the same shock on hedge funds' liquidity provision. This is the coefficient of interest to us for testing Hypothesis 2. The controls in $Z_{i,t}$ are meant to keep trade-level characteristics fixed, as discussed in relation to equation (4).

Estimates of the model in (5) are reported in Panel B of Table 6. The top row of the table indicates the funding liquidity variable that is used in the corresponding column. A few facts are noteworthy. First, the interaction term b_2 is always statistically significant at the 1% level or better. Consistently with Table 4, the coefficient is negative for the market in column (1), and is positive for LIBOR, VIX, TED, and PC. Therefore, there is an additional significant impact of funding liquidity shocks on hedge funds' trading costs relative to those of other institutions. Second, the estimates for b_1 are positive for LIBOR but negative and significant for VIX, TED, and PC. This implies that the trading costs to other institutions decrease in certain periods of market stress, when they are acting as liquidity providers, consistent with Anand, Irvine, Puckett, and Venkataraman (2013). Third, b_2 is about an order of magnitude larger than b_1. Since b_1 captures the baseline effect for all institutions, we conclude that only a limited part of the sensitivity of hedge funds' trading costs we documented in the previous section is due to aggregate fluctuations in the cost of liquidity that affect other investors as well. For example, in the case of VIX the coefficient b_1 is negative at -0.813, but it becomes a positive 2.784 for the hedge fund interaction term. Overall, the results are consistent with Hypothesis 2. Also, it appears that in periods of tight funding, as measured by the VIX, the TED spread, and PC, other institutions than hedge funds shift towards liquidity provision.

3.5 Characteristics of traded stocks and execution speed

Another way of capturing the reaction of hedge funds to capital availability is to look at changes in the type of stocks in which they trade. Working on Ancerno data, Anand, Irvine, Puckett, and Venkataraman (2013) show that in periods of market stress buy-side institutions trade more on liquid stocks and that this flight-to-liquidity has first-order effects for pricing. If hedge funds are acting as ultimate liquidity providers, then we would expect them to trade on less liquid stocks that are neglected by other investors and offer appealing premia for liquidity. Alternatively, they might decide to liquidate more volatile and illiquid stocks because they are costly to hold in terms of margin requirements, as argued by Brunnermeier and Pedersen (2009). In either case, because trading costs are on average higher for illiquid stocks, and their trading costs may very well increase during market stress, the change in the composition of hedge fund trades may be responsible for part of the time-variation in trading costs that we find.

To test for this composition effect, we again use a fully interacted model where the dependent variable is now the volume-weighted average decile (VWAD) of the stocks traded by a given institutional investor on day t. The deciles are computed based on the whole universe of CRSP stocks, separately along the following two relevant dimensions of liquidity: market capitalization (Size), and the Amihud (2002) ratio, which measures price impact and, therefore, captures illiquidity. The deciles are ordered from 1=LOW to 10=HIGH values of the corresponding variables. Thus, the top Size and the bottom Amihud deciles contain the most liquid stocks. The following regression model is then estimated:

$$\begin{aligned} VWAD_{i,t+1} &= a_1 + a_2 HF + \theta_1 FundLiq_t + \theta_2 HF \times FundLiq_t \\ &\quad + \phi_1 VWAD_{i,t} + \phi_2 HF \times VWAD_{i,t} + v_{i,t+1} \end{aligned} \tag{6}$$

Here, the coefficient θ_2 measures the additional tilt in the degree of liquidity of the stocks traded by hedge funds compared to other investors, following the shock in $FundLiq_t$.

Panel A of Table 7 presents the results for Size $VWAD$. The first row of coefficients reports the estimates of the interaction term, θ_2. The coefficient on the market return, R_M, is negative and significant at the 5% level. The estimates of VIX, TED, LIBOR, and PC are instead all positive, and they are statistically significant at the 1% level, with the exception of LIBOR. On the aggregate, it appears that hedge funds react to periods of tightening constraints by tilting their trades towards liquid stocks. This effect is not only statistically, but also economically large if compared to the behavior of other institutions. For example, the loading on VIX is 0.018 for non hedge funds investors, while it is 0.058 (0.040+0.018) for hedge funds. Similarly, the effect of market returns is almost twice as large for hedge funds (-0.007 versus -0.016). Interestingly, the coefficient on TED for the other investors is negative and significant, which suggests that positive shocks to the TED spread tend to be followed by liquidity provision in smaller, neglected stocks. Looking at the combined effect of the liquidity factor PC, the effect of funding liquidity appears to be four times larger for hedge funds than for the other institutions reporting to Ancerno. Panel B of Table 7 displays the results for the Amihud $VWAD$, which lead to similar conclusions. The fact that hedge funds react to funding liquidity shocks by moving toward liquid stocks, and that they do so much more aggressively than other institutional investors, is in stark contrast with the claim that they act as liquidity providers of last resort.

We can delve deeper into hedge funds' demand for immediacy by studying their trading speed.

The speed of order execution, measured by the time between order placement and completion, is related to whether the order is placed in the form of a limit or market order. Market orders are typically characterized by a shorter execution time than limit orders, as they serve the needs of investors with a high appetite for trading immediacy. Viceversa, liquidity provision is generally associated with limit orders. Our data do not provide information on the order type. Still, according to this logic, if hedge funds respond to a tightening in funding constraints by demanding liquidity, we should observe a reduction in order duration, which is a variable that we can measure.

We compute the duration of hedge funds orders as the span (in minutes) between the time of placement of the first trade in an order and the time of execution of the last trade in the same order. The regression equation for testing our conjecture is:

$$ExTime_{i,t+1} = a + \beta FundLiq_t + \gamma' Z_{i,t} + u_{i,t+1} \tag{7}$$

where $ExTime$ is the logarithm of the average duration across all orders placed by hedge fund i on day $t+1$, separately computed for buy and sell trades. $Z_{i,t}$ denotes the following four cross-sectional controls: $Side$, $RelativeVolume$, $SizeVWAD$, and a time trend ($Trend$) capturing the dependence of execution time on the prevailing characteristics of the stock exchange, such as the progressive introduction of automated trading (Hendershott, Jones, and Menkveld (2011)). The timing of the variables is organized so that β measures the expected impact of the aggregate shock in $FundLiq_t$ on the duration of future orders.

The estimates of equation (7) are presented in Table 8. Two aggregate variables, the VIX and the principal component PC, stand out as having a statistically significant negative effect on execution time. The coefficients on these variables imply that a deterioration in funding liquidity is followed by a reduction in the duration of hedge funds orders of about 5 to 9 percent. Given an average order duration of about 1 trading day or 390 minutes (Table 1), a one standard deviation increase in PC and VIX is accompanied by a decrease in the execution time of about 20 and 35 minutes, respectively. Importantly, notice that a higher VIX predicts a *decrease* in execution time. The direction of the effect is the opposite of what we would expect if the results were mechanically driven by the drop in liquidity that typically follows an increase in VIX (Nagel (2012)). Rather, they are consistent with a stronger demand for immediacy by hedge funds in stressed market conditions.[15]

4 Cross-sectional analysis

In this section, we refine the identification of the limits of arbitrage by exploiting cross-sectional heterogeneity in hedge funds and formulate our Hypothesis 3. Also, we study whether the shift in hedge fund positions that follows from a shock in funding liquidity impacts the trading performance of more constrained hedge funds. In principle, if arbitrageurs are obliged to move away from their preferred trading strategies, their performance should suffer.

4.1 Liquidity provision and hedge fund characteristics

A number of hedge fund characteristics are likely to determine different sensitivity of liquidity provision to changes in aggregate funding conditions. For example, higher leverage makes a fund more exposed to changes in the cost of debt and in margin requirements. Then, we expect highly-levered hedge funds to withdraw their liquidity provision more strongly in bad times.

The ease with which investors can redeem their capital makes a hedge fund more susceptible to redemptions in case of poor performance or deteriorating aggregate conditions. According to this argument, we should expect that the liquidity provision of hedge funds with lower share restrictions, e.g. lower redemption notice period, is more sensitive to aggregate funding conditions. Consistent with this conjecture, Jylha, Rinne, and Suominen (2012) find that hedge funds with longer lockup periods have a higher propensity to supply immediacy. The strength of this prediction can be attenuated by the fact that share restrictions are set endogenously to provide a buffer to funds that invest in illiquid assets (Ding, Getmansky, Liang, and Wermers (2009)). If illiquid assets are more exposed to aggregate conditions, funds with stronger share restrictions could actually end up increasing their liquidity demand in bad times. Which effect prevails is ultimately an empirical question.

Related to the last point, hedge funds with an important component of illiquid assets in their

[15] The statistical and economic significance of the aggregate funding shocks in Table 8 holds also after the inclusion of the control variables. *Side* is positively related to execution time, but not significantly so. The execution time is shorter for bigger stocks, that are usually characterized by a higher degree of liquidity. This is reaffirmed by the estimate of about -0.10 for the coefficient on $SizeVWAD$. The loading on $RelativeVolume$ is positive and highly significant, that is, orders that are large relative to the normal volume of a stock take longer time to be executed. Finally, the time trend is negative and significant, and corresponds to a decrease in trading time of about 8% per year.

portfolios may be more likely to alter their provision of liquidity in the stock market if funding conditions deteriorate. The logic is that a negative shock to the illiquid part of their portfolio may force them to liquidate their more liquid positions, which qualifies as demand for liquidity. Manconi, Massa, and Yasuda (2012) provide evidence for the bond market during the recent financial crisis that is consistent with this story. Following Getmansky, Lo, and Makarov (2004), we measure the illiquidity of a fund's portfolio using the first-order autocorrelation of the fund returns. We expect the liquidity provision of more illiquid funds to be more strongly related to aggregate funding conditions.

The extent to which hedge funds can preserve their trading capital when facing adverse conditions also depends on their reputational capital. An established hedge fund can more convincingly negotiate the lending terms with brokers and prevent investors from leaving the boat than a young fund. For similar reasons, funds with a shining track record are more credible vis-a-vis brokers and investors than poor-performers. Thus, we expect the sensitivity of hedge funds' liquidity provision to aggregate conditions to be stronger for young and poor-performing funds.

To summarize, we formulate the following

Hypothesis 3: The sensitivity of hedge funds' liquidity provision to aggregate funding liquidity is related:

· *Positively to leverage*
· *To redemption restrictions with an ambiguous sign*
· *Positively to asset illiquidity*
· *Negatively to fund age*
· *Negatively to past performance.*

To test Hypothesis 3, we regress the measure of hedge fund liquidity provision (TC) on the interaction between aggregate funding liquidity and measures of the hedge fund characteristics that are meant to capture limits of arbitrage. The regression that is run on hedge fund-day level data is:

$$TC_{i,t+1} = \alpha + \beta' FundLiq_t + \gamma' X_{i,m-1} + \eta' FundLiq_t \times X_{i,m-1} + \epsilon_{i,t+1} \tag{8}$$

where $FundLiq$ is, as before, alternatively R_M, VIX, TED, LIBOR, or PC. The vector X collects six cross-sectional characteristics, $X = \{Leverage, Young, Illiquid, Bad, LowRed, NoLock\}$. Notice that the fund characteristics are obtained from the monthly TASS data. Hence, they are constant within a month and are based on prior month information (month $m-1$). *Leverage* is the amount of leverage in place; $Young$ is minus the logarithm of the number of months in which the fund appears in TASS; *Illiquid* is the decile of the distribution of first-order autocorrelation in returns; *Bad* is minus the fund's year-to-date performance; *LowRed* is a dummy variable that equals 1 if the sum of redemption notice period and redemption frequency is lower than 120 days (the sample median); and $NoLock$ is a dummy variable that equals 1 if the fund has zero lockup period. Except for the variables measuring share restrictions (lockup and redemption periods), for which the effect is a priori ambiguous, the fund-level regressors are defined so that a higher score captures higher expected limits of arbitrage. In equation (8), our main interest is on the slope η that captures the differential effect of funding liquidity shocks, originating from fund-level characteristics, on the implicit trading cost.

Table 9 reports the estimates of equation (8) for the different funding liquidity variables. The regression also includes hedge-fund style dummies. The dependent variables is trading costs expressed in basis points. The bold face highlights the coefficients among the η estimates that are consistent with Hypothesis 3 (with 10% significance).

In the first column, the prior-two-weeks market return plays the role of the funding liquidity variable. For the fund-level characteristic to capture limits of arbitrage, we expect the slope on the interaction to be negative. An improvement in funding conditions is expected to benefit more, in terms of lower trading costs, the more constrained funds. The only significant interaction is for the no-lockup period dummy. Its positive sign confirms the ambivalent prediction of Hypothesis 3 with respect to the effect of share restrictions. The evidence is consistent with the view that share restrictions are set endogenously by funds that trade in illiquid assets. In this sense, an improvement in market conditions benefits more the funds with a lockup period in place, which invest in more illiquid assets. This interpretation of the role the lockup period is confirmed across specifications.

In the other specifications of Table 9, an increase in the funding liquidity variable signals a deterioration of aggregate conditions. Hence, the expected sign for the regressors in X is reversed relative to column (1). In column (2), VIX measures funding liquidity. A deterioration of aggregate conditions, as signalled by an increase in the VIX, increases more significantly the trading costs of young and poor-performing funds. This is consistent with Hypothesis 3 as an increase in these variables reflects a lower reputational capital for the fund. As for the negative and significant sign on the interaction between $LowRed$ and VIX, it confirms the evidence above about $NoLock$. That is, funds with higher share restrictions also have more illiquid assets, which harms liquidity provision in bad times.

In columns (3) and (4), the funding liquidity variables are the TED spread and the LIBOR, which capture credit market conditions. As expected from Hypothesis 3, a tightening of credit harms more strongly the trading costs of the more levered funds. So, leverage appears to act as a fund-level limit to arbitrage in bad times. In the same two columns, low share restrictions (as measured by $LowRed$) magnify the impact of a deterioration of aggregate funding conditions on trading costs. Confirming the ambivalence of Hypothesis 3, share restrictions appear in this case to ease the fund-level constraints by shielding the managers from outflows in bad times. In terms of magnitude, the estimates in column (3) suggest that a one-standard deviation increase in the TED spread, increases trading costs by about 14 bps more for funds with low share restrictions ($LowRed = 1$). This seems like an economically important effect, given that the standard deviation of TC is about 66 bps (see Table 3). The positive and significant estimates on the interactions with $Illiquid$ and $Young$ confirm Hypothesis 3 (while Bad is consistent only in column 4) . Finally, column (5), in which deteriorations in funding liquidity are measured by the funding liquidity factor (PC), reiterates some of the previous results.

The analysis in Table 9 is overall consistent with the predictions of Hypothesis 3. Based on this evidence, we ask the question of whether the larger effect of aggregate funding liquidity on the trading costs of hedge funds relative to other institutions (see Table 6) can be relegated to the subset of hedge funds with stronger limits of arbitrage. This is a relevant point, as it seems implausible that the entire hedge fund sector is in a worse position than other institutions to provide liquidity in bad times. Rather, one would expect the results in Table 6 to be driven by the more constrained hedge funds.

To test this conjecture, Table 10 replicates the analysis of Table 6 for the two subsets of constrained and unconstrained funds. Based on the analysis in Table 9, a constrained fund is defined has one that has both non-zero leverage and $LowRed$ equal to one. The comparison between Panel A (constrained funds) and Panel B (unconstrained funds) suggests that the differential impact of the macro variables on hedge funds (slope on HF$\times FundLiq$) is concentrated in the group of constrained funds.

This result gives an important qualification to our previous findings. The statement that hedge funds are more constrained than other institutions in their ability to provide liquidity in bad times has to be confined to the subset of hedge funds with fund level characteristics that magnify their exposure to shifts in funding conditions. The rest of the hedge fund universe can provide liquidity at least as well as other institutions.

4.2 Performance and hedge fund characteristics

The analysis conducted so far is consistent with the view that hedge funds are forced by limits of arbitrage to unwind their positions when funding conditions tighten. One potential alternative description of the evidence, however, is that hedge funds are optimally timing the market and closing down positions in anticipation of further deterioration of aggregate conditions. In support of this alternative conjecture, one may argue that the lack of an explicit benchmark allows hedge funds to change their positions promptly in the face of changing conditions.

To disentangle these two hypotheses, we study the ex-post performance of the trades carried out by constrained hedge funds as a function of aggregate funding conditions. If limits of arbitrage are playing a role, we should observe underperformance of the stocks that are traded by constrained funds when aggregate conditions deteriorate, as these transactions represent a forced deviation from an optimal path. Underpeformance can originate from two sources. First, these positions are initially held by hedge funds because they are expected to be profitable. Closing them down corresponds to a missed profit opportunity. Second, the evidence on trading costs and execution time in Section 3 is indicative of rushed liquidations. Then, hedge fund trades are going to have a price impact which reverts over the next days. In either case, we expect the stocks that are sold by constrained hedge funds to increase in value, while the stocks that are bought (also with the purpose of closing short positions) should drop in value, in the days that follow the transactions.

For each hedge fund-day, we compute the ex-post volume-weighted performance between trade execution (using the execution price provided by Ancerno) and the closing of day $t + 5$ (using the closing price in CRSP), for all the trades occurring on day t. The choice of a five-day horizon is suggested by the consideration that, if these forced liquidations have a price impact, it is going to revert quite soon. Returns of stocks that are sold enter the total return with a negative sign, as in Puckett and Yan (2011). We then take the volume-weighted average of the five-day abnormal returns of all the stocks that are traded on day t by fund i. The abnormal return is computed relative to a market model, for which beta is estimated on the prior sixty days. We estimate the following regression, in which the dependent variable is the abnormal return (in %) of fund i's day-t trades between execution and $t+5$:

$$r_{i,t:t+5} = \alpha + \beta' FundLiq_t + \gamma' X_{m-1} + \eta' FundLiq_t \times X_{m-1} + \epsilon_{i,t:t+5} \tag{9}$$

where $FundLiq$ is alternatively R_M, VIX, TED, LIBOR, or PC. The vector X collects the six cross-sectional characteristics in the prior month $(m-1)$, $X = \{Leverage, Young, Illiquid, Bad, LowRed, NoLock\}$, that are described in relation to equation (8). Once again, our interest is on the vector η that captures the additional effect of funding liquidity shocks on the future performance of a constrained fund.

Table 11 reports the estimates for the regression in equation (9). Returns are measured in percent. The first five rows of the table display the estimates of η. The bold face is for the coefficients that provide significant evidence in favor of the limits of arbitrage hypothesis. While not all slopes in η meet statistical significance, it is interesting to notice that the significant ones point in the same direction and are consistent with the limits of arbitrage hypothesis. For example, from column (1), we infer that the stocks traded by more levered funds outperform the stocks traded by less levered funds, when the market goes up. This seems to suggest that an improvement of aggregate funding conditions eases the constraints on funds that have stretched their borrowing capacity. The effect of leverage is consistent with limits of arbitrage also in columns (2), (4), and (5), where the negative signs are due to the fact that the funding liquidity variables measure a deterioration in aggregate conditions. Further confirmations for limits of arbitrage come from $Young$ and $LowRed$, in column (2), and from $Illiquid$ in column (4). To gauge the economic magnitude, we can focus for example on the estimate for $Illiquid$ in column (4). A one-standard deviation increase in the LIBOR, reduces the five-day abnormal return of a fund in the top illiquidity decile by about 36 bps more than for a fund in the bottom decile of illiquidity (-0.04%×9=0.36%). This seems like a significant number as it translates into a 18% decrease in annual market-adjusted performance (-.36%$\times$250/5 = 18%).[16]

Overall, the analysis in this section provides support of the theories that posit limits on liquidity provisions as a function of investors' ability to attract and retain capital. Our evidence suggests that hedge funds that are more severely constrained are likely to perform relatively worse than other funds when funding liquidity tightens.

5 Liquidity provision and hedge funds' trading style

Another dimension of the cross-sectional heterogeneity in the hedge fund sector relates to hedge funds' trading styles. For a hedge fund, its trading strategy is the ultimate determinant of the availability of funding liquidity. For example, different trading strategies require different levels of leverage to be profitable. A fund whose trading strategy requires higher leverage may be obliged to forced liquidations in bad times. Hence, when aggregate conditions deteriorate, funds pursuing different strategies may be more or less able to provide liquidity to the market. Some funds may even be obliged to demand liquidity in stressed markets.

Hedge funds report a broad classification of their trading style to data providers. However, these categories contain little information, especially for hedge funds operating in the equity domain. The majority of funds in TASS appear in the 'long-short equity' style, but this does not say much about the kind of stocks they actually invest in. Our data give us the unique opportunity to obtain a timely snapshot of the stocks in which hedge funds trade. Differently from the quarterly holdings in the 13F filings, Ancerno reports each trade over the period in which the funds appear in the data set. This fact puts us in a privileged positions, as a high-frequency perspective is crucial for inferring hedge funds' trading strategies.

We focus on three popular trading styles in the equity space. The first one corresponds to short-term reversal strategies, which provide liquidity in stocks that experience temporary price pressure. This style is popular, for example, among those high-frequency traders that exploit signals from prices and volume. The second one is based on the momentum anomaly (Jegadeesh and Titman

[16]Some readers wonder whether the constrained funds' trading performance is lower when funding conditions deteriorate because they switch to more profitable opportunities that open up in other asset classes. According to this story, to be able to promptly rebalance their portfolio, the constrained funds are willing to accept small losses on their equity investments. In Internet Appendix G, we provide evidence that seems to rule out this alternative, as constrained funds suffer more from the point of view of total returns than unconstrained funds when funding conditions tighten.

(1993)). The strategy consists of buying prior-year winners and shorting prior-year losers. The third one is a traditional value strategy (Fama and French (1993)) going long in undervalued stocks (high book-to-market) and short in overvalued stocks (low book-to-market). Each fund in a given month ranked along each of these three dimensions. Then, we study the fund's behavior in terms of liquidity provision, both unconditionally and as a function of aggregate conditions.

In more detail, the definition of a short-term reversal strategy follows Nagel (2012). We assign CRSP stocks to reversal deciles each day based on the average of cumulative returns in excess of the equally-weighted market return over the past 1 to k days, for $k = \{1, 2, 3, 4, 5\}$. We assign scores from -5 to -1 for the 1st to 5th deciles, and scores form 1 to 5 for the 6th to tenth deciles. Next, for each hedge fund and month we compute the value-weighted average Score based on trades in that month, taking into account the sign of the trades.[17] For long-term momentum and value, we reconstruct hedge fund holdings from their trades and use their inferred portfolios to rank the funds along the two dimensions. Specifically, we cumulate each hedge fund's trades starting from the first month a fund appears in Ancerno. Since we do not observe the initial positions, we allow for a burn-in period that is then discarded.[18] We report results for a burn-in period of 24 months, but the results are insensitive to shorter burn-in periods of, e.g., 6 months. Then, at the end of each month, we assign CRSP stocks to deciles (LOW to HIGH) separately based momentum (the return from month -12 to month -1), and book-to-market. We assign scores from -5 to -1 for the 1st to 5th deciles, and scores form 1 to 5 for the 6th to 10th deciles. Finally, for each hedge fund and month we compute the value-weighted average Score, across the two dimensions, taking into account the sign of the trades.[19]

We define dummy variables to classify funds that follow, respectively, a short-term reversal ($rev = 1$), long-term momentum ($mom = 1$), or value ($value = 1$) strategy if their end-of-month reversal, momentum, or book-to-market scores are above zero.[20] This procedure is repeated at the end of each month to capture changes in the trading style of the fund. We use this classification to examine hedge funds' trading costs and their sensitivity to funding conditions in the *following*

[17] Specifically, we first compute the value-weighted average Score for buy and sell trades in that month, separately. We then combine the two sides into $Score = (Score_{Buy} * Volume_{Buy} - Score_{sell} * Volume_{Sell})/(Volume_{Buy} + Volume_{Sell})$. Puckett and Yan (2011) apply a similar procedure to compute the return to interim trading. The resultant $Score$ ranges from -5 to 5.

[18] This is equivalent to assuming that the hedge fund would have turned over its portfolio entirely by the end of this period.

[19] Specifically, we first compute the value-weighted average Score for buy and sell trades, separately. We then combine the two sides as $Score = (Score_{Buy} * Value_{Buy} - Score_{sell} * Value_{Sell})/(Value_{Buy} + Value_{Sell})$, where $Value$ is the product of number of shares (holdings) times price at the end of the month.

[20] Using the median instead of zero produces quantitatively similar results.

month, thus reducing the risk of endogeneity.

Table 5 reports the results in the daily pooled regression of hedge funds' trading costs on their trading style (*rev*, *mom*, or *value*), and its interaction with each funding liquidity variable. In Panel A, we look at the level of the trading costs. The focus in this panel is on how costly the different strategies are. In Panel B, we focus on the sign of trading costs. Here, the goal is to capture switches between liquidity demand (positive trading costs) and liquidity provision (negative trading costs). In the regression, we include time fixed effects to capture aggregate changes in the price of liquidity, but the results are not sensitive to their inclusion.

The results in Table 5 can be summarized as follows. We note that i) funds following reversal strategies exhibit significantly lower trading costs unconditionally. The economic significance of the coefficient is large, as reversal funds have on average 11 basis points lower costs. Recalling that the average cost for all type of funds is about 8 basis points, the evidence that reversal strategies experience negative trading costs provides a validation of the trading cost variable as an effective measure of liquidity provision. The same funds also experience a decrease in trading costs when funding conditions tighten. This evidence suggests that liquidity providing strategies are even more rewarding in bad times, when the price of liquidity increases. ii) Long-term momentum funds have higher trading costs on average, consistent with the view that this strategy requires fast execution. However, somewhat unexpected, the trading costs of momentum funds decrease when funding conditions deteriorate. This seems related to the recent finding by Daniel and Moskowitz (2013) that momentum strategies perform poorly only during market rebounds. So, possibly, in down markets momentum managers are still not constrained by redemptions and can afford to provide liquidity. iii) Value funds also experience somewhat higher trading costs unconditionally, but the difference with other funds is not significant. Most important, however, is the fact that the trading costs of value managers increase significantly when capital availability drops. This fact is consistent with the fact that value strategies are often combined with the high use of leverage, which makes them exposed to funding conditions. Specifically, value stocks tend to be low-beta stocks which, according to Frazzini and Pedersen (2013), appear in arbitrageurs' portfolios using leverage to magnify these stocks' high expected returns.

As a robustness check, we also experimented classifying funds into three groups based on the distribution of the deciles, and obtain very similar findings. To the best of our knowledge, this is the first study to links funds trading styles, as inferred from their trades, to trade-level liquidity provision. Consistent with the limits of arbitrage hypothesis, we show that trading styles that are more likely to be combined with leverage suffer higher trading costs in bad times.

6 Market liquidity and hedge fund trading

After pointing out that hedge funds' liquidity provision is subject to aggregate funding conditions and fund-level measures of financial constraints, we wish to study the extent to which hedge fund trading activity is actually important for market liquidity. Aragon and Strahan (2012) provide convincing evidence that the withdrawal of hedge funds from the market, as a result of Lehman Brothers' collapse, negatively impacted stock liquidity. Our data give us a unique opportunity to directly observe hedge fund trades and to relate them to market liquidity at the stock-level.

We begin by constructing a measure of hedge funds' trading intensity. For each fund in the sample, we compute the total number of shares traded on a given stock in a given week. We then normalize this quantity by the number of shares traded in the previous 12-week period, thus obtaining abnormal turnover.[21] Our proxy for hedge funds' trading intensity (*HF_Tradeint*) is the average abnormal turnover across all hedge funds that trade a given stock in a given week.

As a measure of market liquidity, we follow closely Hameed, Kang, and Viswanathan (2010) who focus on adjusted weekly bid-ask spreads. From CRSP, we compute the daily quoted spread as the ratio of the difference between ask and bid closing prices to their midquote. We filter out seasonalities as in Chordia, Sarkar, and Subrahmanyam (2005) using all available trading days in the 1999-2010 period.[22] The average of the resultant daily seasonal-adjusted spread for stock s in week w is denoted $ASPR_{s,w}$.

We analyze the impact of hedge fund trading intensity on future bid-ask spreads by means of

[21] We opted for a 12-week window in order to avail ourselves of a sufficient number of observations for computing a benchmark volume for the same fund. To prevent unusually high or low activity from exerting undue influence, we trim the abnormal turnover at the top and bottom 2.5%.

[22] To be precise, we trim the series at the top and bottom 0.5% and we regress the quoted spread on day of the week dummies, month dummies, a dummy for trading days that either precede or follow a holiday, a dummy for trading days after the decimal system was introduced on 01/29/2001, and a year trend dummy. The adjusted spread is defined as the sum of the intercept estimate and residuals.

the following model:

$$
\begin{aligned}
ASPR_{s,w} &= const. + \beta_k \sum_{k=1}^{3} HF\_Tradeint_{w-k} + \xi_k \sum_{k=1}^{3} R_{M,w-k} + \psi_k \sum_{k=1}^{3} R_{s,w-k} \\
&\quad + \zeta_1 STD_{M,w-1} + \zeta_2 STD_{s,w-1} + \zeta_3 TURN_{s,w-1} + \phi_k \sum_{k=1}^{3} ASPR_{s,w-k} + u_{s,w} \qquad (10)
\end{aligned}
$$

In addition to three lags of our variable of interest *HF_Tradeint*, the regression includes the following controls: three lags of the weekly market return R_M as proxied by the CRSP VW index; three lags of the weekly stock s's return R_s; the market and stock return volatility (STD_M and STD_s, respectively) computed as the standard deviation of daily returns; the stock turnover $TURN$ computed as the ratio between the weekly number of shares traded to total shares outstanding; and three lags of the dependent variable to account for residual autocorrelation. These controls are also used in Hameed, Kang, and Viswanathan (2010). In order to facilitate the economic interpretation of the slopes, we standardize the regressors to have mean zero and unit variance. The dependent variable is expressed in basis points.

Estimates of the model in (10) pooling all stock-week observations are presented in Table 13. From column (1), we see that all lags of *HF_Tradeint* enter the regression with a negative sign. In particular, the loading on the prior week *HF_Tradeint* equals -0.143, and it is strongly statistically significant with a t-statistic of -2.73. The coefficients on the other lags are not significantly different from zero. Hence, periods when hedge funds participate more actively in the trading of a given stock are followed by a decline in spread. Although not large, the economic magnitude is of the same order as for the return on the market, which Hameed, Kang, and Viswanathan (2010) point out to be an important determinant of market liquidity. This evidence is consistent with hedge funds participation having a beneficial impact on market liquidity.[23]

In the second column, we experiment an alternative specification where we add week fixed effects and include only one lag of the regressors. Fixed effects represent another way of controlling for unobserved aggregate determinants that could affect spreads, and that are not fully captured

[23] We notice that the other variables in the regression have the expected impact on spreads. Market liquidity is higher following a decrease in market return, a decrease in stock return, a decline in turnover, and an increase in idiosyncratic volatility. These effects are consistent with the results in Hameed, Kang, and Viswanathan (2010), and with predictions of several theoretical models of bid-ask spreads.

by market return and volatility.[24] The coefficient on *HF_Tradeint* is now smaller in magnitude at -0.080, but still significantly different from zero at the 5% level. Finally, column (3) shows that our conclusions remain unaltered if we conduct our analysis on changes in spreads, similarly to Hameed, Kang, and Viswanathan (2010).

The results in the previous sections show that hedge funds liquidity provision is more sensitive to changes in funding conditions than that of other institutional investors. Therefore, it is natural to ask whether the trading intensity of hedge funds plays a special role in explaining the dynamics of market liquidity or, instead, our measure is merely proxying for institutional investors' participation. We address this question by including the trading intensity of all other institutions as additional determinant of future spreads (*OI_Tradeint*), constructed using the same procedure.

In column (4) of Table 13, we see that the inclusion of *OI_Tradeint* does not alter the significance of hedge funds' trading intensity. Interestingly, the third lag of *HF_Tradeint* has now a significant impact at -0.094 (t-statistic of -2.09). In contrast, none of the coefficients of *OI_Tradeint* meets statistical significance. In columns (5) and (6) we present the fixed-effect estimates. Notably, the coefficient on *OI_Tradeint* has now a negative sign, indicating that reduced trading activity of these investors is also followed by higher spreads, but the coefficient has a t-statistic of just -1.

In sum, an increase in the trading intensity of hedge funds is accompanied by higher stock level liquidity. This effect appears to persist up to three weeks. The fact that the impact remains economically and statistically significant even after accounting for stock-specific determinants, market-wide observable, and unobservable controls, as well as for other investors' trading intensity makes the case for a causality link stronger. To the best of our knowledge, this is the first study to bring direct evidence of an association between market liquidity and hedge fund trading activity at the stock-level.

7 Robustness checks and additional analysis

We conduct a series of checks to ensure that our results are robust to alternative measures of liquidity provision. Since these results are in general agreement with our main findings, we briefly describe them in the text, and make details and corresponding tables available in the Internet

[24]The coefficients on R_M and STD_M cannot be estimated in the fixed effect specification as they are collinear.

Appendix.

7.1 Comparison with other benchmarks for trading costs

Our choice of VWAP as a benchmark to compute price impact is subject to a few caveats (see Hasbrouck (2007), p. 148). For example, if a trade accounts for a large proportion of the daily volume, the weighted average execution price of the trade is likely to coincide with the VWAP. Also, on a day in which the price has been trending up, a buy transaction executed early on in the day may appear as having negative price impact, while indeed the transaction is meant to chase a trend and, as such, it is consuming liquidity.

To assess the robustness of our measure of liquidity provision to such considerations, we consider valid candidates. That is, we recompute the price impact measure using two alternative benchmarks. In one case, we benchmark the execution price to the price observed at the time the order was placed. This may capture the price at which the trader wished to have execution, Anand, Irvine, Puckett, and Venkataraman (2012). The second benchmark is the opening price of the day on which the order was entered, and is used by Anand, Irvine, Puckett, and Venkataraman (2013). Again, this is meant to serve as reference price for the manager's decision to place the order. We find that using these alternative series does not impact the inference. In the Internet Appendix, we report estimates of the main equations in the paper using either series and show that our main conclusions remain unaltered.

7.2 Comparison with other measures of liquidity provision

More generally, one may object to price impact as a measure of liquidity provision for speculators. As an example, in Brunnermeier and Pedersen's (2009) model, speculators that provide liquidity to a temporarily underpriced security could very well decide to place a buy order at the ask price, which is effectively a market order. Such a trade could still be denoted as liquidity providing to the extent that speculators react to a perceived underpricing of the security following a temporary order imbalance, but its price impact is positive.

As a first alternative to price impact, we focus on the dimension of liquidity provision that underlies reversal strategies, such as those in Lo and MacKinlay (1990) and Nagel (2012). These strategies capture the behavior of contrarian investors who provide liquidity in stocks that undergo temporary price pressure. We construct a measure of proximity of hedge fund trades in Ancerno to those predicated by reversal strategies, and find that it correlates strongly (about 50%) with the negative of our price impact series. Hence, higher trading costs are associated with trades that depart from reversal strategies. The second alternative measure of liquidity provision is inspired by Anand, Irvine, Puckett, and Venkataraman (2013). It captures the intuition 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 document a positive correlation, of about 30%, between TC and the measure in Anand, Irvine, Puckett, and Venkataraman (2013). Importantly, we find that the two measures also display a long term decline that ends with the financial crisis. This confirms that the trend in trading cost that is observed in Figure 2 is not the mere effect of a steady decrease in trading costs, but is rather due to a deliberate shift towards liquidity provision by hedge funds.

7.3 Switch between supply and demand

From the summary statistics in Table 3, hedge funds trades are characterized on average by positive trading costs. One may wonder to what extent hedge funds change from being liquidity demanders to liquidity suppliers, or whether they are systematically demanding liquidity but with time-varying intensity. To answer this question, we construct a dummy variable that equals one if the daily trading cost of a fund is positive, and zero otherwise. Its average over the period is 0.53. Thus, nearly half of the trading costs fall below the VWAP therefore reflecting liquidity provision. Results from probit regressions of this dummy on the funding liquidity determinants are in line with those in Table 6. This evidence testifies of a true shift of the hedge fund sector from liquidity provision to liquidity demand as funding conditions deteriorate.

8 Conclusion

This paper studies the behavior of hedge funds' liquidity provision as a function of changes in funding liquidity. We gain a privileged vintage point on hedge fund trading activity in the U.S. stock market thanks to a data set of institutional trades, among which we are able to identify hedge fund trades. The data cover the long time series from January 1999 to December 2010 for a sample of eighty-seven different hedge fund management companies.

We find that hedge funds' liquidity provision, as measured by the difference in the execution price and the volume-weighted average price, varies significantly both cross-sectionally as well as over time. Consistent with prior studies, hedge funds were heavily demanding liquidity during the dot-com bubble and the last financial crisis. In calmer times, between 2002 and 2007, they were instead more inclined to provide liquidity.

The data give strong support to several predictions that stem from the literature on the limits of arbitrage. Hedge funds' trading costs are systematically higher during persistent declines in market valuations, consistent with a collateral based story that links the ability to provide market liquidity to the value of the underlying assets. Trading costs also increase following periods of higher VIX, TED spread, and LIBOR. We interpret this as the consequence of an increase in holding costs, e.g. higher margins, occurring at times of higher uncertainty, which induces hedge funds to liquidate their positions and demand liquidity. These effects are not simply due to time variation in the cost of liquidity, as the trading costs of other institutional investors show substantially weaker (or even opposite) relation to the same variables. Hedge funds also appear to move more aggressively toward liquid stocks than other investors when funding constraints are tighter and to trade more impatiently.

Funding liquidity shocks do not, however, affect all hedge funds equally. Quite the opposite, the ability to steadily provide liquidity varies across funds as a function of fund characteristics that capture relevant dimensions of funding constraints. In particular, the funding liquidity variables have a stronger impact on young funds, leveraged funds, funds which invest in illiquid assets, and funds with a poor recent performance. The same funds also experience a worsening of the short-term returns to their trades.

Lastly, we provide novel evidence that a decrease in hedge fund trading intensity in a given stock anticipates a future deterioration of stock-level liquidity. A similar effect is not found for the other institutions in our data, suggesting that hedge funds are likely to be crucial providers of liquidity, as pointed out by other studies (Aragon and Strahan (2012)).

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Table 1: Summary statistics for daily series

The table displays the following statistics: mean; standard deviation; minimum; 25th, 50th, and 75th percentiles; maximum. The variables are: the daily number of trades and orders, the daily average execution time, the total daily dollar volume, the daily volume per trade/buy trade/sell trade. The statistics are calculated for trades originating from hedge funds in Panel A and from other institutions in Ancerno in Panel B. The sample is period is January 1999 to December 2010.

Panel A: Hedge funds

	Mean	Std	Min	p25	p50	p75	Max
Number of management companies	21	4	10	18	21	24	34
Number of trades	2,124	2,320	69	530	1,233	2,778	17,308
Number of orders	736	946	1	283	463	815	11,525
Execution time	1.021	0.585	0.069	0.576	1.017	1.353	6.905
Volume ($ millions)	346	308	12	141	252	434	2,534
Volume per trade ($ thousands)	229	131	24	140	195	293	1,128
Volume per trade, buy trades ($ thousands)	226	138	23	129	191	292	1,346
Volume per trade, sell trades ($ thousands)	240	154	23	137	202	306	1,907

Panel B: Other institutions

	Mean	Std	Min	p25	p50	p75	Max
Number of management companies	248	18	134	237	248	260	300
Number of trades	95,367	67,247	8,902	44,091	85,064	127,981	1,706,477
Number of orders	36,593	38,170	3,064	18,641	27,280	47,850	1,513,899
Execution time	1.117	0.401	0.243	0.806	1.104	1.391	3.040
Volume ($ millions)	15,057	5,991	2,248	11,182	14,310	18,156	125,234
Volume per trade ($ thousands)	213	116	10	120	174	290	1,394
Volume per trade, buy trades ($ thousands)	203	111	8	118	169	273	1,128
Volume per trade, sell trades ($ thousands)	226	127	13	128	187	307	1,729

Table 2: Analysis of Representativeness of Ancerno funds: Comparison of slopes and alphas with TASS funds

In Panel A, for each hedge fund management company in TASS we estimate separate regressions of monthly returns on the Fung and Hsieh (2001) risk factors and each of the five funding liquidity variables. These are the market return (R_M), the change in VIX, TED, LIBOR, or the first principal component thereof (PC). When including R_M or change in LIBOR we exclude from the Fung and Hsieh (2001) factors the market and change in 10-year yield, respectively. The first row reports the average loading on the liquidity variable for the funds that are in TASS but not in Ancerno (column 'TASS') and for the funds that are in TASS and report to Ancerno (column 'Ancerno'). The column '*pvalue*' reports the p-value for the null hypothesis that their difference is zero. The second row reports the cross-sectional standard deviation of the loadings for the two groups, and the column *pvalue* reports the p-value for the null hypothesis that the variance of the Ancerno group is greater than that of TASS. Panel B reports the slope ('Coefficient'), Standard Error, and *pvalue* in the regression of either the number of funds in Ancerno (row '# funds') or the average sensitivity of the reporting funds (row 'loading') on a constant and each funding liquidity variable. Panel C reports the average monthly return, percentage flow, first-order autoregressive coefficient of returns, age as log of number of months reporting in TASS, leverage in place, and log assets-under-management (AUM) for the group of funds 'TASS' and 'Ancerno' funds, and the *pvalue* for the null hypothesis that their difference is zero.

Panel A: Risk-Loadings

		TASS	Ancerno	*pvalue*
R_M	Mean	0.768%	0.913%	0.229
	Std	0.895%	1.186%	0.001
VIX	Mean	-0.007%	0.055%	0.053
	Std	0.250%	0.235%	0.725
TED	Mean	-0.185%	-0.151%	0.472
	Std	0.376%	0.297%	0.990
LIBOR	Mean	-0.156%	-0.029%	0.011
	Std	0.385%	0.398%	0.335
PC	Mean	-0.089%	-0.049%	0.201
	Std	0.242%	0.186%	0.995

Panel B: Sample composition

		Coefficient	Std.Err.	*pvalue*
R_M	# funds	-0.385	0.349	0.272
	loading	0.099	1.468	0.946
VIX	# funds	-0.353	-1.020	0.307
	loading	0.298	0.412	0.470
TED	# funds	0.195	0.345	0.573
	loading	-0.337	0.624	0.590
LIBOR	# funds	0.365	0.344	0.291
	loading	-0.136	0.651	0.835
PC	# funds	0.224	0.345	0.518
	loading	-0.386	0.432	0.373

Panel C: Hedge funds characteristics

	TASS	Ancerno	*pvalue*
Return	0.005	0.007	0.139
Flows	0.019	0.015	0.314
AR(1)	0.031	0.025	0.761
Age	3.163	3.598	0.000
Leverage	40.365	52.634	0.195
AUM	17.250	17.826	0.010

Table 3: Summary statistics for trading costs and funding liquidity determinants

The table reports the following statistics: mean; standard deviation; first-order autoregressive coefficient; minimum; 25th, 50th, and 75th percentiles; maximum. The statistics are for trading costs to hedge funds trades in Panel A, for trading costs to other institutions in Ancerno in Panel B and for the funding liquidity determinants in Panel C. Trading costs, expressed in basis points and aggregated at the manager-day level, are computed as volume-weighted (superscript VW) or as equally-weighted (superscript EW) averages, and separately for buy trades (subscript b) and sell trades (subscript s). The funding liquidity determinants are the two-week return to the CRSP value-weighted index (R_M), the VIX, the TED spread, the LIBOR rate, and the first principal component of these four variables (PC). The sample January 1999 and December 2010.

Panel A: Hedge funds

	Mean	Std	AR(1)	Min	p25	p50	p75	Max
TC^{VW}	8.250	66.208	0.097	-232.160	-15.425	5.187	30.266	265.607
TC_b^{VW}	6.628	72.625	0.082	-255.616	-19.711	4.235	32.424	279.016
TC_s^{VW}	8.455	77.586	0.096	-274.106	-19.101	4.934	33.941	305.932
TC^{EW}	4.252	63.419	0.126	-224.560	-19.577	2.352	26.963	243.939
TC_b^{EW}	3.086	70.174	0.101	-249.247	-23.710	1.749	29.695	262.816
TC_s^{EW}	5.293	76.344	0.121	-270.903	-22.766	2.734	31.975	293.345

Panel B: Other institutions

	Mean	Std	AR(1)	Min	p25	p50	p75	Max
TC^{VW}	1.037	54.275	0.091	-207.201	-16.810	1.120	19.195	204.326
TC_b^{VW}	-0.118	60.098	0.081	-229.880	-20.160	0.420	21.280	217.660
TC_s^{VW}	1.106	62.506	0.080	-239.140	-19.270	0.910	21.960	234.930
TC^{EW}	-3.416	52.986	0.120	-205.293	-21.995	-1.916	15.812	188.971
TC_b^{EW}	-4.224	58.907	0.103	-227.249	-25.139	-2.450	18.221	202.666
TC_s^{EW}	-2.754	62.309	0.103	-242.211	-23.950	-1.490	19.398	224.390

Panel C: Time-series determinants

	Mean	Std	AR(1)	Min	p25	p50	p75	Max
R_M	0.002	0.038	0.876	-0.267	-0.018	0.006	0.023	0.222
VIX	0.223	0.092	0.983	0.099	0.160	0.214	0.259	0.809
TED	0.005	0.005	0.963	0.000	0.002	0.003	0.005	0.046
LIBOR	0.032	0.021	1.000	0.002	0.013	0.028	0.052	0.069
PC	0.000	1.301	0.962	-1.773	-0.842	-0.326	0.475	11.721

Correlation matrix

	R_M	VIX	TED	LIBOR
VIX	-0.310			
TED	-0.196	0.497		
LIBOR	-0.067	-0.194	0.258	
PC	-0.605	0.813	0.805	0.131

Table 4: Hedge funds' liquidity provision and funding liquidity

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 as volume-weighted average across all trades in columns (1) to (5) and as equally-weighted average in columns (6) to (10). In Panel B, hedge funds trading costs are volume-weighted and are computed separately for Buy (columns (1) to (5)) and Sell (columns (6) to (10)) trades. 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: All trades

Dep. Var.:	Volume-weighted Trading Costs					Equally-weighted Trading Costs				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_M	-1.515					-1.024				
	(-4.33)					(-3.01)				
VIX		1.750					1.319			
		(4.79)					(3.55)			
TED			1.925					1.397		
			(5.12)					(3.78)		
LIBOR				3.220					2.891	
				(10.84)					(10.58)	
PC					2.618					1.943
					(6.76)					(4.93)
Obs.	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211	53,211
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02

Panel B: Trades by side

Dep. Var.:	Buy-side volume-weighted Trading Costs					Sell-side volume-weighted Trading Costs				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_M	-0.830					-1.727				
	(-1.78)					(-3.17)				
VIX		1.162					2.771			
		(2.50)					(4.89)			
TED			1.911					1.225		
			(3.70)					(1.98)		
LIBOR				2.137					3.058	
				(5.80)					(7.39)	
PC					1.956					2.850
					(3.71)					(4.40)
Obs.	42,961	42,961	42,961	42,961	42,961	42,282	42,282	42,282	42,282	42,282
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 5: Impact of 2007-2009 financial crisis

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 (Panel A) and crisis (Panel B) 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. All regressions include a lag term and an intercept (whose estimates are omitted). The whole sample period is January 1999 to December 2010.

Panel A: Ex-crisis period

Dep. Var.: Volume-weighted trading cost

	(1)	(2)	(3)	(4)	(5)
R_M	-1.027				
	(-2.76)				
VIX		1.995			
		(5.32)			
TED			5.325		
			(7.43)		
LIBOR				3.393	
				(11.11)	
PC					4.304
					(8.69)
Obs.	47,539	47,539	47,539	47,539	47,539
R^2	0.01	0.01	0.01	0.01	0.01

Panel B: Crisis period

Dep. Var. : Volume-weighted trading cost

	(1)	(2)	(3)	(4)	(5)
R_M	-2.899				
	(-3.61)				
VIX		1.887			
		(2.42)			
TED			2.244		
			(2.82)		
LIBOR				-0.083	
				(-0.06)	
PC					2.881
					(3.53)
Obs.	5,642	5,642	5,642	5,642	5,642
R^2	0.01	0.01	0.01	0.01	0.01

Table 6: Hedge funds' and other institutions liquidity provision and funding liquidity

Panel A presents OLS estimates of equation (4) on hedge fund trades:

$$TC_{i,t+1} = a + bFundLiq_t + \delta' Z_{i,t} + \varepsilon_{i,t+1}$$

where $TC_{i,t+1}$ is the volume-weighted average trading cost on day $t+1$, separately computed for buy and sell trades. Panel B presents OLS estimates of equation (5) pooling hedge funds and other institution trades:

$$TC_{i,t+1} = a + b_1 FundLiq_t + b_2 HF \times FundLiq_t + \delta' Z_{i,t} + \varepsilon_{i,t+1}$$

HF equals 1 if the institution is a hedge fund, and 0 otherwise. Each specification from (1) to (5) uses a different funding liquidity variable, *FundLiq*, which are defined as in Table 3. The vector $Z_{i,t}$ collects the following controls for trade difficulty: *Buy* is a dummy that equals 1 for buy trades, and 0 otherwise; *Lagged Return* is the stock return in the prior day; *NYSE* is a dummy that equals 1 for stocks listed at the NYSE, and 0 otherwise; *Inverse Price* is the inverse of day-t stock price; *Relative Volume* is the ratio between the number of shares traded and the average volume in the prior 30 days; *Amihud* is the Amihud illiquidity ratio; *Size* and *Book-to-Market* are the stock market capitalization and book-to-market deciles. All variables are computed as volume-weighted averages at the fund-day-side level. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. The sample period is January 1999 to December 2010.

Dep. Var.	Panel A: Volume-weighted trading cost, only HF					Panel B: Volume-weighted trading cost, HF and MF				
FunLiq	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)
$HF * FundLiq$						-1.382	2.784	2.206	2.360	3.305
						(-3.97)	(7.63)	(5.16)	(9.69)	(8.30)
FundLiq	-1.414	2.280	2.665	3.155	3.332	0.381	-0.813	-0.947	1.021	-0.907
	(-4.49)	(6.52)	(6.22)	(13.54)	(8.39)	(3.13)	(-5.93)	(-7.23)	(13.78)	(-6.43)
Buy	-1.420	-1.419	-1.383	-1.362	-1.445	-1.067	-1.064	-1.070	-1.071	-1.061
	(-2.79)	(-2.79)	(-2.72)	(-2.68)	(-2.85)	(-4.98)	(-4.96)	(-4.99)	(-4.99)	(-4.95)
Lagged Return	-0.260	-0.287	-0.304	-0.300	-0.248	-0.208	-0.205	-0.201	-0.191	-0.213
	(-2.32)	(-2.59)	(-2.73)	(-2.68)	(-2.25)	(-5.94)	(-5.90)	(-5.73)	(-5.49)	(-6.11)
NYSE	-7.267	-7.588	-7.331	-7.039	-7.577	-5.757	-5.694	-5.773	-5.652	-5.735
	(-9.60)	(-10.02)	(-9.70)	(-9.30)	(-10.02)	(-23.55)	(-23.17)	(-23.62)	(-23.34)	(-23.39)
Inverse Price	0.075	0.016	0.089	0.175	0.039	-0.019	0.006	-0.019	0.019	-0.006
	(0.79)	(0.17)	(0.94)	(1.83)	(0.42)	(-0.73)	(0.22)	(-0.70)	(0.72)	(-0.23)
Relative Volume	0.867	0.905	0.896	0.880	0.928	0.412	0.408	0.402	0.409	0.406
	(1.74)	(1.80)	(1.79)	(1.77)	(1.85)	(4.36)	(4.33)	(4.28)	(4.36)	(4.31)
Amihud	1.302	1.296	1.283	0.731	1.184	0.087	0.090	0.090	0.071	0.090
	(0.67)	(0.67)	(0.67)	(0.39)	(0.62)	(0.86)	(0.89)	(0.88)	(0.71)	(0.89)
Size	0.817	0.741	0.830	0.965	0.768	0.862	0.894	0.864	0.906	0.880
	(6.06)	(5.47)	(6.16)	(7.15)	(5.69)	(23.39)	(23.91)	(23.43)	(24.72)	(23.79)
Book/Market	-1.415	-1.300	-1.432	-1.445	-1.327	-1.285	-1.334	-1.281	-1.292	-1.312
	(-9.89)	(-9.02)	(-9.99)	(-10.06)	(-9.30)	(-33.87)	(-33.59)	(-33.77)	(-34.06)	(-34.11)
Obs.	103,673	103,637	103,637	103,637	103,637	1,318,745	1,318,361	1,318,361	1,318,361	1,318,361
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 7: Stock type and funding liquidity

OLS estimates of equation (6):

$$VWAD_{i,t+1} = a_1 + a_2 HF + \theta_1 FundLiq_t + \theta_2 HF \times FundLiq_t + \phi_1 VWAD_{i,t} + \phi_2 HF \times VWAD_{i,t} + \upsilon_{i,t+1}$$

where $VWAD_{i,t+1}$ is the volume-weighted average decile of the stocks traded by institution i on day $t+1$. Decile assignment for a given characteristic is based on the distribution of the universe of stocks in CRSP. The characteristics are market capitalization (Size) in Panel A and the Amihud (2002) measure in Panel B. 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. Dep. Var.: Size VWAD

$FundLiq$:	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)
$HF \times FundLiq$	-0.009	0.040	0.018	0.001	0.033
	(-2.08)	(8.40)	(3.66)	(0.17)	(6.72)
$FundLiq$	-0.007	0.018	-0.004	0.014	0.010
	(-4.56)	(10.86)	(-3.15)	(8.81)	(6.40)
HF	0.838	0.879	0.841	0.837	0.863
	(17.30)	(17.98)	(17.32)	(17.26)	(17.71)
Obs.	659,329	659,329	659,329	659,329	659,329
R^2	0.562	0.563	0.562	0.562	0.562

Panel B. Dep. Var.: Amihud measure VWAD

$FundLiq$:	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)
$HF \times FundLiq$	0.007	-0.034	-0.015	-0.004	-0.028
	(1.74)	(-7.60)	(-3.21)	(-1.02)	(-6.22)
$FundLiq$	0.007	-0.019	0.006	-0.013	-0.010
	(4.40)	(-11.08)	(3.87)	(-8.28)	(-6.18)
HF	0.190	0.199	0.189	0.190	0.193
	(17.64)	(18.29)	(17.62)	(17.66)	(17.89)
Obs.	659,329	659,329	659,329	659,329	659,329
R^2	0.53	0.531	0.53	0.53	0.53

Table 8: Execution time and funding liquidity

OLS estimates of equation (7):

$$ExTime_{i,t+1} = a + \beta FundLiq_t + \gamma' X_{i,t} + u_{i,t+1}$$

where $ExTime_{i,t+1}$ is the log average execution time on day $t+1$ for orders placed by hedge fund i. Execution time is computed as the distance (in minutes) between the first time when an order is placed and last time when order is executed. Data are aggregated at the date-institution-Side level. The vector X contains the following controls. $Side$ equals 1 for buy trades and 0 for sell trades. $Relative\,Volume$ is the value-weighted ratio of the number of stocks traded to the average volume of the stock in the prior 30 days. $Size\,VWAD$ is the volume-weighted average decile of the stocks traded by the hedge fund. $Trend$ is a time trend expressed as fraction of year. Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in Table 3. Below the coefficients, t-statistics based on standard errors clustered at the date and institution-Side level are reported in parentheses. The intercept estimate is omitted. The sample period is January 1999 to December 2010.

	Dep. Var: Order execution time				
	(1)	(2)	(3)	(4)	(5)
R_M	-0.002				
	(-0.23)				
VIX		-0.090			
		(-3.06)			
TED			-0.025		
			(-0.89)		
LIBOR				0.034	
				(1.14)	
PC					-0.053
					(-1.97)
$Side$	0.040	0.040	0.040	0.040	0.040
	(0.49)	(0.48)	(0.48)	(0.49)	(0.48)
$Relative\,Volume$	1.039	1.025	1.033	1.040	1.027
	(8.92)	(9.54)	(9.16)	(8.95)	(9.28)
$Size\,VWAD$	-0.106	-0.098	-0.105	-0.106	-0.103
	(-6.54)	(-6.09)	(-6.48)	(-6.55)	(-6.33)
$Trend$	-0.087	-0.086	-0.086	-0.082	-0.087
	(-6.49)	(-6.63)	(-6.65)	(-5.76)	(-6.54)
Obs.	82,973	82,937	82,937	82,937	82,937
R^2	0.15	0.16	0.15	0.15	0.15

Table 9: Liquidity provision, funding liquidity, and hedge funds' characteristics

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 $m-1$). 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					
$FundLiq$:	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)
$Leverage \times FundLiq$	-0.001	-0.002	**0.006**	-0.001	**0.003**
	(-0.62)	(-0.97)	**(3.76)**	(-0.46)	**(1.99)**
$Young \times FundLiq$	0.369	**2.387**	**4.694**	**2.038**	**4.096**
	(0.37)	**(2.19)**	**(3.12)**	**(1.96)**	**(3.29)**
$Illiquid \times FundLiq$	0.096	0.026	**0.503**	**0.303**	0.133
	(0.50)	(0.12)	**(2.38)**	**(1.68)**	(0.58)
$Bad \times FundLiq$	-4.486	**6.693**	-10.086	**7.381**	0.991
	(-1.15)	**(1.65)**	(-2.39)	**(1.82)**	(0.24)
$LowRed \times FundLiq$	0.476	**-3.647**	**13.740**	**12.858**	**4.816**
	(0.32)	**(-2.43)**	**(5.19)**	**(10.23)**	**(2.53)**
$NoLock \times FundLiq$	**3.596**	-1.397	**-11.984**	**-3.777**	**-8.235**
	(2.49)	(-0.94)	**(-5.68)**	**(-3.01)**	**(-4.57)**
$Leverage$	-0.015	-0.017	-0.015	-0.014	-0.016
	(-7.81)	(-6.55)	(-7.53)	(-6.20)	(-8.33)
$Young$	3.126	3.150	3.948	-0.055	3.882
	(3.83)	(3.81)	(3.97)	(-0.06)	(4.47)
$Illiquid$	0.080	0.115	0.282	0.170	0.139
	(0.50)	(0.70)	(1.71)	(1.06)	(0.86)
Bad	7.947	7.537	10.254	5.887	7.458
	(2.05)	(1.91)	(2.60)	(1.52)	(1.94)
$LowRed$	5.141	5.986	8.284	5.342	5.516
	(4.28)	(4.91)	(5.74)	(4.48)	(4.44)
$NoLock$	0.779	0.535	-1.781	-1.128	-0.021
	(0.65)	(0.44)	(-1.37)	(-0.96)	(-0.02)
$FundLiq$	-1.475	11.700	22.480	9.932	21.365
	(-0.33)	(2.32)	(2.97)	(2.01)	(3.61)
Obs.	26,659	26,659	26,659	26,659	26,659
R^2	0.01	0.01	0.02	0.03	0.02

Table 10: Constrained hedge funds' liquidity provision and funding liquidity

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. In Panel A, only trades from constrained hedge funds and other institutions are used. In Panel B, only trades from unconstrained hedge funds and other institutions are used. Constrained hedge funds are defined as those reporting to TASS and having positive leverage and a redemption notice period plus redemption frequency lower than 120 days (the median value in the sample). 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: Constrained hedge funds and other institutions

	Dep. Var.: Volume-weighted trading costs				
$FundLiq$:	R_M	VIX	TED	LIBOR	PC
	(1)	(2)	(3)	(4)	(5)
$HF \times FundLiq$	0.318	2.086	1.735	3.209	1.966
	(0.35)	(1.96)	(1.53)	(4.19)	(1.78)
$FundLiq$	0.094	-0.338	-0.347	0.260	-0.340
	(0.63)	(-2.41)	(-2.04)	(2.66)	(-2.00)
HF	4.100	4.044	4.313	3.617	4.179
	(5.32)	(5.32)	(5.23)	(4.99)	(5.31)
Obs.	393,908	393,908	393,908	393,908	393,908
R^2	0.01	0.01	0.01	0.01	0.01

Panel B: Unconstrained hedge funds and other institutions

	Dep. Var.: Volume-weighted trading costs				
$FundLiq$:	R_M	VIX	TED	LIBOR	PC
	(6)	(7)	(8)	(9)	(10)
$HF \times FundLiq$	-0.079	-1.384	1.473	-0.282	-0.011
	(-0.06)	(-0.90)	(0.90)	(-0.26)	(-0.01)
$FundLiq$	0.094	-0.338	-0.347	0.260	-0.340
	(0.63)	(-2.41)	(-2.04)	(2.66)	(-2.00)
HF	7.022	7.052	7.107	7.022	7.015
	(6.88)	(6.95)	(6.73)	(7.02)	(6.80)
Obs.	390,015	390,015	390,015	390,015	390,015
R^2	0.01	0.01	0.01	0.01	0.01

Table 11: Performance, funding liquidity, and hedge funds' characteristics

OLS estimates of equation (9):

$$r_{i,t:t+5} = \alpha + \beta' FundLiq_t + \gamma' X_{m-1} + \eta' FundLiq_t \times X_{m-1} + \epsilon_{i,t+1:t+5}$$

where $r_{i,t:t+5}$ is the volume-weighted abnormal return (in %) to hedge fund i trades between days t and $t+5$. Each column uses a different funding liquidity variable, $FundLiq$, which are defined as in Table 3. The cross-sectional characteristics in X are measured in the month prior the trade and are defined as in Table 9. Below the coefficients, t-statistics based on robust standard errors clustered at the date level are reported in parentheses. The intercept estimate is omitted. Leverage amount is divided by 100. Bold face denotes estimates whose significance (at the 10% level) is consistent with a significant relation between fund-level limits of arbitrage and a deterioration in trade performance when funding liquidity tightens. The sample period is January 1999 to December 2010.

	Dep. Var.: 5-day Ex-post Performance				
$FundLiq$:	R_M (1)	VIX (2)	TED (3)	LIBOR (4)	PC (5)
$Leverage \times FundLiq$	**0.064**	**-0.039**	-0.017	**-0.050**	**-0.044**
	(3.33)	**(-2.00)**	(-1.43)	**(-2.04)**	**(-3.13)**
$Young \times FundLiq$	-0.070	**-0.223**	0.028	0.011	-0.063
	(-0.61)	**(-1.91)**	(0.20)	(0.10)	(-0.46)
$Illiquid \times FundLiq$	-0.029	0.012	-0.021	**-0.040**	0.006
	(-1.46)	(0.72)	(-1.04)	**(-2.18)**	(0.29)
$Bad \times FundLiq$	0.028	-0.068	0.302	0.351	0.060
	(0.06)	(-0.17)	(0.74)	(0.72)	(0.14)
$LowRed \times FundLiq$	0.009	**-0.267**	0.019	0.065	-0.141
	(0.06)	**(-1.76)**	(0.10)	(0.49)	(-0.78)
$NoLock \times FundLiq$	-0.182	0.227	0.073	-0.007	0.287
	(-1.22)	(1.56)	(0.51)	(-0.06)	(1.71)
$Leverage$	-0.009	-0.029	-0.009	0.008	-0.009
	(-0.74)	(-1.54)	(-0.68)	(0.45)	(-0.76)
$Young$	-0.030	-0.055	0.006	-0.013	-0.039
	(-0.36)	(-0.65)	(0.06)	(-0.13)	(-0.43)
$Illiquid$	-0.041	-0.047	-0.039	-0.041	-0.044
	(-2.52)	(-2.86)	(-2.40)	(-2.48)	(-2.71)
Bad	-0.429	-0.551	-0.361	-0.350	-0.528
	(-0.93)	(-1.17)	(-0.79)	(-0.78)	(-1.17)
$LowRed$	-0.168	-0.153	-0.161	-0.198	-0.166
	(-1.39)	(-1.28)	(-1.21)	(-1.57)	(-1.37)
$NoLock$	0.115	0.108	0.105	0.120	0.096
	(0.96)	(0.89)	(0.85)	(1.00)	(0.79)
$FundLiq$	-0.187	-0.949	0.370	0.291	-0.196
	(-0.36)	(-1.83)	(0.56)	(0.60)	(-0.32)
Obs.	26,613	26,613	26,613	26,613	26,613
R^2(%)	0.074	0.088	0.086	0.062	0.089

Table 12: Liquidity Provision and Hedge Funds Trading Style

OLS estimates in the daily fixed effect pooled regression of hedge funds trading costs on trading style, and trading style interacted with funding liquidity variables. Funds are classified as following either a short-term reversal (rev = 1), long-term momentum (mom = 1), or value ($value$ = 1) strategy if the value-weighted decile of the stocks in their portfolios is above 0, following the procedure described in Section 5. The dependent variable is the daily volume-weighted trading cost TC_{VW} in Panel A, and a dummy that takes the value of 1 if trading costs are positive, TC_+, in Panel B. The sample period is January 1999 to December 2010.

Panel A. Dep. Var. : Volume-weighted trading cost, TC_{VW}

FundLiq	-	R_M	VIX	TED	LIBOR	PC
rev	-11.282	-11.197	-11.163	-11.331	-10.962	-11.392
	(-14.76)	(-14.84)	(-14.93)	(-14.51)	(-13.49)	(-14.72)
$rev \times FundLiq$		3.445	-2.955	-0.552	1.048	-2.922
		(3.54)	(-3.11)	(-0.53)	(1.22)	(-2.88)
FundLiq	-	R_M	VIX	TED	LIBOR	PC
mom	4.697	4.702	4.532	4.650	5.148	4.561
	(7.10)	(7.13)	(6.67)	(6.89)	(7.35)	(6.64)
$mom \times FundLiq$		0.598	-2.527	-0.694	1.831	-1.711
		(0.73)	(-3.04)	(-0.78)	(2.36)	(-1.89)
FundLiq	-	R_M	VIX	TED	LIBOR	PC
value	0.759	0.758	0.936	1.149	0.682	1.189
	(1.20)	(1.20)	(1.45)	(1.74)	(0.98)	(1.79)
$value \times FundLiq$		-2.222	3.092	2.984	-0.247	3.778
		(-2.72)	(3.87)	(3.28)	(-0.34)	(4.18)

Panel B. Dep. Var. : Dummied Volume-weighted trading cost, TC_+

FundLiq	-	R_M	VIX	TED	LIBOR	PC
rev	-0.089	-0.088	-0.089	-0.088	-0.089	-0.089
	(-14.26)	(-14.23)	(-14.25)	(-14.17)	(-13.22)	(-14.26)
$rev \times FundLiq$		0.011	-0.000	0.004	-0.000	-0.002
		(1.91)	(-0.06)	(0.68)	(-0.05)	(-0.42)
FundLiq	-	R_M	VIX	TED	LIBOR	PC
mom	0.059	0.059	0.058	0.058	0.060	0.058
	(10.45)	(10.45)	(10.23)	(10.30)	(10.20)	(10.22)
$mom \times FundLiq$		0.002	-0.019	-0.011	0.004	-0.015
		(0.34)	(-3.58)	(-2.01)	(0.54)	(-2.75)
FundLiq	-	R_M	VIX	TED	LIBOR	PC
value	0.003	0.003	0.004	0.004	-0.001	0.004
	(0.60)	(0.60)	(0.69)	(0.83)	(-0.20)	(0.81)
$value \times FundLiq$		-0.006	0.008	0.010	-0.014	0.010
		(-1.12)	(1.70)	(1.83)	(-2.20)	(1.97)

Table 13: Liquidity and Hedge Funds Trading Intensity

OLS estimates of the pooled regression of future weekly adjusted bid-ask spread $ASPR_{i,w}$ on lagged determinants. The spread enters in levels in columns (1), (2), (4), and (5), while columns (3) and (6) use the weekly change (Δ) in spread. *HF_Tradeint* is the trading intensity of hedge funds in Ancerno, as defined in Section 6, while *OI_Tradeint* is the trading intensity of all other institutions in Ancerno. R_M and STD_M denote, respectively, the weekly sum and standard deviation of the daily returns to the CRSP VW Index. R_i and STD_i denote analogous measures for company i returns. $TURN_i$ is the ratio between the weekly volume, computed as the sum of number of shares traded in each day of the week, to the number of shares outstanding. All variables are standardized to mean zero and variance one. 'F-test' reports the p-value of the F-test for the null hypothesis that the coefficients on *HF_Tradeint* are jointly zero. Below the coefficients, t-statistics based on robust standard errors clustered at the permno level are reported in parentheses. Each regression also includes three lags of the dependent variable. The estimates of the intercept and lag terms are omitted. The sample period is January 1999 to December 2010.

Dep. Var.:	$ASPR_{i,w}$ (1)	$ASPR_{i,w}$ (2)	$\Delta ASPR_{i,w}$ (3)	$ASPR_{i,w}$ (4)	$ASPR_{i,w}$ (5)	$\Delta ASPR_{i,w}$ (6)
$HF\_Tradeint_{i,w-1}$	-0.143	-0.080	-0.085	-0.108	-0.074	-0.069
	(-2.73)	(-2.07)	(-2.27)	(-2.15)	(-2.17)	(-2.08)
$HF\_Tradeint_{i,w-2}$	-0.026			-0.020		
	(-0.42)			(-0.39)		
$HF\_Tradeint_{i,w-3}$	-0.047			-0.094		
	(-0.76)			(-2.09)		
$OI\_Tradeint_{i,w-1}$				0.043	-0.075	-0.092
				(0.43)	(-0.90)	(-1.10)
$OI\_Tradeint_{i,w-2}$				-0.066		
				(-0.62)		
$OI\_Tradeint_{i,w-3}$				0.037		
				(0.37)		
$R_{M,w-1}$	-0.203			-0.179		
	(-2.01)			(-2.50)		
$R_{M,w-2}$	-0.193			-0.176		
	(-2.34)			(-2.97)		
$R_{M,w-3}$	-0.038			-0.005		
	(-0.50)			(-0.09)		
$R_{i,w-1}$	-1.592	-2.193	-2.275	-1.369	-1.957	-2.023
	(-8.97)	(-19.68)	(-20.70)	(-10.25)	(-20.89)	(-21.95)
$R_{i,w-2}$	-0.761			-0.708		
	(-6.26)			(-6.45)		
$R_{i,w-3}$	0.157			0.106		
	(1.34)			(1.09)		
$STD_{M,w-1}$	-0.103			-0.177		
	(-1.52)			(-3.29)		
$STD_{i,w-1}$	0.116	0.023		0.190	0.128	
	(0.78)	(0.20)		(1.47)	(1.21)	
$TURN_{i,w-1}$	-0.017	-0.031		-0.032	-0.026	
	(-1.30)	(-2.00)		(-1.40)	(-1.87)	
$\Delta STD_{i,w-1}$			0.501			0.411
			(4.76)			(4.52)
$\Delta TURN_{i,w-1}$			-0.026			-0.029
			(-1.97)			(-2.41)
Obs.	197,040	459,900	457,896	192,342	447,820	445,967
Fixed Effects	No	Week	Week	No	Week	Week
R^2	0.96	0.95	0.26	0.97	0.96	0.26
F-test	0.04	0.04	0.02	0.01	0.03	0.04

Figure 1: Sensitivity to Funding Liquidity for Funds in TASS and Ancerno

For each hedge fund management company in TASS we estimate separate regressions of monthly returns on the Fung and Hsieh (2001) risk factors and each of the five funding liquidity variables. These are the market return (R_M), the change in VIX, TED, LIBOR, or the first principal component thereof (PC). When including R_M or change in LIBOR we exclude from the Fung and Hsieh (2001) factors the market and change in 10-year yield, respectively. The figures report the kernel densities of the loadings on the liquidity variables for the funds that are in TASS but not in Ancerno (solid line) and for the funds that are in TASS and report to Ancerno (dotted line).

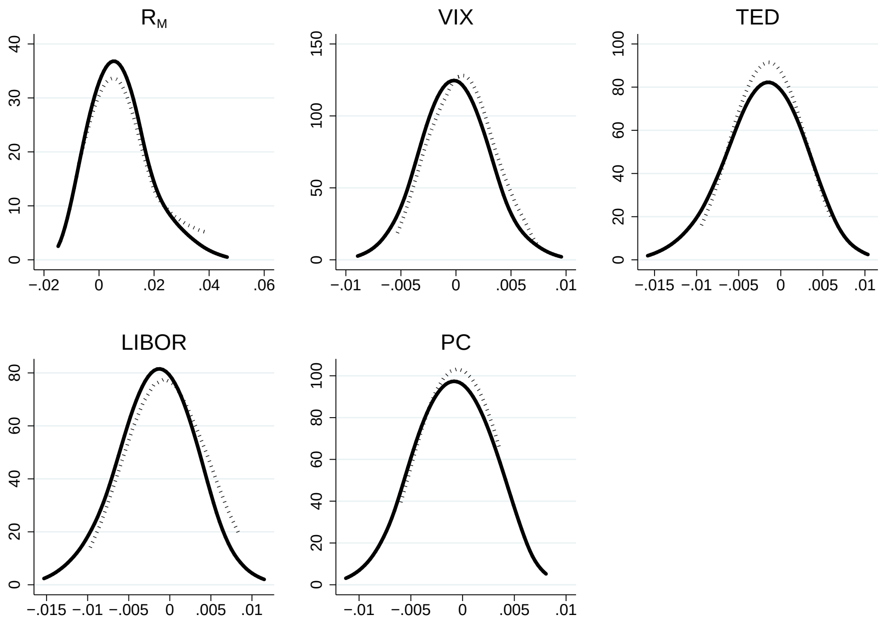

Figure 2: Hedge funds' and other institutions trading costs

Quarterly volume-weighted (top plot) and equally-weighted (bottom plot) trading costs of hedge funds and other institutional investors reporting to Ancerno. The sample is January 1999 to December 2010.