DISCUSSION PAPER SERIES

DP13645

WHAT CONSTRAINS LIQUIDITY PROVISION? EVIDENCE FROM HEDGE FUND TRADES

Francesco Franzoni, Alberto Plazzi and Efe Cotelioglu

FINANCIAL ECONOMICS

ISSN 0265-8003

WHAT CONSTRAINS LIQUIDITY PROVISION? EVIDENCE FROM HEDGE FUND TRADES

Francesco Franzoni, Alberto Plazzi and Efe Cotelioglu

Discussion Paper DP13645
Published 02 April 2019
Submitted 28 March 2019

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

WHAT CONSTRAINS LIQUIDITY PROVISION? EVIDENCE FROM HEDGE FUND TRADES

Abstract

The paper investigates the determinants of limits of arbitrage for liquidity providers. Using data on institutional transactions, we find that hedge funds' liquidity provision is more exposed to financial conditions than that of other institutions, notably mutual funds. We identify leverage, age, asset illiquidity, and reputational capital as a relevant set of characteristics that explain the exposure of hedge funds' liquidity supply to funding conditions. Stocks with more exposure to constrained liquidity providing hedge funds suffered more during the financial crisis. Finally, we find that the trades of financially constrained hedge funds underperform for at least one quarter following negative funding shocks.

JEL Classification: G20, G23

Keywords: Hedge Funds, Limits of arbitrage, Liquidity Provision, Trading Costs, funding liquidity

Francesco Franzoni - francesco.franzoni@usi.ch
Università della Svizzera Italiana, Swiss Finance Institute and CEPR

Alberto Plazzi - alberto.plazzi@usi.ch
Università della Svizzera italiana, Swiss Finance Institute

Efe Cotelioglu - efe.cotelioglu@usi.ch
Università della Svizzera italiana

What Constrains Liquidity Provision? Evidence From Hedge Fund Trades

EFE ÇÖTELIOĞLU, FRANCESCO FRANZONI, AND ALBERTO PLAZZI*

March 26, 2019

ABSTRACT

The paper investigates the determinants of limits of arbitrage for liquidity providers. Using data on institutional transactions, we find that hedge funds' liquidity provision is more exposed to financial conditions than that of other institutions, notably mutual funds. We identify leverage, age, asset illiquidity, and reputational capital as a relevant set of characteristics that explain the exposure of hedge funds' liquidity supply to funding conditions. Stocks with more exposure to constrained liquidity providing hedge funds suffered more during the financial crisis. Finally, we find that the trades of financially constrained hedge funds underperform for at least one quarter following negative funding shocks.

JEL classification: G20, G23
Keywords: hedge funds, limits of arbitrage, liquidity provision, trading costs, funding liquidity

*All authors are with the Swiss Finance Institute, Università della Svizzera Italiana, Via Buffi 13 Lugano, 6900, Switzerland. Franzoni is also with the Center for Economic Policy Research (CEPR). Email Cötelioglu: efe.coetelioglu@usi.ch. Email Franzoni: francesco.franzoni@usi.ch. Email Plazzi: alberto.plazzi@usi.ch. A prior draft of this paper circulated under the title "Do Hedge Funds Provide Liquidity? Evidence from Their Trades". We are especially grateful to Lasse Pedersen (AFA discussant), Andy Puckett, and Dimitri Vayanos for extensive comments. We thank Tobias Adrian, Pierre Collin-Dufresne, Jens Jackwerth, Terrence Hendershott, Joan Hombert, Paul Irvine, Dong Lou, Albert Menkveld, Tobias Moskowitz, Joanid Rosu, Youchang Wu, and seminar and conference participants at the: National University of Singapore; 6^{th} Hedge Fund Conference, Paris; 2^{nd} Asset Management Summit, Luxembourg; University of Konstanz; Norwegian School of Economics; and University of Lugano. The authors gratefully acknowledge financial support from the Swiss Finance Institute, Inquire Europe, and the Swiss National Science Foundation.

1 Introduction

In the theoretical literature, a liquidity provider is a trader that satisfies other investors' demands for immediate execution of orders (e.g. Grossman and Miller (1988)). In real-world financial markets, different classes of investors perform this function. While the typical market makers (i.e., the specialists, the dealers and, more recently, the high-frequency traders) are at the forefront in filling the temporary gap between buyers and sellers, recent empirical evidence points out the importance of long-term suppliers of liquidity in preventing large price fluctuations when the order flow becomes large and persistent. Using data on institutional trades, Anand, Irvine, Puckett, and Venkataraman (2013) show that the market participation of buy-side institutions crucially determines a stock's resiliency to negative shocks. Moreover, these authors find that liquidity supply in illiquid stocks by long-term institutions became more scarce during the last financial crisis.

The finding that liquidity suppliers curtail their trading of illiquid stocks in bad times contributes to a growing body of work establishing a link between funding conditions and market liquidity (e.g. Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010), Hameed, Kang, and Viswanathan (2010), and Nagel (2012)). The sobering message from this literature is that the re-equilibrating forces in financial markets seem to falter in bad times, that is, when their contribution is mostly needed. Given its important consequences for market stability, this evidence raises further questions on the behavior of liquidity providing institutions, which we tackle in this paper. Are all institutions similarly impacted by funding conditions? What institutional characteristics make some investors more prone to withdrawing liquidity in bad times? How long lasting is the impact of negative funding shocks on liquidity providers?

We combine information about institutional characteristics with trade level data to study the dependence of liquidity provision on funding conditions. We focus first on the role of the type of institution as a driver of liquidity provision and contrast hedge funds to mutual funds. A priori, it is not clear which institutional structure is more exposed to funding liquidity shocks. Mutual funds provide daily liquidity, while hedge funds often times have share restrictions in place that constrain investors' ability to redeem capital at will. This element would suggest that hedge funds are better positioned to provide liquidity when other investors withdraw from the market. On the other hand, hedge funds engage in leveraged strategies and invest in illiquid securities. The first element exposes hedge funds to margin calls, which may force hedge funds to fire sales (e.g. Ben-David, Franzoni, and Moussawi (2012)). The second characteristic exacerbates strategic complementarities (e.g. Chen, Goldstein, and Jiang (2010)), giving hedge fund investors a stronger incentive to run on the fund assets in bad times. It is, therefore, an empirical question which effect prevails in determining mutual and hedge funds' sensitivity to funding conditions.

The innovation of this paper relative to prior work on hedge funds and limits of arbitrage is the use of trade level data. Previous work resorts to quarterly portfolio holdings or monthly returns to infer the trading behavior of hedge funds in equity markets during crisis periods (e.g. Ben-David, Franzoni, and Moussawi (2012)). Transaction data can shed new light on the liquidity provision behavior along several dimensions. First, liquidity provision is, strictly speaking, a trade-level concept. In this sense, a trade is liquidity providing if it rests on the limit order book until it is hit by an impatient order, notably a market order. The literature sometimes refers to a broader notion of liquidity provision, which is a strategy trading against mispricing (e.g. Brunnermeier and Pedersen (2009)), i.e. a contrarian strategy. While the latter behavior may be detected by a study of quarterly portfolio holdings (e.g. by studying if investors hold value stocks or other mispriced securities), one can only study the strict version of liquidity provision by inspecting trade-level data. Second, the use of trade-level data allows us to detect shifts in liquidity provision in a timely fashion, that is, at higher frequencies than measures derived from quarterly holdings or monthly returns. This timeliness is essential when the focus is on hedge funds, given that these institutions are known to trade at higher frequencies. Related, changes in liquidity provision can be short-lived. Transaction data, by focusing on each trade, can detect short-term changes in behavior. Instead, measures that rely on rolling-window regressions using multiple months of data necessarily miss the high-frequency components of liquidity provision. Finally, it is possible that indirect measures of liquidity provision that are drawn from lower frequency data give a false impression of an active liquidity providing behavior, while the fund does not actually engage in trading in the period under consideration. Specifically, the prices of assets that are already in a fund portfolio can move along with aggregate measures of market liquidity, while the fund does not actually revise its positions. In sum, we believe trade-level data can shed light on previously unexplored dimensions of hedge funds' liquidity provision.

Our data set contains trade-level observations for over eight hundred different institutions (primarily hedge funds and mutual funds) during the January 1999 to June 2013 period. The data source is Abel Noser Solutions (also called 'Ancerno').[1] Ancerno provides researchers with data on the trading activity of its clients' portfolio managers. Using portfolio managers' names we are able to identify ninety-six distinct hedge-fund management companies. These firms appear to be highly representative of the overall industry along several dimensions. 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 provision that we state above inspires our empirical proxy for the price of immediacy. Liquidity demanders trade impatiently and, consequently, they are likely to have a positive price impact. The opposite is true for liquidity suppliers. Thus, we follow Anand, Irvine, Puckett, and Venkataraman (2013) and construct our measure of price impact as the percentage difference between the execution price and the Price at Market Open for the same stock on the same day, and we label it execution shortfall. The execution shortfall is the main dependent variable in the analysis relating liquidity provision to funding conditions.

We begin by studying the dependence of liquidity provision on funding conditions. Drawing inspiration from prior literature, we use the following variables to measure funding liquidity: the return on the stock market in the prior two weeks, the VIX index, the TED Spread, and dealer repos. These variables measure funding liquidity through the value of collateral (related to the return on the stock market), the tightness of margins (related to the VIX), the cost of leverage (measured by the TED Spread), and the availability of capital to financial intermediaries (proxied

[1] Other recent studies using 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), Anand, Irvine, Puckett, and Venkataraman (2012), Jame (2018), Barbon, Maggio, Franzoni, and Landier (2019), Di Maggio, Franzoni, Kermani, and Sommavilla (2019). Also see Hu, Jo, Wang, and Xie (2018) for a detailed description of the Ancerno database.

by dealer repos). We aggregate these variables in a unique funding liquidity factor.

The first original finding is that the execution shortfall of hedge funds is significantly more sensitive to funding conditions than that of mutual funds. Indeed, it appears that the the execution shortfall of mutual funds does not display a significant relation to funding liquidity. This evidence suggests that hedge funds, which play the role of liquidity providers in normal times, curtail this activity in bad times.

An alternative interpretation of this evidence may be that, in tight markets, the price of immediacy is higher. Thus, liquidity demanding trades end up having a larger price impact, even if the attitude of hedge funds towards liquidity provision does not change. To address this concern, we split hedge funds between liquidity providers and demanders using the trading style measure of Anand, Irvine, Puckett, and Venkataraman (2013), which categorizes investors based on whether their order flow in a given stock is in the same direction as the daily stock return (liquidity demanders) or in the opposite direction (liquidity providers). For liquidity providing funds, a regression of execution shortfall on funding liquidity reveals that the price impact also increases in bad times. In this case, the alternative explanation cannot apply, as it would predict that a rise in the price of immediacy would benefit these funds, that is, decrease their execution shortfall. This result holds also when we split liquidity providers and suppliers based on the whole distribution of institutions in Ancerno. Given this evidence, we interpret the positive relation of trading cost and funding conditions as suggesting that liquidity supplying hedge funds in our sample do indeed switch toward liquidity demand when these conditions tighten.

The observation that hedge funds withdraw from liquidity provision in bad times is suggestive of a constrained behavior, in line with the theories of limits to arbitrage. To further explore this explanation, we propose a set of fund-level characteristics that are likely to make a fund more sensitive to funding conditions. We find that the exposure of liquidity provision to aggregate conditions is significantly larger for funds with higher leverage, more illiquid assets, and lower reputational capital (as measured by fund age and past performance). These characteristics are related to hedge funds' ability to retain capital in bad times. As such, they serve as proxies for funding constraints.

Combining these fund-level characteristics, we construct an indicator to denote constrained funds. We find that, among the liquidity providing hedge funds, only the constrained ones reduce liquidity supply. The original contribution of this analysis is the ability to identify a set of institutional features that are sufficient to explain the withdrawal of hedge funds from liquidity provision.

Next, we focus on the persistence of negative funding shocks to hedge fund trading performance. The goal of this analysis is to establish the duration of the effect of a funding shock on liquidity provision for constrained hedge funds. We find that the impact of a shock on trading performance lasts for at least a quarter. Especially relevant is the fact that liquidity supplying funds exhibit the largest and longest-lasting effect, which likely reflects the detrimental effect of altering their portfolio allocation. This finding can explain Anand, Irvine, Puckett, and Venkataraman's (2013) evidence that liquidity providing institutions abstained for several quarters from trading illiquid stocks during the financial crisis. Moreover, the abnormal performance of unconstrained hedge funds is consistent with the result in Grinblatt, Jostova, Petrasek, and Philipov (2016) that some contrarian hedge funds possess superior investment skills.

Finally, our data give us the unique opportunity to study whether hedge funds' liquidity provision impacts stock-level resiliency. We show that the stocks that were most highly dependent on liquidity supplying hedge funds, and in particular on constrained funds, at the inception of the last financial crisis later experienced lower abnormal returns and higher trading costs compared to the stocks that were least dependent. Along with prior literature suggesting the importance of hedge funds for stock liquidity (Aragon and Strahan (2012)), this finding singles out hedge funds as a group of liquidity providers that deserves special attention.

Some recent papers explore trading activity of institutional investors using Ancerno data. Most closely related to our work, Anand, Irvine, Puckett, and Venkataraman (2013) study the implications of liquidity providing institutions for stock price resiliency. We elaborate on their work by investigating the relevance of the institutional form (hedge funds vs. other institutions) and of institutional characteristics (leverage, asset illiquidity, age, etc.) in determining a deviation from liquidity provision. Also novel, we study the impact of negative funding conditions on the trading performance of constrained liquidity suppliers. Jame (2018) studies the performance of star hedge fund managers and finds that liquidity provision is an important determinant of this performance. Our paper, instead, is concerned with the constraints to liquidity provision. Gantchev and Jotikasthira (2015) 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.

Other work relies on lower frequency data. Regressing hedge fund returns on returns to a long-short contrarian trading strategy, Jylha, Rinne, and Suominen (2014) find that hedge funds typically supply liquidity in the stock market. Consistent with our evidence, they show that hedge funds decrease liquidity provision in bad times and this is the more likely for funds that are more exposed to redemptions. We complement their evidence by directly measuring liquidity provision at the trade level. Importantly, suggesting that we capture a different dimension of liquidity provision from their study, we find that the correlation between our trade-level measure of liquidity provision and a measure based on factor loadings from monthly data, while positive, is not perfect, at 40%. Also, using our direct measure of trading costs, we broaden the perspective by contrasting the exposure to funding conditions of hedge funds to that of other institutions. Also novel, we are in the position to compute the high-frequency impact of funding conditions on trading performance, which allows us to make claims on the duration of negative funding shocks to the financial position of liquidity providers.

Similar to our work, the recent paper by Giannetti and Kahraman (2017) is inspired by the notion that the organizational form matters for the exposure to limits of arbitrage. Using quarterly holdings data, they show that closed-end funds, as well as hedge funds with restrictions to redemptions, are better poised to trade against mispricing. Our results are also consistent with those in Cao, Chen, Liang, and Lo (2013) and Ben-David, Franzoni, and Moussawi (2012) that hedge funds do not to act as liquidity providers of last resort in bad times. The evidence that their future performance suffers, especially for constrained funds, is suggestive of a forced behavior rather than deliberate market timing ability. As hedge funds tend to behave more as short-term investors (Ben-David, Franzoni, and Moussawi (2012)), our study further relates to Cella, Ellul, and Giannetti (2013) who link price pressure to investors preference for the investment horizon. While they focus on the impact of trading horizon on the direction of trading, we document the impact of funding constraints on liquidity provision as measured by the price impact of these trades and expand on their findings by providing trade-level indirect evidence of forced sales. Finally, with respect to the theoretical literature, our results are in line with models that posit time-varying financial constraints for arbitrageurs (Shleifer and Vishny (1997), 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, the identification of hedge funds, and the representativeness of our sample. Section 3 compares the exposure of liquidity provision to funding conditions for hedge funds and other institutions. Then, it develops a fund-level measure of financial constraints to explain this exposure. Section 4 computes hedge funds' trading performance over different horizons to measure the duration of funding liquidity shocks. Finally, Section 5 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. Then, we detail the procedure to identify hedge funds. Finally, we tackle issues of sample representativeness.

2.1 Institutional trading data

Our data on institutional trades spans the January 1, 1999 to June 30, 2013 sample period. The data provider is Abel Noser Solutions, formerly Ancerno Ltd. (We retain the shorter name of 'Ancerno').[2] 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. An advantage of

[2]Other recent studies using 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), Anand, Irvine, Puckett, and Venkataraman (2012), Jame (2018), Barbon, Maggio, Franzoni, and Landier (2019), Di Maggio, Franzoni, Kermani, and Sommavilla (2019). See Hu, Jo, Wang, and Xie (2018) for a detailed description of the structure and the merits of the Ancerno database.

Ancerno data is that it contains 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 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 opening price for the traded stock. In the top layer, trades are part of a unique order, which can span several days. Our analysis is carried out at the day-manager level. Hence, we do not use information from the top layer.

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 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 combined data from three commercial databases – the Lipper/TASS Hedge Fund Database, Morningstar CISDM, and Hedge Fund Research – which contain 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 (see Ben-David, Franzoni, Landier, and Moussawi (2013)). 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 96 distinct hedge fund management companies that are present in Ancerno at various times throughout the sample.[3] As a validation of our matching procedure, in the Internet Appendix, we assess the extent to which the hedge fund trades in Ancerno relate

[3]In a recent paper, Jame (2018) also uses Ancerno to identify hedge funds following a procedure that resembles our own. He ends up with a sample of 70 hedge fund management companies, which is comparable albeit smaller to the size of our own sample.

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, confirming the evidence in Jame (2018).

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 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%. We also remove observations from the residual/unclassified category with *managercode* equal to zero. The filtered sample consists of nearly 12 million of hedge fund 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 23, and ranges from a minimum of 3 to a maximum of 39 managers. These managers are responsible for an average of 3,265 daily transactions (second row), but the distribution is highly skewed with a maximum of 36,369. The last four rows in the panel provide information on dollar volume. The average daily volume is about $500 million. Volume per trade is on average $175 thousand, and varies between $12 thousand and about $2 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 $186 thousand versus $171 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 buy trades more than sell trades.

In Panel B of Table 1, similar statistics are displayed respectively 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. There are on average 218 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. The large bulk of these other institutions consists of mutual fund clients, whose statistics are reported in Panel C. There are on average 163 mutual funds, whose volume per trade is comparable to that of other the institutions.

2.4 Is the sample representative?

Next, we tackle the important question of whether our sample of hedge funds is representative of the broader universe. 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, in Internet Appendix C we provide statistical evidence that further dispels the concern of a self-selected sample. In short, we show that the hedge funds in Ancerno load on funding liquidity variables in a similar way to other funds reporting to the commonly used Lipper/TASS database, and are comparable in terms of characteristics.[4] Hence, it appears that our sample is representative of the hedge fund universe as far as the exposure to funding liquidity is concerned.

[4]In addition, we also examine whether the number and risk profile of funds varies systematically over time thus biasing our inference, but find no significant evidence of this.

3 Funding conditions and liquidity provision

We investigate the relation between liquidity provision at the trade-level and aggregate variables capturing funding conditions. Anand, Irvine, Puckett, and Venkataraman (2013) show that liquidity providing institutions do not curtail their activities when aggregate conditions deteriorate. They find, however, that liquidity supply in risky stocks decreased during the financial crisis. We build on their analysis and explore whether the institution type matters for the exposure to funding conditions.

3.1 Measuring liquidity provision

The standard approach in the empirical market microstructure literature is to identify liquidity provision with limit orders and liquidity demand with market order. Our data, similar to other trade level data sets, does not report the order type. Thus, 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 the execution shortfall, which 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.

We construct the execution shortfall on day t for manager i as the dollar volume-weighted average of the relative difference between the execution price of trade j, P_j, and a benchmark price, P^*:

$$ES_{i,t} = \sum_j \frac{\$Vol_j}{\sum_j \$Vol_j} \left(\frac{P_j - P^*}{P^*} \right) \times Side_j \tag{1}$$

where $Side$ equals 1 for a buy and -1 for a sell trade. Lacking the observation of the bid-ask quote prevailing at the time of the trade, we follow Anand, Irvine, Puckett, and Venkataraman (2013) and rely on Price at Open.[5]

[5]We obtain similar results using other common alternatives, such as Price at Placement (Anand, Irvine, Puckett, and Venkataraman (2012)) or the

Panel A of Table 2 contains summary statistics for ES expressed in basis points (bps) pooling all fund-day observations. Over the sample, the average ES is about 38bps with a standard deviation of 178bps. Its distribution is positively skewed, reaching peaks around 750bps. Price impact tends to be on average larger for sell trades (about 44bps) than buy trades (about 29bps), which is arguably a symptom of fire sales. The series are characterized by a modest degree of time-series persistence at the day-manager level, with first-order autocorrelations below 0.20.

The following panels of the table report analogous statistics for all institutions (Panel B), and for mutual fund clients only (Panel C). It is striking to note that the ES of these institutions is on average quite smaller than that of hedge funds, averaging about 8 and 8.5bps respectively. This evidence is likely on account of the fact that hedge funds and other institutions trade off very differently execution costs and returns from trading. It is common view that several hedge fund strategies exploit private, possibly short-lived signals. For these funds, execution costs may be of smaller concern when confronted with the gain from exploiting the signal, so they will tend to trade very aggressively. Other institutions, instead, lacking valid information signals, must pay more attention to execution costs and may decide to trade more patiently than hedge funds.[6]

In order to offer a low-frequency view on the evolution of aggregate trading costs, Figure 1 displays the ES series averaged over the quarter. We provide separate evidence for hedge funds (dark-colored bars) and other institutions (light bars). In line with prior studies (e.g. Anand, Irvine, Puckett, and Venkataraman (2013)), trading costs in our data exhibit a secular decline. Focusing on hedge funds, there is also clear evidence of a cyclical pattern. Execution shortfall shows a substantial increase in 2000Q4 and 2001Q1, 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

volume-weighted average price (see Berkowitz, Logue, and Noser (1988) and Puckett and Yan (2011)). These results are available from the authors upon request.

[6]This argument is consistent with the findings in Puckett and Yan (2011), who document that the best performing funds in the Ancerno data set on average demand immediacy. Hedge funds are likely to be among the funds that in their paper display positive alpha from interim activity, as they deliver on average significant abnormal performance compared to other institutions such as mutual funds. See their Table VII and related discussion.

series, execution shortfall starts decreasing from the 2001 peak and remains at its lowest levels until early 2008, when they start increasing again to a max of 80bps during the recent financial crisis. This evidence lines up with the findings in Ben-David, Franzoni, and Moussawi (2012) who report that hedge funds were massively unwinding their equity positions in that period. In contrast, other institutions display much less sensitivity to aggregate conditions, suggesting that much of the exposure to funding conditions that Anand, Irvine, Puckett, and Venkataraman (2013) identify is located in the hedge fund sector. Interestingly, towards the end of the sample, which was characterized by lower cost of capital, the gap in ES between two groups has closed in part.

3.2 The role of the institution type in the exposure to funding conditions

The preliminary impression from Figure 1 is that hedge funds' trading style is more exposed to market conditions than that of other institutions.

A priori, it is not clear whether hedge funds are more subject to limits of arbitrage than other institutions, notably mutual funds. On the one hand, mutual funds provide daily liquidity, while hedge funds often times have share restrictions in place that constrain investors' ability to redeem capital at will. This element would suggest that hedge funds are better positioned to provide liquidity when other investors withdraw from the market. On the other hand, hedge funds' sophisticated clientele has a higher sensitivity to losses (Ben-David, Franzoni, and Moussawi (2012)). Also, hedge funds make intensive use of leverage in the form of borrowed capital, short selling, and derivative positions. As a result, they are under close scrutiny by their brokers and trading counterparties, who 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. By contrast, mutual funds make very limited use of leverage. These considerations suggest a study of the role of the institution type in determining the sensitivity of liquidity provision to funding conditions.

To investigate this issue, we provide more systematic evidence from regression analysis relating the execution shortfall to funding conditions. To measure funding conditions, we draw on prior literature. Based on the findings in Hameed, Kang, and Viswanathan (2010) that liquidity supply by financial intermediaries is positively related to market performance, we select the market return in the prior two weeks as a proxy for an improvement in funding liquidity. Brunnermeier and Pedersen (2009) argue that the margins imposed by brokers to arbitrageurs depend on the volatility of asset prices and Nagel (2012) shows that market liquidity deteriorates when the VIX increases. Garleanu and Pedersen (2011) 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 (the three-month LIBOR minus the three-month T-bill rate) to proxy for systematic time-series variation in funding liquidity. Finally, Anand, Irvine, Puckett, and Venkataraman (2013) suggest that dealer repos are a close proxy for the availability of capital to market intermediaries. Thus, we use dealer repos, computed as the cumulative difference in short-term lending by U.S. primary dealers (source: Federal Reserve Bank of New York), as another measure of funding conditions. In our regressions, each of these variables is standardized in the time series.[7] As a catch-all variable, we compute a liquidity factor (LF) by adding the four standardized proxies.[8] The factor is also standardized in the time series. Panel D of Table 2 collects summary statistics for these variables.

To explore the relevance of the institution type for the exposure to funding conditions, we estimate the following model using as dependent variable the volume-weighted execution shortfall at the day-manager level (in basis points):

$$ES_{i,t+1} = a + b_1 FundLiq_t + b_2 HF_i + b_3 HF_i \times FundLiq_t + \delta' Z_{i,t} + \epsilon_{i,t+1} \tag{2}$$

where HF_i 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 the proxy for

[7] An obvious variable to measure funding conditions is fund flows. 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.

[8] We want the factor to measure a deterioration in funding conditions. So, the signs of its components are changed where necessary. The liquidity factor therefore equals: $LF = -R_M + VIX + TED - Repo$. As an alternative, we also experiment taking the first principal component. Results are still qualitatively similar, although generally weaker in economic and statistical magnitude. The reason is that the principal component approach captures only correlated moves, whereas the present approach allows funding conditions to react if any (of just some) of the liquidity proxies is shocked. As a matter of example, during the burst of the Internet bubble the VIX and the market experienced large movements whereas the TED and Repo were not as affected.

funding conditions ($FundLiq_t$) on the execution shortfall of investors that are not hedge funds. $FundLiq_t$ denotes alternatively one of the five funding liquidity determinants (R_M, VIX, TED, Repo, or LF). The loading on the interaction term, b_3, captures instead the additional effect of the same shock on hedge funds' execution shortfall. The vector $Z_{i,t}$ collects the following set of controls for trade-level characteristics that are inspired by prior literature (e.g. Keim and Madhavan (1997)): *Buy*, a dummy that equals 1 for buy trades, and 0 otherwise; *Lagged Return*, the stock return on day t; *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 by hedge fund i on day $t+1$ to the average volume of the stock in the prior 30 days; *Amihud*, the Amihud illiquidity ratio; *Size* and *Book-to-Market*, the stock market capitalization and book-to-market deciles. All variables are computed as volume-weighted averages at the manager-day level. We also interact the lagged return with the *Buy* dummy to account for possible differential effect of momentum on buy versus sell trades.

Table 3 reports estimates of the model in equation (2). Standard errors are clustered at the date level. The main finding is a significant interaction term b_3 (in bold in the table) for all the funding liquidity proxies. The signs are consistent with an aggregate increase in liquidity demand for the hedge funds sector when funding conditions tighten. That is, it is negative for the market return and Repo, and is positive for VIX, TED, and LF. All coefficients are statistically significant at the 1% level or better. The economic magnitude is also significant. The largest effect is observed for LF, suggesting that aggregating different liquidity shocks improves our identification. A one-standard deviation deterioration in funding conditions as captured by LF predicts an increase of about 7bps in the ES on the next day. In contrast, the estimates for b_1 are either of the opposite sign of b_3 (for market, TED, and LF) or much smaller in magnitude (for VIX and Repo).[9]

In specifications (1)-(5) of Table 3, we benchmark hedge funds against all other institutions in Ancerno. In column (6), we estimate equation (2) with $FundLiq = LF$ when restricting the

[9]The coefficients on the control variables are broadly consistent with previous studies and economic priors. A notable exception is the stock size decile, which enters the regression with a positive sign. This is due to its correlation with other covariates that proxy for size, such as the Amihud measure. We verify that when entering as a stand-alone control, Size has the expected negative sign.

sample to hedge funds and mutual funds only (that is, we exclude pension funds within the group of other institutions). As we can see, hedge funds trading costs remain much more sensitive to funding conditions even when contrasted to mutual funds.

We further account in two ways for persistence in execution shortfall that may not be captured by our design. First, in specification (7) we replace the dependent variable with a measure of manager-level abnormal ES, defined as the residual with respect to the average fund-level ES over the prior month. When using this measure, our conclusions on the sensitivity of hedge funds' liquidity provision to funding conditions continue to hold. Second, in specification (8) we verify that our results are robust to double-clustering standard errors at both the time and manager level. Finally, in unreported results we find that our evidence remains intact when excluding the years 2007-2009. Hence, the effects we identify are not confined to the financial crisis. The results also hold true when estimating the regression on data aggregated at the manager-week frequency, and require the number of trades for each manager to be at least 20 to filter out infrequently trading funds.

In sum, the regression analysis confirms the significance of the graphical impression from Figure 1. The trading costs of hedge funds are significantly more sensitive to a deterioration in funding conditions than those of mutual funds. This evidence is a novel contribution to the literature.

3.3 Trading style and funding conditions

Possibly, the aggregate evidence in Figure 1 and Table 3 conceals heterogeneous behavior along the trading style dimension. Anand, Irvine, Puckett, and Venkataraman (2013) categorize institutions into liquidity providers and liquidity demanders based on the difference between the monthly volume of trades that are in the same direction as the daily stock return (volume with) versus those in the opposite direction (volume against). They show that the ES of the two groups moves in opposite direction. In bad times, when liquidity becomes more costly, the trading costs of liquidity demanders are magnified to the advantage of liquidity suppliers.

We apply this methodology to different institutional types. Specifically, based on the trading style in the prior month, we sort different types of institutions into terciles based on the trading style score. The managers in the bottom tercile are classified as liquidity providers, while the top tercile contains liquidity demanders. The top plot of Figure 2 displays the ES series averaged over the quarter for liquidity demanding and providing hedge funds. We note that, as expected, the liquidity demanders experience a positive ES while liquidity suppliers' ES is on average negative (also see Panel A of Table 4). While the two series move in opposite directions for most of the sample period, during severely stressed markets (the early 2000, and the last financial crisis), the ES of liquidity providing hedge funds rises significantly above zero and moves in the same direction as for the liquidity demanders. This novel evidence suggests that a crucial class of liquidity providers curtails its activities to the point that it mimics the behavior of liquidity demanders in bad times.

The bottom plot of the figure displays the analogous series for the group of mutual funds. Unlike hedge funds, we find that liquidity supplying mutual funds decrease their trading costs during bad times, thereby taking advantage of the high premium for liquidity provision. Their execution shortfall moves systematically in the opposite direction to that of liquidity demanding funds. This graphical evidence adds to the impression that mutual funds are a more reliable source of liquidity provision during bad times than hedge funds.

Next, we provide more systematic evidence. The leftmost columns of Panel A of Table 4 report the average ES and its t-statistic for the group of LD and LS hedge funds. Consistently with Figure 2, the average ES for liquidity supplying hedge funds is negative at -8bps, whereas that of liquidity demanding funds is largely positive at 77bps. As documented by Anand, Irvine, Puckett, and Venkataraman (2013), a given fund's tendency to provide or demand liquidity is also persistent over time. The rightmost columns of Panel A show that the average trading style is negative for LS and positive for LD funds in the formation month, as well as in the following six months.

Then, we estimate equation (2) separately for each LD/LS group (Panels B and C of Table 4). We do not include the control variables for the purpose of interpreting the constant as the average

ES in normal times. (Remember that the FundLiq variables are standardized.) The results are, however, robust to the inclusion of the controls.

In specification (1) , we estimate the regression on hedge fund data only. The coefficient on HF therefore measures the average ES during normal times, while that of the interaction term HF$\times$ LF captures the expected response to a funding shock. Panel B suggests that LD funds end up consuming more liquidity in bad times, which is not a surprising finding. The original result is for the set of LS hedge funds. From Panel C, we note that, also for this group, a tightening in funding conditions leads to an increase in the execution shortfall. In particular, while the average ES is significantly negative at -8, consistent with liquidity provision, the estimated coefficient on the interaction term is positive at 2.5 and statistically significant, meaning that a tightening in funding condition pushes the average LS fund towards liquidity demand.

We next ask whether the behavior of hedge funds is statistically any different from that of other institutions, and in particular mutual funds. To this end, in specification (2) we add mutual funds (separately classified into LS and LD) and estimate an interacted model. The constant term now captures their average ES, while the loading on LF measures the effect of funding conditions on their ES. In Panel B, we learn that the sensitivity to funding shocks of LD hedge funds is somewhat higher than that of LD mutual funds, as the interaction term HF$\times$ LF is positive at 3.554, but is quite noisily estimated with a t-stat of only 0.74. For the group of LS hedge funds, however, the evidence is quite different. Namely, the execution shortfall of LS mutual funds is negatively related to LF, with a significant coefficient of -8.745, meaning that these institutions earn a higher liquidity premium during bad times. In contrast, the coefficient on HF$\times$ LF is positive and large at 11.259, and significant at the 1% level (with double-clustered standard errors). Hence, the reaction of LS hedge funds to funding shocks runs opposite to that of other institutions, and reveals a shift towards liquidity demand.

Our results thus far obtain when classifying hedge funds and mutual funds into LS/LD based on the distribution of trading style computed *within* each group of institution. A natural concern is whether the LS hedge funds in our sample are liquidity suppliers in absolute terms – i.e. with respect to the full cross-section of institutions in the market – or only relative to other hedge funds that tend to consume more liquidity (LD), in which case the comparison with other truly LS institutions would be misleading. In specifications (3)-(4) of Table 4 (labeled "ES, Joint class."), we tackle this concern directly by re-estimating our analysis when the LS/LD classification is based on the trading style breakpoints from the *pooled* data of hedge funds and mutual funds, thereby comparing institutions with similar attitude towards liquidity provision in absolute rather than relative terms. Our evidence becomes indeed stronger under this classification. Namely, the sensitivity of LS hedge funds to LF is positive and significant, as the coefficient on HF $\times$ LF in column (3) is now 3.273, higher than estimate in column (1). Moreover, when benchmarked against mutual funds in column (4), hedge funds appear to react even more strongly to funding conditions, as the interaction coefficient increases to 12.021 (from 11.259) and so does the difference with respect to the coefficient for mutual funds (captured by LF).

We further assess the sensitivity of our results to the use of prior month's trading style. This measure has the benefit of tracking month-by-month, and hence short-lived changes in the extent of a fund's liquidity provision. However, since funding conditions are characterized by persistent components, such classification may also potentially underestimate the effect as some LS funds may switch to LD (and remain such) as soon as capital starts being scarce. For this reason, columns (5)-(6) in Table 4 report estimates for an alternative specification (labelled "ES, Long-term") where the LS/LD classification is based on a fund's trading style computed over the past six months, thereby capturing long-term liquidity provision. With this classification, hedge funds' execution shortfall appears even more sensitive to funding conditions compared to the baseline results, as the coefficient on HF$\times$LF for liquidity suppliers (Panel C) increases now to 3.884, and so does its statistical significance (t-statistic from 1.87 to 2.54). The difference in the sensitivity to funding conditions compared to mutual funds also widens.

Finally, in specifications (7)-(8) we re-estimate our baseline specification when replacing the dependent variable with the abnormal ES defined above (see Table 3). Our main conclusions continue to hold. We are thus reassured that our results are not picking up differences in the composition of funds (and the stocks they trade) within the hedge fund sample, and compared to other institutions.

In sum, while the prior literature shows that the subset of liquidity supplying institutions experiences an improvement in the execution shortfall in bad times (Anand, Irvine, Puckett, and Venkataraman (2013)), consistent with increased liquidity provision, our evidence suggests that hedge funds adopt a different behavior, withdrawing from liquidity provision in bad times. This distinction has important implications for the well-functioning of financial markets, in light of the significant role of hedge funds for market liquidity, as evidenced by Aragon and Strahan (2012).

3.4 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-leveraged hedge funds to withdraw their liquidity provision more strongly in bad times.

Hedge funds with an important component of illiquid assets in their 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 its 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.[10]

We ask if the characteristics that correlate with a fund's tendency to provide liquidity also result in a higher sensitivity of its liquidity provision (ES) to funding conditions.[11] To that end, we regress the execution shortfall ES on the interaction between aggregate funding liquidity and the hedge fund characteristics that are meant to capture limits of arbitrage. A priori, the fund-level regressors are defined so that a higher score captures higher expected limits of arbitrage. Table 5 reports the estimates for the interaction coefficients, which capture the differential effect of funding liquidity shocks, originating from fund-level characteristics, on the implicit trading cost. The dependent variables is the execution shortfall in basis points.[12] The regressions are run separately for liquidity demanding (Panel A) and liquidity supplying hedge funds (Panel B).

We note that all variables enter the regression with the expected positive sign, meaning that leveraged, younger, poor-performing funds and those with more illiquid stocks are more impacted by funding shocks. From a comparison of the two panels, it is clear that financial constraints are generally more relevant for LD funds, which is consistent with their higher sensitivity to funding conditions documented in Table 4. All coefficients except Young meet statistical significance for these funds in the joint specification. For LS hedge funds, the evidence is somewhat weaker, with leverage (in the univariate specification) and prior performance being the most important and statistically significant determinants.

Armed with this evidence, we construct an overall fund-level proxy of financial constraints to identify the funds for which limits to arbitrage are more binding. We standardize the variables $Leverage$, $Illiquid$, $Young$, and Bad. The fund-level score of financial constraints ($Constrained$) is the sum of these four standardized variables, and is normalized to range between 0 and 1 for ease of interpretation. Given this measure, we test whether the more constrained funds are responsible

[10] At a first approximation, share restrictions (i.e. lockup period, redemption notice period, and redemption frequency) represent another legitimate candidate for a fund-measure of constraints. At a closer scrutiny, however, share restrictions are endogenous relative to the funds' clientele. That is, a fund can afford to keep lower restrictions if it expects its clients to be less inclined to redeem. This consideration suggests that the effect of share restrictions is ambiguous. We have tried to include them among our measures of constrains, without a significant improvement of the results. Therefore, we leave them out of our main specifications to focus on a parsimonious set of constraints that appear to be empirically relevant.

[11] In Appendix D, we analyze the determinants of liquidity provision by relating these and other characteristics to a fund's trading style. We find that funds with higher leverage, funds with better performance to date, older funds, and those holding less illiquid assets engage more strongly in liquidity supply.

[12] While the characteristics are available monthly, we retain the daily frequency of the analysis to exploit within-month changes in funding conditions that improve our identification compared to the alternative of aggregating the data monthly.

for the observed withdrawal of hedge funds from liquidity provision in tight funding conditions via the following model:

$$ES_{i,t+1} = a_1 + a_2 Constrained_{i,t} + b_1 LF_t + b_2 Constrained_{i,t} \times LF_t + \delta' Z_{i,t} + \varepsilon_{i,t+1}. \quad (3)$$

Table 6 collects the corresponding estimates, when the regression is run separately for liquidity demanding (LD, Panel A) and liquidity supplying (LS, Panel B) hedge funds. In the table, specification (1) refers to the model without the control variables $Z_{i,t}$, column (2) adds the controls, while column (3) classifies the funds based on long-term liquidity provision as described in Section 3.2.

As expected, LD funds experience an increase in trading costs when funding liquidity deteriorates (coefficient on the interaction, columns (1)-(3)). These funds pay a liquidity premium in normal times. Consequently, when the cost of liquidity goes up, their trading costs rise. The cost of liquidity increases even more for the funds that are forced to unwind their positions because of financial constraints. Perhaps more surprising is the evidence that also for LS funds the slope on the interaction term is positive and significant (columns (5)-(7)). That is, liquidity provision decreases in bad times for the more constrained funds. Given that $Constrained$ ranges between 0 and 1, the slope on LF captures the effect of funding conditions on the least constrained funds. Then, the negative and significant slope on LF implies that the non-constrained funds increase their supply of liquidity in bad times (their ES falls), which is consistent with Anand, Irvine, Puckett, and Venkataraman's (2013) evidence for the set of all institutions in Ancerno.

As a final check, we compute an alternative $Constrained$ fund-level score based on the Ancerno dataset directly, rather than relying on the more sparser information from hedge fund datasets.[13] With this approach, the number of available funds increases from 58 (when the classification is based on commercial databases) to 96 (the full set of funds). Columns (4) and (8) of Table 6 report the corresponding results. Notably, we still find that constrained LS hedge funds are mostly

[13] Specifically, we construct the $Constrained$ fund-level score based on size (as measured by the trading volume quintile in the previous month), illiquidity (the Amihud of the stocks that are traded in the previous month), and performance (the return from interim activity computed as in Puckett and Yan (2011) over the past year). We then combine these variables (standardized) into a single Constrained index, with constrained funds being those that are smaller in size, more illiquid, and least performing.

impacted by funding conditions, even with this alternative measure. The interaction term between Constrained and LF in column (8) has a positive and significant coefficient, meaning that the execution shortfall of these funds increases following a tightening in funding constraints, whereas that on LF alone is negative, meaning that unconstrained funds are able to benefit from liquidity provision in these times. We are, therefore, reassured on the validity of the previously reported results.

3.5 Liquidity provision and stock resiliency

The evidence that hedge funds are more exposed to funding conditions than other institutions, to the point of changing their ability to provide liquidity during bad times, begs further questions. If hedge funds are not acting as ultimate liquidity providers, 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). Therefore we ask if hedge funds react to funding shocks by changing the stocks they trade. And if so, does this behavior ultimately affect stock-level resiliency?

To investigate these questions, we begin by regressing the volume-weighted average decile of a given stock characteristic across the stocks traded on a given day by an institution onto LF, controlling for the lagged dependent variable. Table D.1 in the Internet Appendix shows that both LD and LS hedge funds indeed react to funding liquidity shocks by tilting their trades toward larger, more liquid, less volatile, lower book-to-market and lower momentum stocks. Interestingly, LS hedge funds appear to respond to the shock by eschewing small and high book-to-market stocks more strongly than LD funds.

As LS hedge funds switch toward liquidity consumption and change the type of stocks they trade when funding conditions tighten, we expect stocks that are traded mostly by LS hedge funds in normal times to be negatively affected in bad times. To test this conjecture, we explore whether the stocks with more trading from LS hedge funds experience a decline in resilience during the 2007–2009 financial crisis. To be precise, we first compute the fraction of the volume traded by LS hedge funds over the total volume by all liquidity supplying institutions (including hedge funds and other institutions) over the 1-year period preceding the crisis (i.e. June, 2006 to May, 2007). Next, we sort each stock based on this fraction into quintiles and focus on the top and bottom quintiles. Stocks in the bottom quintile are the ones for which liquidity provision is least dependent on LS hedge funds. We expect these stocks to recover faster in terms of both performance (as measured by cumulative abnormal returns with respect to the 3-factor Fama and French (1993) model) and trading costs (as measured by execution shortfall) over the June, 2007 to March, 2009 crisis period.

The left plot of Panel A of Figure 3 shows that stocks in the top quintile (mostly dependent on hedge funds' liquidity provision) indeed experience significantly lower average cumulative abnormal returns and exhibit a slower recovery pattern after the crisis. The difference in cumulative returns hits a maximum of -15%, and is -10% at the end of the crisis period. Similarly, the right plot of Panel A shows that, although the average execution shortfall for the stocks in the top and bottom quintiles were almost the same prior to the crisis, trading costs are significantly higher in the crisis period for stocks in the top quintile, with differences in the order of 12.5 basis points during the third quarter of 2008.

Furthermore, we investigate the differential effect of constrained and unconstrained hedge funds in light of the evidence from Table 6 that the two groups' trading costs have different exposure to funding conditions. To this extent, we break down the group of stocks that are dependent on LS hedge funds (top quintile) in two groups based on whether they are mostly dependent on Constrained and Unconstrained funds, where the former are funds whose Constrained index is above the median. Panel B of Figure 3 plots the average cumulative abnormal returns (left plot) and execution shortfall (right plot) for the two portfolios formed according to the dependence of liquidity provision by constrained and unconstrained liquidity provider hedge funds. We find that stocks that are mostly dependent on constrained LS hedge funds suffer the most during the crisis both in terms of performance and trading costs (i.e. liquidity). These results are consistent with and lend further support to those from the panel regressions.

4 Hedge funds' trading performance and funding conditions

Institutional investors' financial performance is a key driver of their ability to provide liquidity (Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010)). As modeled by Brunnermeier and Pedersen (2009), losses on arbitrageurs' positions can trigger margin calls from brokers which force the arbitrageur to liquidate the losing positions and to experience further losses as a result of price pressure. In this situation, a liquidity supplier turns into a liquidity demander. A related case is that in which arbitrageurs' underperformance causes investors to withdraw their capital, so that profitable positions have to be unwound before convergence (Shleifer and Vishny (1997)). Also in this case, poor performance impairs liquidity provision.

Given the importance of financial performance for liquidity provision, we next study the impact of funding shocks on hedge funds' trading performance. Our goal is to use the returns on hedge fund trades as a proxy for their financial conditions. Computing these returns over different horizons allows us to measure the duration of negative funding shocks to hedge funds' portfolios. We expect the impact of negative funding conditions to be exacerbated for those institutions that are financially constrained. These funds are more likely to engage in forced liquidations to meet margin calls and redemptions. Because they unwind their positions in illiquid markets, their performance is probably going to suffer. Further, we expect the sign of the sensitivity to funding conditions to depend on the trading style (i.e., liquidity provision vs. liquidity demand) because in bad times the cost of liquidity is higher.

To test these conjectures, we again split the sample of hedge funds between liquidity demanders (LD) and suppliers (LS). To compute trading performance, we modify Puckett and Yan's (2011) methodology to suit our application. First, for each hedge fund trade we compute the cumulative abnormal return over three different horizons: one week (5 days), two weeks (10 days), and one month (21 days). The returns are computed over non-overlapping windows to avoid introducing spurious correlation in the regression. Second, we form portfolios of all trades from funds in one of the four subsamples that result from the intersection of the LS vs. LD and the constrained vs. unconstrained splits.[14] When computing total portfolio returns, sell trade returns are subtracted from buy trade returns. The buy and sell portfolios are equally weighted. (Using the trade size to construct volume-weighted portfolios gives similar results.) As a result, we obtain daily series of cumulative abnormal returns over three different horizons for the four groups of funds.

In Ancerno data, buy trades can represent newly initiated long positions as well as the covering of previously opened short positions. Vice versa, sell trades capture liquidations of long positions as well as newly initiated short positions. Then, the returns of our portfolios measure both the performance of new positions and the opportunity cost of unwinding existing positions. These returns can be negatively impacted by funding conditions if financial constraints cause hedge funds to deviate from their preferred path. Instead, institutions that are not constrained can even profit from providing liquidity to other investors when funding conditions tighten.

We regress the cumulative abnormal returns of portfolios based on day $t+1$ trades on the liquidity factor on day t, separately for LD and LS funds, through the model:

$$r_{i,t+k} = a_1 + a_2 Constrained\,Pf_i + b_1 LF_t + b_2 Constrained\,Pf_i \times LF_t + u_{t+1}. \tag{4}$$

where $Constrained\,Pf_i$ is 1 for if portfolio i is made of constrained funds, and 0 otherwise. The coefficient b_1 measures the effect of funding conditions on the abnormal performance of unconstrained funds, whereas b_2 captures the additional effect on the group of constrained funds. The horizon k is either 5, 10, or 21 days.

Panel A of Table 7 reports the estimates for LD hedge funds. We note that unconstrained LD funds earn positive abnormal returns in the order of 1% up to two weeks after the funding shock, but this over-performance vanishes thereafter. The view is more negative for constrained LD funds, as their the reaction over the same two-week period tends to be negative, although quite noisily estimated. This result confirms the evidence in the previous section that fund-level constraints interact with aggregate conditions to affect performance. In the rightmost panels, we examine the performance of buy and sell trades separately. The question that we address is which side of the

[14] As above, funds in the constrained portfolio are those with an above-median $Constrained$ index.

trade is driving our results. We see that unconstrained LD funds gain from buy trades in bad times, but they lose from sell trades, consistent with the view that in down markets the main demand for liquidity is on the sell side. As for constrained LS, the underperformance can be equally imputed to both buy and sell trades.

The estimates for LS hedge funds in Panel B are economically and statistically stronger. When funding conditions tighten, unconstrained LS funds experience an increase in trading performance up to 3% in the one month after the trade. This result suggests that the subset of hedge funds that are not exposed to financial constraints can take advantage of the profit opportunities that open up in bad times. However, constrained LS funds experience a significant and persistent deterioration in trading performance when funding liquidity dries up. For these funds, the returns on trades that are initiated on a day in which funding conditions worsen by one standard deviation are lower (with respect to unconstrained funds) by about 1.6% after a week, 2.0% after two weeks, and 1.5% after a month. We also notice some significant differences in performance between buy and sell trades. The impact of funding shocks on the performance of buy trades is short-lived, as it is no longer significant after the first week and reverses sign after a month. In contrast, the performance of sell trades is progressively worsening for constrained funds, and persists up to a month after the shock in funding conditions.

The finding that more financially constrained hedge funds earn negative returns from their trades in bad times is fully consistent with the evidence that the same funds also withdraw from liquidity provision (Table 6). As mentioned above, poor returns trigger margin calls and redemptions which cause forced liquidations and deprive these hedge funds of the necessary capital to provide liquidity. Also, the result that the underperformance is protracted for at least a month possibly contributes to explain Anand, Irvine, Puckett, and Venkataraman's (2013) evidence that LS institutions exited the market for riskier stocks for an extended period of time during the last financial crisis. If liquidity suppliers were losing capital, they could not commit to trading securities that required high margins.

To further evaluate the duration of the above-documented effect, Appendix Figure D.1 reports the impulse-response function from a weekly Vector Autoregression (VAR) model with 3 lags on the bivariate system consisting of the stock return portfolios and the liquidity factor. As in Table 7, the reaction of constrained LS funds' performance following a positive shock to the funding liquidity factor is negative and pronounced, and persists for several weeks – about 12, i.e. a full quarter after the shock. The pattern for LS unconstrained is almost the opposite, with a large and positive initial return. Also noteworthy is the fact that negative abnormal returns for Constrained funds peak three weeks after the shock, which suggests that these institutions become progressively more unable to hold on to their positions.

In sum, arbitrageurs' financial conditions, as captured by their trading performance, is sensitive to funding liquidity. The subset of institutions that are not subject to financial constraints can take advantage from the widening of mispricing and the increased premium from liquidity provision. However, those institutions that are more exposed the negative funding shocks because of less stable sources of funding experience a prolonged trading underperformance. Among these hedge funds, even the liquidity suppliers show signs of financial distress, which probably explains their withdrawal from liquidity provision.

5 Conclusion

This paper draws inspiration from the existing theoretical results and empirical evidence pointing out limits of arbitrage in financial markets. Our goal is to identify more closely the determinants of liquidity providers' exposure to funding shocks. The empirical analysis relies on trade-level data that provides a privileged vintage point on liquidity supply and trading performance.

First, we document that the liquidity provision of hedge funds, as measured by price impact, exhibits much stronger sensitivity to funding conditions compared to that of other institutions, notably mutual funds. Importantly, we find that this behavior extends to hedge funds that are typically liquidity providers which suggests that these funds are no longer able to perform their role but are forced to switch toward liquidity consumption.

Next, we study the institutional characteristics that make hedge funds' liquidity supply exposed to funding shocks. The ability to steadily provide liquidity varies in the cross-section as a function of attributes relating to the availability and stability of hedge funds' capital. In particular, funding conditions have a stronger impact on young funds, leveraged funds, funds which invest in illiquid assets, and funds with a poor recent performance. Such institutions are more prone to margin calls and redemptions at times of market stress. The main result of this analysis is that, among the more financially constrained hedge funds, even the institutions that provide liquidity in normal times turn into liquidity demanders when funding conditions tighten.

Lastly, we recognize that financial performance is a key determinant of the stability of funding because margin calls and redemptions respond to portfolio returns. Hence, we measure the returns of hedge fund trades as a function of aggregate conditions, trading style, and fund-level measures of financial constraints. Our main finding is that fund-level measures of financial constraints interact with aggregate conditions to generate trading losses in stressed markets, even for institutions that are normally providing liquidity. For these funds, the underperformance persist for at least a month after the initial funding shock, which contributes to explain their withdrawal from liquidity provision.

To conclude, the empirical evidence in the paper sheds further light on the behavior of the liquidity providing sector in financial markets. Hedge funds are important actors in this field. However, their funding structure makes their provision of liquidity exposed to aggregate conditions. When funding dries up, there is a significant increase in liquidity demand coming from this group of institutions. The finding has obvious implications for the evaluation of market stability. Under severe stress, some stabilizing forces in financial markets appear to lose their ability to oppose the main trend and they actually contribute to put further pressure on asset prices. Our result that stocks that were most highly dependent on liquidity supplying hedge funds at the crisis inception later suffered the most is indeed in line with this argument.

References

Anand, Amber, Paul Irvine, Andy Puckett, and Kumar Venkataraman, 2012, Performance of institutional trading desks: An analysis of persistence in trading costs, *Review of Financial Studies* 25, 557–598.

———, 2013, Institutional trading and stock resiliency: Evidence from the 2007–2009 financial crisis, *Journal of Financial Economics* 108, 557–598.

Aragon, George O., and Philip E. Strahan, 2012, Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy, *Journal of Financial Economics* 103, 570 – 587.

Barbon, Andrea, Marco Di Maggio, Francesco Franzoni, and Augustin Landier, 2019, Brokers and order flow leakage: evidence from fire sales, *Journal of Finance* forthcoming.

Ben-David, Itzhak, Francesco Franzoni, Augustin Landier, and Rabih Moussawi, 2013, Do Hedge Funds Manipulate Stock Prices?, *Journal of Finance* 68, 2383–2434.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, Hedge Fund Stock Trading in the Financial Crisis of 2007–2009, *Review of Financial Studies* 25, 1–54.

Berkowitz, Stephen A., Dennis E. Logue, and Eugene A. Noser, 1988, The total cost of transactions on the nyse, *Journal of Finance* 43, 97–112.

Brunnermeier, Markus K., and Stefan Nagel, 2004, Hedge funds and the technology bubble, *Journal of Finance* 59, 2013–2040.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Cao, Charles, Yong Chen, Bing Liang, and Andrew W. Lo, 2013, Can hedge funds time market liquidity?, *Journal of Financial Economics* 109, 493 – 516.

Cella, Cristina, Andrew Ellul, and Mariassunta Giannetti, 2013, Investors' Horizons and the Amplification of Market Shocks, *Review of Financial Studies* 26, 1607–1648.

Chemmanur, Thomas J., Shan He, and Gang Hu, 2009, The role of institutional investors in seasoned equity offerings, *Journal of Financial Economics* 94, 384–411.

Chemmanur, Thomas J., Gang Hu, and Jiekun Huang, 2010, The role of institutional investors in initial public offerings, *Review of Financial Studies* 23, 4496–4540.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2010, Payoff complementarities and financial fragility: Evidence from mutual fund outflows, *Journal of Financial Economics* 97, 239–262.

Comerton-Forde, Carole, Terrence Hendershott, Charles M Jones, Pamela Moulton, and Mark Seasholes, 2010, Time variation in liquidity: The role of market-maker inventories and revenues, *Journal of Finance* 65, 295–331.

Di Maggio, Marco, Francesco Franzoni, Amir Kermani, and Carlo Sommavilla, 2019, The relevance of broker networks for information diffusion in the stock market, *Journal of Financial Economics* forthcoming.

Gantchev, Nickolay, and Chotibhak Jotikasthira, 2015, Hedge fund activists: Do they take cue from institutional exit?, Working paper.

Garleanu, Nicolae, and Lasse Heje Pedersen, 2011, Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies* 24, 1980–2022.

Getmansky, Mila, Andrew W Lo, and Igor Makarov, 2004, An econometric model of serial correlation and illiquidity in hedge fund returns, *Journal of Financial Economics* 74, 529–609.

Giannetti, Mariassunta, and Bige Kahraman, 2017, Open-end organizational structures and limits to arbitrage, *Review of Financial Studies* 31, 773–810.

Grinblatt, Mark, Gergana Jostova, Lubomir Petrasek, and Alexander Philipov, 2016, Style and Skill: Hedge Funds, Mutual Funds, and Momentum, UCLA Working Paper.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* 66, 361–407.

Grossman, Sandford J., and Merton H. Miller, 1988, Liquidity and market structure, *Journal of Finance* 43, 617–633.

Hameed, Allaudeen, Wenjin Kang, and Shivesh Viswanathan, 2010, Stock Market Declines and Liquidity, *Journal of Finance* 65, 257–293.

Hu, Gang, Koren M Jo, Yi Alex Wang, and Jing Xie, 2018, Institutional trading and abel noser data, *Journal of Corporate Finance* 52, 143–167.

Jame, Russell, 2018, Liquidity provision and the cross section of hedge fund returns, *Management Science* 64, 3288–3312.

Jylha, Petri, Kalle Rinne, and Matti Suominen, 2014, Do hedge funds supply or demand immediacy?, *Review of Finance* 18, 1259–1298.

Keim, Donald B., and Ananth Madhavan, 1995, The anatomy of the trading process, *Journal of Financial Economics* 37, 371–398.

———, 1997, Transactions costs and investment style: an inter-exchange analysis of institutional equity trades, *Journal of Financial Economics* 46, 265–292.

Manconi, Alberto, Massimo Massa, and Ayako Yasuda, 2012, The role of institutional investors in propagating the crisis of 2007-2008, *Journal of Financial Economics* 104, 491 – 518.

Nagel, Stefan, 2012, Evaporating Liquidity, *Review of Financial Studies* 25, 2005–2039.

Puckett, Andy, and Xuemin (Sterling) Yan, 2011, The interim trading skills of institutional investors, *Journal of Finance* 66, 601–633.

Shleifer, Andrei, and Robert W. Vishny, 1997, The Limits of Arbitrage, *Journal of Finance* 52, 35–55.

Table 1. Summary Statistics for Trade-Level Data

The table displays the following statistics: mean; standard deviation; minimum; 25th, 50th, and 75th percentiles; maximum. The variables are: the number of management companies, the daily number of trades, 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, from all other institutions in Ancerno in Panel B, and from the subset of other institutions that are mutual funds in Panel C. The sample period is from January, 1999 to June, 2013.

Panel A: Hedge funds (HF)

	Mean	Std	Min	p25	p50	p75	Max
Number of management companies	23	5	3	19	22	26	39
Number of trades	3’265	2’643	69	1’018	2’829	4’782	36’639
Volume ($ millions)	501	463	12	164	372	691	9’199
Volume per trade ($ thousands)	175	95	16	111	155	216	1’858
Volume per trade, buy trades ($ thousands)	171	106	20	103	150	210	2’411
Volume per trade, sell trades ($ thousands)	186	108	9	113	160	231	1’335

Panel B: All other institutions (OI)

	Mean	Std	Min	p25	p50	p75	Max
Number of management companies	218	26	28	211	224	235	269
Number of trades	70’873	54’958	7’283	36’635	55’968	93’484	1’476’334
Volume ($ millions)	10’358	4’005	1’530	7’904	9’995	12’216	117’460
Volume per trade ($ thousands)	204	126	7	105	149	284	720
Volume per trade, buy trades ($ thousands)	193	119	6	103	146	269	740
Volume per trade, sell trades ($ thousands)	218	139	8	111	161	306	792

Panel C: Other institutions classified as mutual funds (MF)

	Mean	Std	Min	p25	p50	p75	Max
Number of management companies	163	17	85	159	168	175	196
Number of trades	63’004	39’234	7’164	35’096	52’646	80’584	307’484
Volume ($ millions)	10’128	3’946	1’512	7’698	9’769	11’980	117’134
Volume per trade ($ thousands)	211	124	21	117	158	287	758
Volume per trade, buy trades ($ thousands)	200	118	23	111	151	272	780
Volume per trade, sell trades ($ thousands)	227	136	21	125	170	309	827

Table 2. Summary Statistics for Execution Shortfall 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 the execution shortfall of hedge funds (Panel A), of all other institutions in Ancerno (Panel B), and of the subset of other institutions that are mutual funds (Panel C), and for the funding liquidity determinants in Panel D. Execution shortfall, expressed in basis points and aggregated at the manager-day level, is computed as volume-weighted averages across all trades, and separately for buy trades (superscript b) and sell trades (superscript s). The funding liquidity determinants are: the two-week return to the CRSP value-weighted index (R_M); the VIX; the TED spread; the volume of dealer Repos (Repo); and the combined liquidity factor (LF) that is obtained by summing the four variables, after having standardized them and changed the signs, where necessary, so that the factor measures deterioration in funding conditions. The sample period is from January, 1999 to June, 2013.

	Mean	Std	AR(1)	Min	p25	p50	p75	Max
				Panel A: Hedge funds (HF)				
ES	38.21	178.42	0.18	-523.33	-38.76	24.56	102.26	726.69
ES^b	29.10	197.14	0.15	-615.59	-61.44	19.65	111.66	737.39
ES^s	44.15	211.27	0.15	-602.38	-52.28	24.52	120.65	877.63
				Panel B: Other institutions (OI)				
ES	7.89	151.08	0.16	-514.32	-52.66	6.18	65.07	559.84
ES^b	3.81	170.12	0.13	-584.66	-71.01	3.70	78.74	578.98
ES^s	17.55	177.61	0.14	-550.11	-60.38	7.31	85.08	701.32
				Panel C: Mutual Funds (MF)				
ES	8.47	140.69	0.17	-477.89	-48.23	7.03	62.06	521.49
ES^b	4.08	162.08	0.13	-557.14	-67.99	4.45	76.61	546.44
ES^s	17.14	168.85	0.14	-519.58	-58.00	7.51	82.34	665.36
				Panel D: Funding liquidity variables standardized				
R_m	0.00	1.00	0.88	-7.36	-0.51	0.10	0.55	5.95
VIX	0.00	1.00	0.98	-1.35	-0.69	-0.16	0.39	6.62
TED	0.00	1.00	0.99	-0.90	-0.62	-0.31	0.19	8.69
Repo	0.00	1.00	0.99	-1.78	-0.72	-0.01	0.58	2.46
LF	0.00	1.00	0.96	-1.67	-0.69	-0.24	0.53	8.58

Table 3. Hedge funds' Liquidity Provision and Funding Liquidity

The table reports OLS estimates of equation (2):

$$ES_{i,t+1} = a + b_1 FundLiq_t + b_2 HF_i + b_3 HF_i \times FundLiq_t + \delta' Z_{i,t} + \epsilon_{i,t+1}$$

$ES_{i,t+1}$ is institution i's value-weighted execution shortfall on day $t+1$. $FundLiq$ is a funding liquidity variable. The funding liquidity variables are defined as in Table 2. The dummy HF_i equals 1 if the institution is an hedge fund, and 0 otherwise. $Z_{i,t}$ denotes 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 on day t, and *Buy*$\times$*Lagged Return* is their interaction; *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 by hedge fund i on day $t+1$ 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. In column (6), we consider only mutual funds among the group of other institutions. In column (7), the dependent variable is the abnormal execution shortfall defined as the residual with respect to the average fund-level ES over the prior month. Below the coefficients, t-statistics based on clustered standard errors are reported in parentheses. The sample period is from January, 1999 to June, 2013. During this period, we observe on average (total distinct) 23 (96) hedge funds; on average (total distinct) 218 (727) other institutions, of which on average (total distinct) 163 (397) mutual funds.

						HF vs MF	Abn. ES	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FundLiq$:	R_M	VIX	TED	Repo	LF	LF	LF	LF
$FundLiq$	0.358	0.122	-0.628	-0.459	-0.175	0.120	0.178	-0.175
	(1.62)	(0.55)	(-2.82)	(-2.47)	(-0.77)	(0.48)	(0.80)	(-0.23)
HF	23.88	23.69	24.03	23.25	23.50	22.700	5.531	23.50
	(41.19)	(41.25)	(40.99)	(41.04)	(41.51)	(39.86)	(9.70)	(3.29)
$\boldsymbol{HF \times FundLiq}$	**-4.083**	**4.961**	**4.576**	**-3.800**	**7.388**	**7.135**	**2.858**	**7.388**
	(-5.58)	**(6.38)**	**(5.57)**	**(-5.94)**	**(9.46)**	**(9.15)**	**(3.77)**	**(3.04)**
Buy	-16.87	-16.90	-16.87	-16.87	-16.87	-16.478	-16.14	-16.87
	(-26.59)	(-26.63)	(-26.59)	(-26.59)	(-26.59)	(-21.84)	(-26.46)	(-10.62)
Lagged Return	-5.524	-5.512	-5.528	-5.531	-5.503	-5.708	-3.718	-5.503
	(-27.95)	(-28.09)	(-28.15)	(-28.15)	(-28.03)	(-23.92)	(-20.13)	(-22.51)
Buy$\times$Lagged Return	10.25	10.25	10.25	10.25	10.24	10.719	6.262	10.24
	(32.33)	(32.33)	(32.32)	(32.33)	(32.31)	(27.59)	(21.04)	(22.58)
NYSE	-24.78	-24.90	-24.80	-24.87	-24.89	-26.051	-7.412	-24.89
	(-36.48)	(-36.49)	(-36.53)	(-36.53)	(-36.48)	(-32.29)	(-11.19)	(-7.31)
Inverse Price	0.179	0.150	0.181	0.167	0.165	-0.050	0.579	0.165
	(2.04)	(1.69)	(2.06)	(1.91)	(1.87)	(-0.46)	(6.55)	(0.77)
Relative Volume	0.973	0.981	0.966	0.967	0.982	0.828	1.138	0.982
	(3.66)	(3.70)	(3.63)	(3.63)	(3.71)	(2.93)	(4.08)	(2.68)
Amihud	-1.319	-1.325	-1.321	-1.346	-1.343	-1.614	-0.484	-1.343
	(-2.00)	(-2.01)	(-2.00)	(-2.02)	(-2.02)	(-1.73)	(-0.94)	(-1.83)
Size	1.954	1.922	1.958	1.951	1.948	1.919	1.433	1.948
	(13.83)	(13.57)	(13.85)	(13.90)	(13.81)	(12.01)	(10.38)	(3.78)
Book/Market	-3.680	-3.639	-3.682	-3.624	-3.650	-3.866	-0.494	-3.650
	(-31.49)	(-30.48)	(-31.51)	(-30.86)	(-30.82)	(-28.37)	(-4.41)	(-7.30)
Obs.	875,424	875,424	875,424	875,424	875,424	677,428	858,323	875,424
R^2	0.017	0.017	0.017	0.017	0.017	0.019	0.005	0.017
Cluster	Time	Time	Time	Time	Time	Time	Time	Double

Table 4. Liquidity Provision and Trading Style

The rightmost columns in Panel A report the mean Execution Shortfall (ES), and the p-value for the null hypothesis of zero, separately across hedge funds classified in terciles of the trading style variable (TS), computed as in Anand, Irvine, Puckett, and Venkataraman (2013). We label hedge funds in the first tercile Liquidity Suppliers (LS) and those in the third tercile Liquidity Demanders (LD). The leftmost columns report the average trading style at the formation month, and in the following six months for the funds in these two groups.
Panel B and C report OLS estimates of the following model for the group of LD and LS, respectively:

$$ES_{i,t+1} = a + b_1 LF_t + b_2 HF_i + b_3 HF_i \times LF_t + \epsilon_{i,t+1}$$

where $ES_{i,t+1}$ is hedge fund i's value-weighted execution shortfall on day $t+1$, and LF is the combined funding liquidity factor defined in Table 2. Odd columns estimate the model only on the sample of hedge funds (so that a and b_1 are not estimated), while even columns estimate the model when pooling hedge fund and mutual fund data. In columns (3)-(4), the classification in LS/LD is performed pooling hedge funds and mutual funds together. In columns (5)-(6), the classification in LS/LD is based on a fund's trading style computed over the past six months, thereby capturing long-term liquidity provision. In columns (7)-(8), the dependent variable is the abnormal execution shortfall defined as the residual with respect to the average fund-level ES over the prior month. Below the coefficients, t-statistics based on clustered standard errors are reported in parentheses. The sample period is from January, 1999 to June, 2013. During this period, we observe on average (total distinct) 23 (96) hedge funds; on average (total distinct) 218 (727) other institutions, of which on average (total distinct) 163 (397) mutual funds.

Panel A: ES and Trading Style

	ES		Trading Style				
Type	mean	t-stat	Formation mo. M	M+1	M+2	M+3	M+6
LD	76.898	72.929	0.475	0.241	0.237	0.243	0.235
LS	-7.959	-7.135	-0.283	-0.017	-0.004	-0.020	-0.001

Panel B: Liquidity Demanders

	(1) ES HF	(2) ES HF vs MF	(3) ES, Joint class. HF	(4) ES, Joint class. HF vs MF	(5) ES, Long-term HF	(6) ES, Long-term HF vs MF	(7) Abn. ES HF	(8) Abn. ES HF vs MF
LF		10.525		10.844		12.236		3.326
		(8.20)		(8.32)		(8.70)		(5.57)
HF × LF	14.079	3.554	14.141	3.297	17.714	5.477	4.437	1.111
	(10.22)	(0.74)	(10.18)	(0.68)	(11.98)	(1.13)	(3.32)	(0.58)
HF	76.552	33.566	77.032	33.340	85.240	36.947	11.556	7.470
	(71.60)	(3.26)	(71.30)	(3.22)	(76.58)	(3.59)	(11.09)	(2.55)
Constant		42.985		43.692		48.294		4.086
		(11.15)		(11.00)		(12.88)		(3.69)
Obs.	28,239	204,960	27,745	196,326	25,823	199,722	27,935	203,357
R^2	0.006	0.010	0.006	0.011	0.009	0.014	0.001	0.001
Cluster	Time	Double	Time	Double	Time	Double	Time	Double

Panel C: Liquidity Suppliers

	(1) ES HF	(2) ES HF vs MF	(3) ES, Joint class. HF	(4) ES, Joint class. HF vs MF	(5) ES, Long-term HF	(6) ES, Long-term HF vs MF	(7) Abn. ES HF	(8) Abn. ES HF vs MF
LF		-8.745		-8.748		-10.347		-1.776
		(-7.09)		(-7.10)		(-8.09)		(-3.09)
HF × LF	2.514	11.259	3.273	12.021	3.884	14.231	3.160	4.936
	(1.87)	(3.53)	(1.99)	(3.22)	(2.54)	(4.16)	(2.46)	(3.39)
HF	-8.087	20.778	-15.294	13.641	-13.100	20.754	0.162	6.180
	(-7.67)	(2.78)	(-11.94)	(1.71)	(-11.98)	(2.72)	(0.16)	(2.78)
Constant		-28.865		-28.935		-33.855		-6.018
		(-10.55)		(-10.57)		(-12.32)		(-7.09)
Obs.	22,558	195,306	15,790	188,269	19,803	187,235	22,282	193,823
R^2	0.001	0.005	0.001	0.004	0.001	0.007	0.001	0.001
Cluster	Time	Double	Time	Double	Time	Double	Time	Double

Table 5. Liquidity Provision and Hedge Funds' Characteristics

The table reports OLS estimates of regressing the volume-weighted execution shortfall $ES_{i,t+1}$ on the LF combined funding liquidity factor, and its interaction with the following funds' cross-sectional characteristics: 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 ($Illiquid$); and minus the year-to-date performance (Bad). The model is estimated separately for hedge funds that are Liquidity Demanders (columns 1–5) and Suppliers (columns 6–10). Below the coefficients, t-statistics based on time-clustered standard errors are reported in parentheses. The sample period is from January, 1999 to June, 2013. During this period, we have on average (total distinct) 10 (58) hedge funds for which we have information both the dependent and independent variables.

	Liquidity Demanders					Liquidity Suppliers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage×LF	4.448				5.408	1.650				0.953
	(2.12)				(2.65)	(1.90)				(1.08)
Young×LF		0.057			2.056		1.732			1.199
		(0.04)			(1.33)		(1.03)			(0.67)
Illiquid×LF			3.234		4.726			1.227		3.309
			(1.40)		(2.07)			(0.53)		(1.39)
Bad×LF				8.919	10.592				5.142	6.035
				(4.15)	(4.75)				(2.74)	(3.15)
LF	18.824	17.173	17.576	15.399	16.869	-3.494	-4.464	-2.490	-6.112	-3.596
	(9.04)	(8.76)	(8.25)	(7.75)	(7.69)	(-1.46)	(-2.01)	(-1.00)	(-2.74)	(-1.39)
Constant	96.272	95.414	94.732	94.737	94.515	-10.431	-8.060	-9.342	-7.864	-10.279
	(59.93)	(65.33)	(57.93)	(63.90)	(56.40)	(-5.46)	(-4.61)	(-4.98)	(-4.50)	(-5.17)
Observations	12,498	14,766	12,344	14,737	12,147	8,860	9,925	8,753	9,859	8,473
R-squared	0.008	0.007	0.007	0.009	0.011	0.001	0.001	0.001	0.002	0.002

Table 6. Liquidity Provision and Financial Constraints

The table reports OLS estimates of equation (3):

$$ES_{i,t+1} = a_1 + a_2 Constrained_{i,t} + b_1 LF_t + b_2 Constrained_{i,t} \times LF_t + \delta' Z_{i,t} + \varepsilon_{i,t+1}$$

$ES_{i,t+1}$ is hedge fund i's value-weighted execution shortfall on day $t+1$; LF is the liquidity factor from Table 3; $Constrained$ is an index of hedge fund financial constraints, constructed as explained in Section 3.4, ranging from 0 (=Low) to 1 (=High); $Z_{i,t}$ are the controls for trade difficulty from Table 3. Results are shown for hedge funds separately classified as Liquidity Demanders (Panel A) or Liquidity Suppliers (Panel B) in the previous month based on the Trading Style measure of Anand, Irvine, Puckett, and Venkataraman (2013). In columns (3) and (7), the classification in LS/LD is based on a fund's trading style computed over the past six months, thereby capturing long-term liquidity provision. In columns (4) and (8), the $Constrained$ index is constructed using trade-level information from the Ancerno database as explained in Section 3.4. Below the coefficients, t-statistics based on time-clustered standard errors are reported in parentheses. The sample period is from January, 1999 to June, 2013. During this period, we have on average (total distinct) 10 (58) hedge funds for which we can obtain the Constrained classification, increasing to 23 (96) when we use the classification from Ancerno (columns 4 and 8).

	Panel A: Liquidity Demanders				Panel B: Liquidity Suppliers			
	(1) ES	(2) ES	(3) ES, Long-Term	(4) ES, Ancerno	(5) ES	(6) ES	(7) ES, Long-Term	(8) ES, Ancerno
Constrained×LF	92.044***	70.695***	63.063***	-67.664	53.283***	52.297***	65.123***	45.857**
	(4.60)	(3.56)	(2.64)	(-1.43)	(3.41)	(3.43)	(3.53)	(2.10)
Constrained	44.723***	43.258***	105.786***	-152.806***	50.950***	50.376***	46.082***	-167.230***
	(2.79)	(2.74)	(5.79)	(-4.41)	(3.74)	(3.67)	(3.13)	(-7.84)
LF	-17.505**	-11.205	-8.904	20.328***	-23.445***	-24.078***	-33.349***	-7.872*
	(-2.29)	(-1.48)	(-0.97)	(4.09)	(-3.61)	(-3.71)	(-4.39)	(-1.84)
Buy		-24.788***	-31.940***	-23.338***		-17.437***	-8.509	-17.110***
		(-4.03)	(-4.91)	(-6.52)		(-2.96)	(-1.36)	(-4.63)
Lagged Return		-4.833***	-4.632***	-5.485***		-7.904***	-3.898**	-7.336***
		(-3.95)	(-3.64)	(-6.37)		(-5.23)	(-2.30)	(-7.57)
Buy × Lagged Return		6.835***	6.883***	9.067***		15.511***	9.535***	13.386***
		(3.37)	(3.03)	(6.25)		(6.45)	(3.68)	(8.76)
NYSE		-84.659***	-67.753***	-54.024***		-23.035***	-16.019**	-7.424*
		(-13.77)	(-10.39)	(-13.66)		(-3.62)	(-2.35)	(-1.83)
Inverse Price		0.030	1.637**	1.202**		-0.341	0.345	0.474
		(0.04)	(2.12)	(2.18)		(-0.48)	(0.47)	(0.90)
Relative Volume		14.152*	37.005***	4.568		17.610	45.057***	4.740
		(1.82)	(2.79)	(1.26)		(1.25)	(5.21)	(1.16)
Amihud		-44.112***	-398.633***	-17.423*		2.831	0.400	8.777
		(-2.66)	(-3.61)	(-1.91)		(1.30)	(0.09)	(1.52)
Size		-1.675	-2.578*	-0.658		2.041	3.738***	1.867**
		(-1.31)	(-1.92)	(-0.78)		(1.51)	(2.61)	(2.16)
Book/Market		-0.708	-0.800	-2.592***		-3.526***	-3.167**	-2.711***
		(-0.58)	(-0.58)	(-3.38)		(-2.78)	(-2.29)	(-4.06)
Observations	12,147	12,147	11,462	27,709	8,473	8,473	6,982	21,766
R-squared	0.010	0.045	0.044	0.031	0.003	0.026	0.017	0.020

Table 7. Returns and Funding Liquidity, by Financial Constraints and Trading Style

We separately classify hedge funds as Liquidity Demanders (Panel A) or Liquidity Suppliers (Panel B) based on the Trading Style measure of Anand, Irvine, Puckett, and Venkataraman (2013), and in Constrained (resp. Unconstrained) if their $Constrained$ index from Table 6 falls above (below) the median. Each day, we form equally-weighted portfolios of the stocks that are traded by the hedge funds in each of these four groups. For these portfolios, we compute non-overlapping cumulative abnormal returns over different horizons (one week, two weeks, and one month). The table reports OLS estimates of equation (4):

$$r_{i,t+k} = a_1 + a_2 Constrained\,Pf_i + b_1 LF_t + b_2 Constrained\,Pf_i \times LF_t + u_{t+1}$$

where r is the portfolio abnormal return, $ConstrainedPf_i$ is 1 for the portfolio of constrained funds and 0 otherwise, and LF is the liquidity factor. The horizon k is either 5, 10, or 21. Each panel reports three specifications for all horizons, one where the cumulative abnormal returns are computed from both buy and sell trades, and the other two when buy and sell trades' cumulative returns are examined separately. Sell trades' returns are multiplied by minus one. Below the coefficients, t-statistics based on robust time-clustered standard errors are reported in parentheses. The sample period is from January, 1999 to June, 2013. During this period, we have on average (total distinct) 10 (58) hedge funds for which we can obtain the Constrained classification.

Panel A: Liquidity Demanders

	All trades			Buy trades			Sell trades		
	(1) 1-week	(2) 2-week	(3) 1-month	(4) 1-week	(5) 2-week	(6) 1-month	(7) 1-week	(8) 2-week	(9) 1-month
Constrained Pf ×LF	-0.005	-0.012	0.002	-0.005	-0.007	-0.008	-0.001	-0.006	0.012
	(-1.14)	(-1.24)	(0.14)	(-1.17)	(-0.89)	(-0.40)	(-0.29)	(-0.62)	(1.15)
Constrained Pf	-0.000	-0.008	-0.004	-0.002	-0.005	-0.002	0.002	-0.004	-0.003
	(-0.04)	(-1.09)	(-0.33)	(-0.71)	(-0.85)	(-0.15)	(0.70)	(-0.64)	(-0.35)
LF	0.006	0.010	-0.003	0.007	0.011	0.012	-0.001	-0.000	-0.017
	(1.93)	(1.63)	(-0.25)	(2.87)	(1.83)	(0.78)	(-0.21)	(-0.10)	(-2.07)
Constant	0.003	0.006	0.000	0.003	0.002	-0.005	-0.000	0.005	0.006
	(0.91)	(1.10)	(0.04)	(1.27)	(0.43)	(-0.55)	(-0.10)	(1.24)	(0.94)
Obs.	1,092	547	308	1,029	521	287	1,004	499	284
R-squared	0.004	0.007	0.001	0.009	0.012	0.007	0.001	0.006	0.020

Panel B: Liquidity Suppliers

	All trades			Buy trades			Sell trades		
	(1) 1-week	(2) 2-week	(3) 1-month	(4) 1-week	(5) 2-week	(6) 1-month	(7) 1-week	(8) 2-week	(9) 1-month
Constrained Pf ×LF	-0.016	-0.020	-0.015	-0.014	-0.006	0.017	-0.004	-0.018	-0.035
	(-2.75)	(-1.92)	(-0.76)	(-3.31)	(-0.74)	(0.72)	(-0.72)	(-2.01)	(-1.65)
Constrained Pf	-0.011	-0.015	-0.049	-0.008	-0.014	-0.045	-0.004	-0.004	-0.014
	(-2.26)	(-1.69)	(-3.08)	(-2.01)	(-2.03)	(-2.98)	(-1.00)	(-0.50)	(-1.15)
LF	0.012	0.018	0.027	0.013	0.011	0.008	0.001	0.010	0.023
	(3.17)	(3.38)	(2.33)	(3.92)	(2.31)	(0.90)	(0.15)	(2.41)	(2.14)
Constant	0.012	0.017	0.029	0.007	0.015	0.029	0.005	0.004	0.006
	(3.14)	(3.08)	(2.94)	(2.56)	(3.10)	(3.50)	(1.69)	(0.91)	(0.73)
Obs.	763	387	272	656	329	226	661	339	233
R-squared	0.023	0.032	0.051	0.040	0.029	0.043	0.003	0.019	0.038

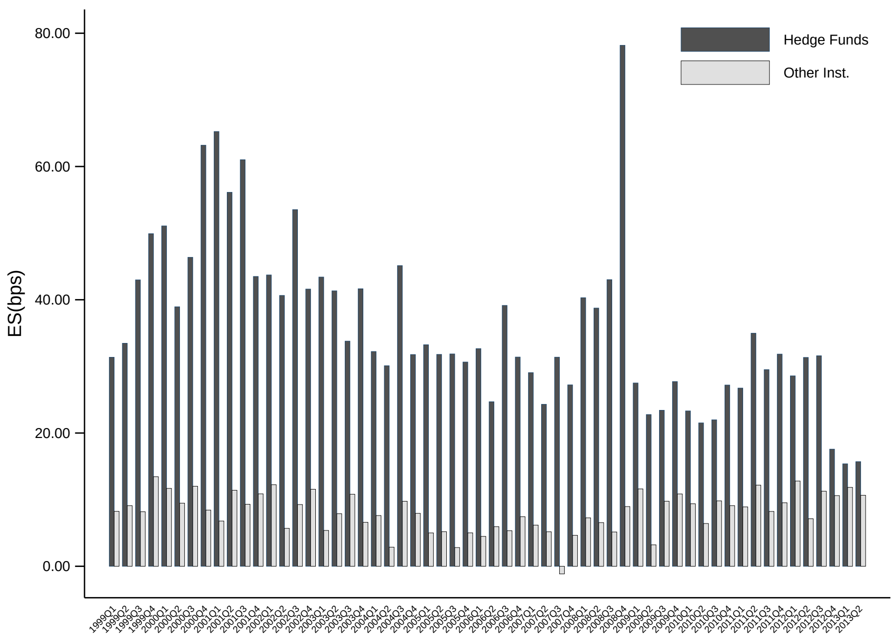
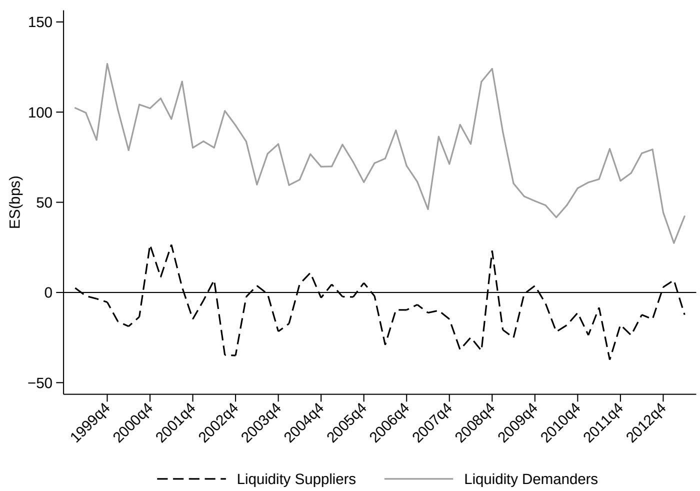


Figure 1. Execution Shortfall of Hedge Funds and Other Institutions. Quarterly averaged execution shortfall (in bps) for hedge funds and other institutional investors reporting to Ancerno. For each manager-day, we construct the execution shortfall as the dollar volume-weighted average of the relative difference between the execution price of each trade and the opening price. Then, we average the execution shortfall across days and managers in a quarter. The sample period is from January, 1999 to June, 2013.

Panel A: Hedge Funds



Panel B: Mutual Funds

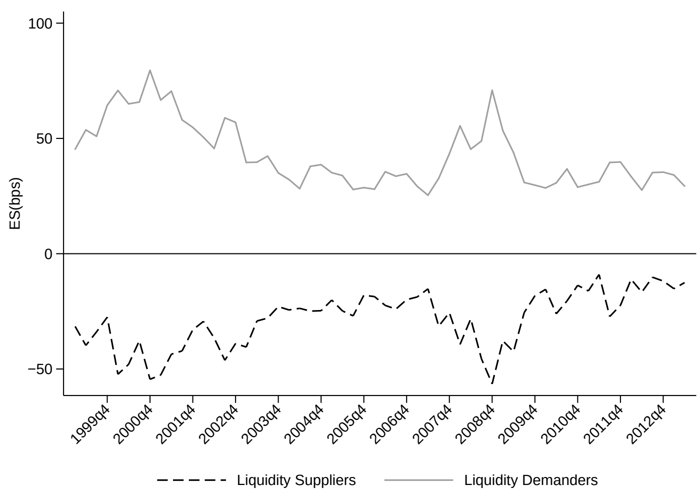


Figure 2. Execution Shortfall and Trading Style. Each month, we compute hedge funds' trading style (TS) as in Anand, Irvine, Puckett, and Venkataraman (2013). We label hedge funds in the first tercile Liquidity Suppliers (LS) and those in the third tercile Liquidity Demanders (LD). The figure shows the quarterly averaged execution shortfall (in bps) separately among LS and LD for hedge funds (Panel A) and mutual funds (Panel B) reporting in Ancerno. The sample period is from January, 1999 to June, 2013.

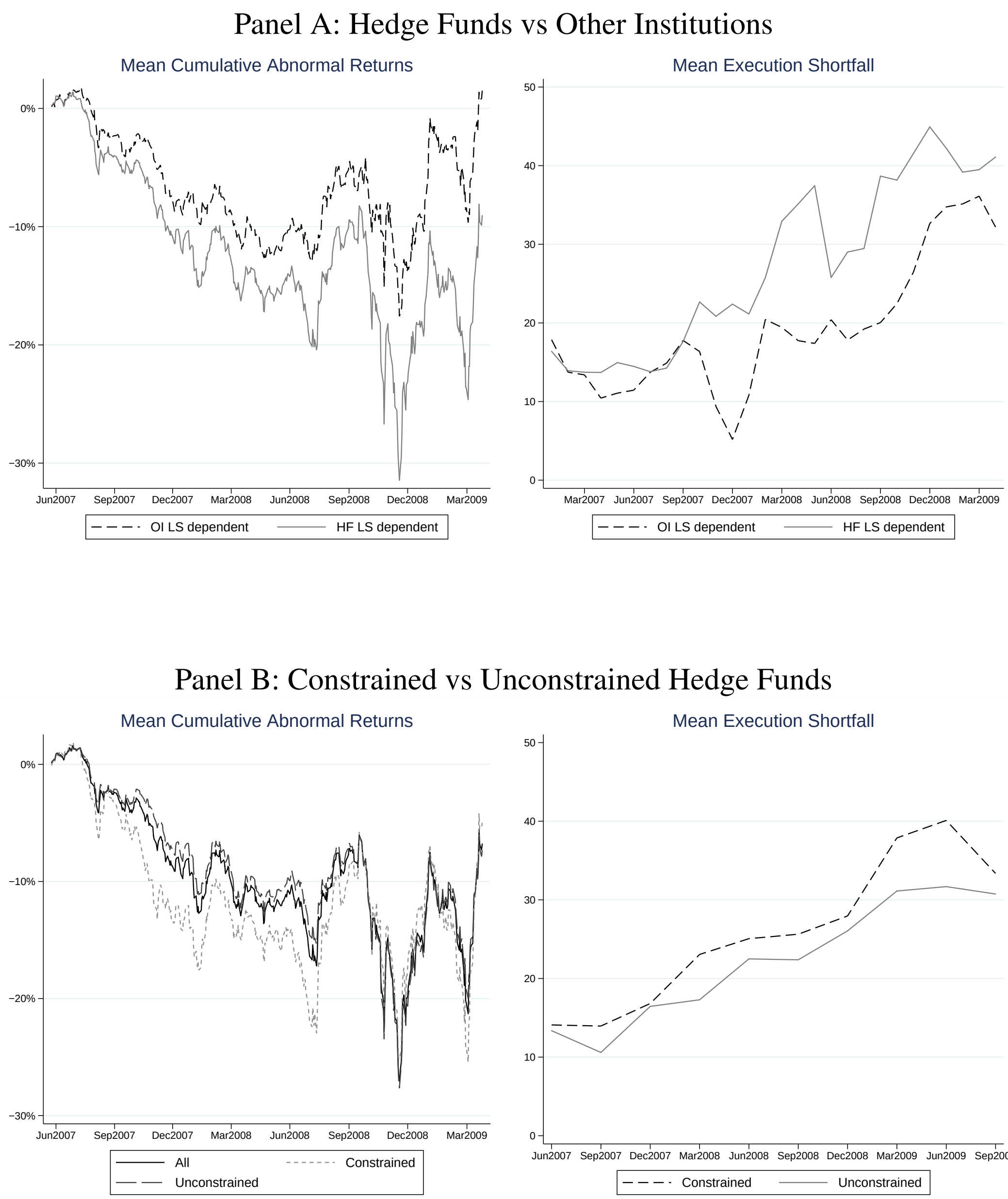


Figure 3. Stock Resiliency and Hedge Funds' Liquidity Provision. We compute the fraction of the volume traded by LS hedge funds over the total volume by all liquidity supplying institutions over June, 2006 to May, 2007 period. Next, we sort each stock based on this fraction into quintiles and focus on the top (HF LS dependent) and bottom (OI LS dependent) quintiles. Panel A reports the cumulative abnormal return (left panel) and execution shortfall (quarterly moving average, right panel) over the June, 2007 to March, 2009 crisis period for the two portfolios of stocks. In Panel B, we provide similar plots when breaking down the stocks that are HF LS dependent in two groups based on whether they are mostly traded by Constrained or Unconstrained hedge funds, defined as funds above (resp. below) the median $Constrained$ index from Table 6.