Flight-to-Liquidity in the Equity Markets during Periods of Financial Crisis

By

Azi Ben-Rephael*

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* Doctoral Program, The Leon Recanati Graduate School of Business Administration, Tel Aviv University azibenr@tau.ac.il

Abstract

In this paper, I examine flight-to-liquidity in the equity markets during 1986-2008, using ten periods of financial crisis defined by a positive jump in the VIX measure. I find that illiquid stocks experience a larger price decline, relative to liquid stocks, in the three months following the beginning of the crises; for example, the four-factor alpha return difference between illiquid and liquid stocks accumulates to -2% (-4%) for the NYSE (NASDAQ), over these months. Importantly, these differences revert during the subsequent three months, during which market liquidity improves. I find that mutual funds, as a group, reduce their holdings of illiquid stocks, while other institutional investors increase their holdings of illiquid stocks. This is a result of larger customer withdrawals from funds with less liquid stocks. Moreover, funds with less liquid stocks experience lower returns, which can explain mutual fund customer withdrawal decisions. Overall, the price differences followed by a reversal can be explained by changes in the pricing of liquidity; however, this mutual fund activity may suggest that these price changes are partially due to temporary price pressure.

1 Introduction

Liquidity is important for investors, and its importance increases during periods of financial crisis; when market uncertainty is high, investors' capital erodes and liquidity in the market "dries up."[1] Investors' need for liquidity is frequently mentioned in the financial press. For example, an article that was published in *The New York Times* amid the 2010 Euro sovereign debt crisis states:

"There is no sector that is being spared …You have heard the phrase 'flight to quality'? We are having a flight to liquidity. Everybody is trying to get liquid." [2]

Flight-to-liquidity (henceforth, "FTL") occurs when investors (or a sub-group of investors) want to reduce (reduce) their holdings of illiquid assets toward holding more liquid assets. This may results in a relative price decrease of illiquid assets vs. liquid assets. In this paper, I ask two main questions regarding FTL: (i) What is the return difference between illiquid and liquid stocks during periods of financial crisis, and is this return difference reversed following the crises? (ii) Can we identify a group of investors who reduce their illiquid stocks' positions during crises?

To address these research questions, I investigate 10 financial crisis events, defined by a positive jump in the VXO measure, which is available dating from 1986.[3,4] Focusing on common stocks, I find that illiquid stocks experience larger price declines, relative to liquid stocks, in the three months **following** the beginning of the crises. For example, the four-factor alpha return difference between illiquid and liquid stocks accumulates to -2% (-4%) for the NYSE

[1] *Liquidity* is hard to define and has various different meanings. The meaning of liquidity, as it used in this paper, is best described by Harris (2003): "Liquidity is the ability to trade large size quickly, at low cost, when you want to trade".

[2] "Stocks Fall Amid Concerns About Europe", by Graham Bowley and Christine Hauser, The New York Times, May 20, 2010.

[3] The VXO is the implied volatility on the S&P100, and is highly correlated with the VIX, which is the implied volatility on the S&P500. Similar to Ang, Hodrick, Xing and Zhang (2006), I use the VXO instead of the VIX, due to its availability from 1986 (as opposed to the VIX which is only available from 1991). Similar to AHXZ, I also refer to the VXO measure as "VIX."

[4] Justification for the use of market volatility can be found in Vayanos (2004) and Brunnermeier and Pedersen's (2008) theoretical models. Both models include aspects of FTL in their results. In both models, periods of financial crisis or financial stress, which are the key driver of their models' results, are defined by an increase in market volatility.

(NASDAQ), over these months.[5] Importantly, these price differences are only temporary and revert back over the **subsequent** three months. Next, I find that mutual funds, as a group, reduce their holdings of illiquid stocks, while other institutional investors increase their holdings of illiquid stocks. This is a result of larger customer withdrawals from funds with less liquid stocks. Moreover, funds with less liquid stocks experience lower returns, which can explain mutual fund customer withdrawal decisions. Overall, the price differences followed by a reversal can be explained by changes in the pricing of liquidity; however, this mutual fund activity may suggest that these price changes are partially due to temporary price pressure.[6]

Throughout the paper's analysis, I use the sample of common stocks traded on the NYSE and NASDAQ, and two illiquidity measures. The first is Amihud's (2002) illiquidity measure (henceforth, "Amihud"), which is a measure of the daily price impact caused by trade. The second is Hasbrouck's (2009) measure for the bid-ask spread, which is a Bayesian estimation of Roll's (1984) measure (henceforth, "HR"). Both measures capture different aspects of liquidity. Similar to Hasbrouck (2009), I separate the analysis between the NYSE and the NASDAQ. This allows me to account for different institutional details associated with the measurement of volume, and the different attributes of these exchanges.[7] AMEX is excluded because the number of common stocks is very small, starting from the mid 90's.

I start with the analysis of the price patterns using liquidity-based trading strategies, which are long in the liquid stocks and short in the illiquid stocks. To prevent a possible hindsight problem (i.e. the use of information that is known only after the event occurs), the estimation starts from the month **subsequent** to the month of the defined event. I control for risk

[5] Amihud (2002) finds that contemporaneous innovations in market liquidity affect small (and accordingly illiquid) stocks more negatively than larger stocks. Amihud relates these price differences to FTL. In a non-reported result, I find a negative price difference in the month of the event.
[6] The change in the pricing can stem solely from a change in preferences, without any specific change in illiquid stock positions. In this case, a few trades are needed to incorporate investors' preferences into the prices. Thus, the trades only reflect the information and do not affect the prices directly. See a detailed discussion regarding the changes in pricing of liquidity and temporary price pressure in Section 7.
[7] In their summary statistics, Ben-Rephael, Kadan and Wohl (2010) show that the NASDAQ illiquidity average is more than 10 times higher than that of the NYSE. Thus, the NASDAQ is much less liquid than the NYSE.

by out-of-sample alpha returns.[8,9] Additionally, to control for size, I also analyze strategies that are pre-sorted by size into three long-short liquidity strategies, one for each size group.

Consistent with FTL, the results indicate that illiquid stocks experience larger price declines, relative to liquid stocks. For example, the long-short trading strategy based on the HR measure yields an accumulated four-factor alpha of -5% (-10%) for the NYSE (NASDAQ), over the three months following the beginning of the crises. Similarly, the average of the strategies that are pre-sorted by size yields an accumulated four-factor alpha of -2% (-4%) over the same period.

Importantly, these negative alphas revert in the **subsequent** three months, when market liquidity improves. Furthermore, the results are stronger for the NASDAQ, which seems natural, due to the fact that the NASDAQ is less liquid than the NYSE. Consistent with this point, the results are also stronger for the smallest size group. Specifically, the results hold for all NASDAQ size groups, but in contrast hold only for the smallest size on the NYSE.[10]

To sum up, the answer to the first question is: Yes, illiquid stocks decline more following financial crises. However, this effect is reversed within six months after the beginning of the crises.

Before turning to explore the change in illiquid stock positions, I analyze the cross-section of the changes in the stocks' turnover, which can indicate whether illiquid stocks experience excessive trade, relative to their liquid counterparts. Controlling for risk and other explanatory variables, I find that the changes in turnover are larger for illiquid stocks. This may suggest a position change between groups of investors.

A natural group of investors, which may have an incentive to trade illiquid stocks, are mutual-fund managers who can experience large outflows from their funds during these periods

[8] The control for risk is needed to separate a possible effect of flight-to-quality (FTQ), which is the tendency to decrease the relative demand for risky assets. For example, in the 1998 Russian debt crisis, there were both FTL and FTQ episodes. Investors preferred less risky and more liquid assets.

[9] The out-of-sample alpha returns are calculated as in Brennan, Chordia, and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001).

[10] These results are consistent with Ben-Rephael, Kadan and Wohl's (2010) liquidity-based trading strategies, which find stronger pricing in the smaller size group.

(see the theoretical model by Vayanos (2004)).[11] Moreover, other institutional investors with a longer investment horizon, such as insurance companies, can step in and take the other side of the trades. Exploring this conjecture, I calculate for each stock the change in the aggregate holdings for two groups of investors: mutual funds (henceforth, "MF"), and other institutional investors (henceforth, "OINST"). Controlling for risk and other explanatory variables, the cross-sectional regressions indicate that the coefficients of the liquidity measures are negative and significant for MF, and positive and significant for OINST. This means that, on aggregate, mutual funds reduce their holdings of illiquid stocks, while other institutional investors increase their holdings of illiquid stocks. For example, on the NASDAQ a one standard deviation change in the liquidity measures reduces the share holdings of illiquid stocks by 0.4%-0.5% from the outstanding shares. To assess the magnitude of this number, the monthly turnover of the most illiquid quintile on the NASDAQ (based on Amihud's illiquidity measure) during the crises is around 3%. Thus, the change in shares can reach around 15% of the monthly turnover of these stocks.[12]

Realizing that mutual funds reduce their holdings of illiquid stocks, it is important to understand the drivers behind this result. Specifically, is it a result of a strategic decision made by the fund managers, or a result of some other reason? In order to explore whether the aggregate outcome is a result of strategic decisions on the part of fund managers, I analyze the actual trading activity of each fund manager's portfolio, using fund level cross-sectional regressions. I define a measure for the trading activity for each stock that is bought or sold in the fund portfolio during the quarters of events. Then, for each fund I run a cross-sectional regression with the trading measure on the left hand side, and the set of explanatory variables - including the liquidity variables of interest - on the right hand side. Although the average of this distribution is negative, it is only marginally significant and, more importantly, the economic magnitude is negligible.

[11] Vayanos (2004) models the behavior of fund managers who face customer withdrawals. In Vayanos's model, during times of high volatility the probability of customer withdrawal is higher. Due to stock-specific transaction costs, withdrawals are costly to the fund manager. Thus, when volatility increases, the frequency of withdrawals also increases, and fund managers are less willing to hold illiquid stocks.

[12] Moreover, Coval and Stafford (2007) find that mutual fund trades with a magnitude of 2% of stock average volume can have a large effect on the stock's price.

If the fund manager's trading decision does not seem to drive the results, the result might be driven by an explanatory variable at the fund level. Consistent with this conjecture, a panel regression of the stock trading activity measure - on both the stock level and the fund level's explanatory variables - indicates that the stock liquidity explanatory variables are not significant; in addition, the fund's quarterly flow explanatory variable is positive, highly significant, and seems to be the main driver behind the panel results. For example, a negative one standard deviation change in the fund's quarterly flow reduces the share holdings from the outstanding shares roughly by 0.6%.

Finally, to relate the fund outflows to funds with less liquid stocks, and to better understand mutual fund customer withdrawal decisions, I analyze cross-sectional regressions of fund outflows and the fund returns. The results indeed indicate that funds with less liquid stocks face higher withdrawals: for example, a one standard deviation change in the HR measure affects the flows by – 1.00% over the event period. Furthermore, funds with less liquid stocks also have lower returns: a one standard deviation change in the HR measure affects the return (alpha return) by -3.00% (-1.40%) over the event period. Thus, if investors are affected by fund performance, these results can explain the investors' withdrawal decisions.

To summarize, the answer to the second question is: While mutual funds, as a group, decrease their positions of illiquid stocks during financial crises, other institutions increase their positions. The mutual funds position change is explained by investor withdrawals from funds with more illiquid stocks, rather than fund managers' strategic activities. The results also indicate that fund performance can explain these mutual fund customer withdrawal decisions.

This paper provides some robustness and extensions: (i) The adding of the market volatility risk factor, which has both empirical and theoretical justification.[13] The factor is estimated as in Ang, Hodrick, Xing and Zhang (2006). (ii) Analyzing trading strategies which are based on systematic liquidity measures, instead of characteristic liquidity measures in the spirit of Pastor and Stambaugh (2003). The robustness and extensions yield consistent results with the main results presented in the paper. See Appendix C.

[13] The theoretical justification can be found inVayanos (2004), who proposes a capital asset pricing model, which includes both the market portfolio factor and the market volatility factor. The empirical justification is found in Ang, Hodrick, Xing and Zhang (2006).

Overall, I reach two main conclusions in this paper: (i) The price differences between illiquid and liquid stocks are temporary, and basically revert within six months from the beginning of the crises. (ii) These price differences can be explained by changes in the pricing of liquidity; however, mutual fund customer withdrawals may suggest that these price changes are partially due to temporary price pressure.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data, event definition and main liquidity variables. Section 4 analyzes the change in stock prices and presents results from the liquidity-based trading strategies. Sections 5 and 6 analyze the change in shares; Section 5 presents results from the change in aggregate share holdings, and Section 6 presents results regarding fund managers' trading activities. Section 7 discusses possible explanations for these price patterns, and Section 8 concludes the paper.

2 Related Literature

This paper contributes to three lines of literature: First, this paper contributes to the growing literature regarding periods of financial crisis. Kasch, Ranger and Weigand (2010) find that a stock's volatility, turnover, and market beta are important determinants of the stock returns in periods of both crashes and recovery. The current paper adds the stock liquidity dimension during periods of crashes and recoveries. Ben-David, Franzoni and Moussawi (2010) explore hedge fund trading patterns in the stock market during liquidity crises, and find that hedge funds, as a group, reduce their equity holdings in the market and, in turn, consume liquidity. My paper adds to their results by finding that mutual funds, as a group, reduce their holdings of illiquid stocks, while other institutional investors seem to provide liquidity, and increase their holdings of illiquid stocks. Regarding the aspect of trading decisions by portfolio managers during periods of crisis, the evidence is mixed. Anand, Irvine, Puckett and Venkataraman (2010) study a unique data set of institutional trading during the period of 2007-2008 and find that institutions tilt their selling activity toward liquid stocks. Huang (2010) studies the relationship between expected market volatility and the demand for liquidity by fund managers during the period of 1999-2008. Huang finds an increase in the percentage of liquid stocks from the total portfolio market-cap, when the market is expected to be more volatile, and interprets the results as being a strategic decision made by the fund manager. The present paper adds to this mixed evidence by providing evidence that mutual fund managers reduce their holdings as a result of withdrawals by their customers.[14] Finally, Hameed, Kang and Viswanathan (2010) show that stock liquidity decreases during market declines. This paper expands their results by showing that the market becomes illiquid during these crisis events. Importantly, this paper shows that the market's illiquidity continues to deteriorate after the event occurs, and takes up to six months to revert back to pre-crisis liquidity levels.

Second, the present paper presents additional evidence to the literature regarding the effect of flows on stock prices. Ben-Rephael, Kandel and Wohl (2010) find that monthly shifts between bond funds and equity funds are positively correlated with market returns, and most of the contemporaneous relation is reversed within four months. They relate these findings to "noise" in aggregate market prices induced by investor sentiment. Moreover, the effect is stronger for smaller (which are also illiquid) stocks. Wermers (2003) finds evidence that flow-related buying, especially among growth-oriented funds, pushes stock prices. Coval and Stafford (2007) find evidence of price pressure in securities held in common by distressed funds when managers are forced to trade by flows. Regarding flow magnitude, Coval and Stafford find that a 2% average volume can have a significant effect on stock prices. A recent working paper by Cella, Ellul and Giannetti (2010) finds that after negative shocks investors with a short trading horizon sell their holdings to a larger extent than those with a longer trading horizon. As a result, stocks that are held by short-term institutional investors experience more severe price drops and larger price reversals. My paper contributes to the existing literature by adding another perspective - the effect of flow-motivated trades on liquid vs. illiquid stocks prices.[15]

Finally, the paper contributes to the literature regarding liquidity pricing. Amihud's (2002) paper is closely related to the current paper. Amihud finds that, during the period of 1964-

[14]The difference between Huang's (2010) interpretation and the interpretation presented in this paper can result from the following reasons: (i) I use specific crisis periods (ii) I use the actual share trades of the fund managers, instead of stock prices.

[15]Moreover, as regards the effect of flow-motivated trade, Frazzini and Lamont (2008) find that, on average, retail investors direct their money to funds which invest in stocks that have low future returns, and these reallocations generally reduce their wealth. In other words, an external customer's decisions affect the fund's aggregate performance. Similar evidence is presented by Friesen and Sapp (2007), who find that, at the individual fund level, the dollar-weighted average return is lower than the geometric average return. In sum, the above studies show that induced trade affects market prices and the fund manager's decisions.

1997, contemporaneous innovations in market liquidity affect small (and accordingly illiquid) stocks more negatively than larger stocks. Amihud relates these price differences to FTL. This paper expands Amihud's results by: (i) using specific crisis periods and (ii) documenting the complete evolvement of the price patterns during these crisis periods. Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Korajczyk and Sadka (2008), among others, provide evidence for the pricing of liquidity as systematic liquidity, which is considered a compensation for poor states of the economy.[16] Moreover, recent papers, such as those of Watanabe and Watanabe (2008) and Acharya, Amihud and Bharath (2010) go one step further and investigate the conditional pricing of liquidity using regime-switch models. Watanabe and Watanabe (2008) find that the liquidity premia is earned during the short-lived "abnormal" state, defined by high liquidity-beta, heavy trade, and high volatility. The paper contributes to these papers by adding evidence regarding the pricing of liquidity during specific periods of financial crisis.

3 Sample, Event Definition and Liquidity Variables

3.1 Sample and Data

The sample used in this paper consists of all common stocks traded on the NYSE and NASDAQ, obtained from the CRSP between January 1986 and December 2008 with share codes 10 or 11 (common shares).[17] Similar to Hasbrouck (2009), I separate the analysis between the NYSE and NASDAQ. This allows me to account for different institutional details associated with the measurement of volume, and the different attributes of these exchanges. The AMEX is excluded because the number of common stocks is very small, starting from the mid 90's. Moreover, to prevent "noise" caused by new stocks entering the sample, the sample is rebalanced on an annual basis.

[16] Studies from the bond market also find evidence consistent with FTL. For example, Krishnamurthy (2002) compares the yields on "on-the-run" and "off-the-run" treasury bonds. Longstaff (2004) examines whether there is a flight-to-liquidity premium in U.S. Treasury bond prices. Beber, Brandt, and Kavajecz (2008) take advantage of the fact that credit risk changes are not correlated with liquidity demands in the Euro-area market.

[17] The sample starts from 1986, since the VXO is only available from 1986. Moreover the NASDAQ trade volume data, which is needed for the calculation of the liquidity measures, is only available from 1983.

In this paper, I analyze the change in stock returns, change in stock share holdings, and each fund manager's trading activity. Stock returns and most of the explanatory variables are derived from the CRSP and COMPUSTAT and their calculation is straightforward. The data regarding the analysis of the change in share holdings is derived from two data sources obtained from Thompson CDA/Spectrum. The first data set is comprised of all institutional share holdings (S34 or 13F). The primary source of the institutional holdings data is the 13F form that investment companies and professional money managers are required to file with the SEC on a quarterly basis. A 1978 amendment to the Securities and Exchange Act of 1934 requires institutions with more than $100 million of securities under management to report all equity positions that are greater than 10,000 shares or $200,000 in value. The second data set is comprised of mutual fund share holding (S12). The primary source for the mutual fund holdings data is SEC N-30D filings. Finally, the data for the fund level activity is derived from the merged CRSP's Survivor-Bias Free Mutual Fund Database and Thomson Reuters CDA/Spectrum Mutual Fund Holdings Database (S12), merged by WRDS's "MFlink" based on Wermers (2000) methodology.[18] The Survivor-Bias Free Mutual Fund Database enables me to use important information at the fund level, such as total fund net assets (*TNA*), and fund returns.

3.2 Definition of Financial Crisis Events

The paper analyzes periods of financial crisis, (henceforth, "financial crises" or "events") and performs a statistical analysis on all of the events together. To focus on the major events on one hand, and to enable statistical power on the other hand, I use 10 events. The events are defined by the changes in market volatility. The use of market volatility as an event definer is natural and gains support from theoretical models, such as those of Vayanos (2004) and Brunnermeier and Pedersen (2009), who use market volatility as their models' driver. As in Ang, Hodrick, Xing and Zhang (2006) (henceforth, "AHXZ"), I use the VXO measure, which is the implied volatility of the S&P100. This measure is closely related to the VIX, and enables me to start the analysis from 1986 instead of 1991. This measure has the beneficial property of being

[18] Here is the quote from the WRDS files: "The MFLINKS tables provide a reliable means to join CRSP Mutual Fund (MFDB) data that covers mutual fund performance, expenses, and related information to equity holdings data in the TFN/CDA S12 datasets." Further information is available at: http://wrds-web.wharton.upenn.edu/wrds/ds/mfl/index.cfm.

forward looking; it is the expected volatility for the next month set by the option traders. To answer the research questions regarding FTL, I want to choose the significant crisis periods. To do this, I look at the 10 most significant jumps in the VXO measure, where the VXO jump is measured by the difference between the VXO levels at the end of the current month and the previous month.[19] Appendix A presents the list of events ordered by date, with information regarding the VXO jump, VXO level, and the market return during the month of the jump. As can be seen, 8 of the events coincide with large negative shocks to the market return, which is estimated by the CRSP value weighted index. Graph A of Figure 1 plots the VXO levels over the sample period with a solid line at the level of 30. Similarly, Graph B plots the market return, estimated by the CRSP value weighted index, with a solid line at the level of -9%. Importantly, the event criteria capture most of the known crises starting from the 80's. Several examples include the 1987 market crash, the invasion to Kuwait in 1990, the 1997 Asian crisis, the Russian debt crisis in 1998, and naturally the sub-price crisis which began in 2007 with the "hedge-funds meltdown" and reached its full magnitude in September 2008 with the Lehman Brothers' bankruptcy.[20]

3.3 Liquidity Measures

This paper explores the channels behind flight-to-liquidity. Thus, liquidity is the main variable of interest is this paper. *Liquidity* has many facets as is evident in the following definition: "Liquidity is the ability to trade large size quickly, at low cost, when you want to trade" (Harris (2003), p.394). In order to capture the different aspects of liquidity, I use two characteristic liquidity measures.[21] The first is a modified version of the measure presented in Amihud (2002). This is a measure of illiquidity in the spirit of Kyle's (1985) lambda, calculated based on the average of daily absolute price changes, adjusted for dollar volume and inflation. For the sake of accuracy, I calculate the measure for each month, based on three months of daily

[19] The number 10 seems to be a good cutoff point for choosing the most significant events during this period; to select the last two events (descending order) additional information regarding the VXO level was needed.

[20] See Khandani and Lo's series of working papers regarding the hedge-fund meltdown and institutional trading in the summer of 2007.

[21] In Appendix C (Robustness and Extensions), I also analyze two systematic liquidity measures. The use of a characteristic liquidity measure is generally accepted, and is supported by theoretical models, such as those of Vayanos (2004) and Brunnermeier and Pedersen (2009) who use characteristic liquidity in their models.

data which ends at month *m*.[22] Hasbrouck (2009), and Goyenko, Holden, and Trzcinka (2009) find, using intraday data, that Amihud's measure is a good proxy for price impact. Formally, Amihud's measure for stock *i*, at the end of each month *m*, based on three months of data is denoted by $\text{Amihud}_{\text{i,m}}$ and is given by:

$$Amihud_{i,m} = \frac{1}{D_{i,m}} \sum_{d=1}^{D_{i,m}} \frac{|R_{i,d,m}|}{DVOL_{i,d,m} \cdot \inf_{d,m}} \tag{1}$$

where $D_{i,m}$ is the number of days for which data are available for stock *i* in month *m,* based on the last three months of data, *DVOl* is the dollar volume (in millions), and *inf* is an adjustment factor for inflation (end-of-2008 prices), which allows Amihud's measure to have the same real economic meaning over the sample period.

The second measure is Hasbrouck's (2009) measure for the effective half bid-ask spread, which is a Bayesian estimation of Roll's (1984) measure. The measure is estimated via the Gibbs estimator using Hasbrouck's (2009) programs. Similar to Amihud's measure, I use Hasbrouck's programs to estimate this measure for each month, based on the last three months. To avoid outliers, for each month of estimation, both measures are winzorised at the upper and lower 1% of their distribution.

To ensure the reliability of the estimates, the liquidity measures are calculated only for stocks that satisfy the following two requirements at the end of each previous year: (i) the stock must have return data for at least 60 trading days during the year; and (ii) the stock must be listed at the end of the year and have a year-end price that is higher than $2.[23]

To get a notion about the market liquidity conditions during these events, Figure 2 plots the monthly averages of the market end of day bid-ask quotes, obtained from the CRSP. The market end of day quotes are the cross-sectional average across the eligible sample of stocks. As can be seen from the presented graphs, the market becomes illiquid during these events. Importantly, the illiquidity of the market continues to deteriorate after the event occurs, and takes around two- to three months to begin to revert back to the pre-event liquidity levels. This is

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[22] Days with zero volume are not included in the calculation of Amihud's measure, while days with zero returns associated with a non-zero volume are included.

[23] These filters are also used in Ben-Rephael, Kadan and Wohl (2010). Other papers, for example, that use this kind of filter are Amihud (2002), Acharya and Pedersen (2005), and Kamara, Liu, and Sadka (2008).

consistent with Hameed, Kang and Viswanathan (2010) who show that stock liquidity decreases during market declines. Additionally, the market liquidity conditions seem to recover and revert back to the pre-event levels roughly after six month from the beginning of the event. Graph B of Figure 2 also demonstrates the liquidity differences between the NYSE and NASDAQ.

More formally, Table 1 provides statistical inputs regarding the market changes in both liquidity and volatility. Similar to Figure 2, the market liquidity measure is the cross-sectional average of the individual stock's liquidity measure. Because the average across the entire sample is taken, and the recent monthly information is needed for calculating the liquidity changes, I use Amihud and HR's measures, estimated based on the days in the last available month (instead of three months). The table confirms what is plotted in Figure 2. Consider, for example, the change in Amihud's measure. For both the NYSE and the NASDAQ, we see a significant change for the event month and the subsequent months, relative to the pre-event (month m-1) liquidity conditions. Contrary to market liquidity, in Panel B of Table 1, market volatility seems to revert faster. Looking at the changes between the subsequent months, we can immediately observe a partial decrease in Month 1.

4 Analysis of Price Changes during the Events

I start the analysis by exploring the expected price pattern of the illiquid stocks around periods of financial crisis. I am specifically interested in exploring the following questions: (i) Do illiquid stocks experience larger price drops, relative to liquid stocks during times of financial crisis? (ii) Do the price differences evolve quickly or gradually? (iii) Are these price differences permanent or can we document a reversal after the market conditions improve?

To test these questions, I employ liquidity-based trading strategies. The reason for this is simple: if illiquid stock prices drop more, relative to liquid stocks, we should expect that a strategy, which hold in a long position a portfolio of illiquid stocks and in a short position a portfolio of liquid stocks, to have a negative outcome. Most importantly, to prevent a possible hindsight problem - which uses information that is unknown to the investors, instead of estimating the strategies starting from the month of the event (denoted as month 0) - the estimation starts from the month following the event month.

I start with “simple” monthly liquidity-based trading strategies, which are long in the most illiquid decile and short in the most liquid decile. This allows me to analyze different sub-periods during the crisis periods. Then, in order to observe the evolvement of the price pattern over time, I estimate accumulated daily return strategies. Moreover, in the cumulative strategies, I also pre-sort by size. This allows me to explore the long-short strategy in each size group, and the average price across size groups. This can reveal the different price patterns among size groups, which can be masked by using the “simple” liquidity-based strategies.

4.1 Monthly Liquidity-based Strategies

As seen in Graph A of Figure 2, the effect of the crises in not confined only to the event month. Moreover, the market liquidity seems to revert to the pre-event conditions after roughly 6 months. Therefore, I estimate the trading strategies for each event, over the subsequent six months (month 1 up to month 6). Specifically, for each month, I sort the eligible stocks in the sample into ten liquidity deciles, based on the pre-event illiquidity measure (month m-1). Then, I construct a portfolio that is long in the top decile, which consists of the most illiquid stocks, and short in the bottom decile, which consists of the most liquid stocks. The top decile portfolio assigns equal weight to the most illiquid stocks; the bottom decile portfolio assigns equal weight to the most liquid stocks. The portfolios are not rebalanced during the event. To control for risk, I use alpha returns instead of raw returns. The alpha returns for each portfolio are calculated as in Brennan, Chordia, and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001). In particular, for each portfolio, I estimate the Fama-French-Carhart four-factor loadings, in a regression of the portfolio’s monthly excess returns (return net of a 30-day risk-free rate) on the MktRf, SMB, HML and UMD factors. The regressions are estimated based on the previous 60 months (m-60 up to m-1). In order to get meaningful loadings, I require the stock to have at least 36 months. Using the estimation of the loading, the out-of-sample alpha of portfolio p is given by,

$$\begin{aligned} AlphaRet_{p,j,m} = & \left(RET_{p,j,m} - Rf_{j,m}\right) - \widehat{\beta}_{MktRf,p,j} MktRf_{j,m} - \widehat{\beta}_{SMB,p,j} SMB_{j,m} \\ & - \widehat{\beta}_{HML,p,j} HML_{j,m} - \widehat{\beta}_{UMD,p,j} UMD_{j,m} \end{aligned} \quad (2)$$

where p is the subject portfolio, j is the event, m is the month in event j. The factor loadings (denoted by hats) are the pre-event estimated loadings, and the factors (MktRf, SMB, HML, and UMD) are the actual monthly realization of the Fama-French-Carhart portfolios for each event j and month m.

Table 2 presents the result of the trading strategies over the six subsequent months, for Amihud and HR measures. I consider two equal sub-periods: Period1, which is the first three months after the event month and Period2, which is the subsequent three months after Period1. The table presents the average of these trading strategies from all the events, and the *t*-Statistics are based on the average's standard errors.[24] First, let us consider the results for the NYSE. The averages of Period1 are negative, as expected with a monthly significant return of -1.66% (-1.74%) for Amihud's (HR) measure, which roughly accumulates over the period to -5%. Furthermore, these price differences seem to revert during Period2 with a positive and significant return of 0.72% (1.85%) for Amihud (HR). The NASDAQ presents a similar pattern, although the magnitude is larger. The accumulated monthly return over Period1 is roughly around -10%, which seems natural, due to the fact that the NASDAQ is less liquid than the NYSE.

4.2 *Cumulative Liquidity-based Trading Strategies*

Next, I estimate the accumulated daily returns over the 100 days after the event. Specifically, for each event, I first sort the eligible stocks in the sample into three size groups, based on the pre-event size (market-cap at the end of month m-1), where sizes 1 to 3 refer to the smallest-to-largest size groups. Similar to the approach in the previous sub-section, within each size group, I sort the stocks into five liquidity quintiles, based on the pre-event illiquidity measures (month m-1). Then, for each size group, I form long-short liquidity-based trading portfolios. The portfolios are long in the top quintile, which consists of the most illiquid stocks and short in the bottom quintile, which consists of the most liquid stocks. The top quintile portfolio assigns equal weight to the most illiquid stocks; the bottom quintile portfolio assigns equal weight to the most liquid stocks. The portfolios are not rebalanced during the event.

[24] The *t*-Statistic is calculated as in Fama-MacBeth, using the standard errors of the series average. I also considered an event clustered standard errors, and the results are qualitatively similar.

Furthermore, to incorporate the information from all size terciles, I form a portfolio which assigns equal weight to all three size portfolios. I refer to this portfolio as "Full information portfolio" or "Full." The portfolio's alpha returns are calculated as in the previous sub-section. Specifically, I apply Eq.2's methodology to the accumulated daily return over the 100 days from the event. For example, the accumulated alpha return of portfolio *p* from day 1 up to day D is given by,

$$\begin{aligned} AlphaRet_{p,j,[1,D]} &= \left(RET_{p,j,[1,D]} - Rf_{j,[1,D]}\right) - \widehat{\beta}_{MktRf,p,j} MktRf_{j,[1,D]} - \widehat{\beta}_{SMB,p,j} SMB_{j,[1,D]} \\ &\quad - \widehat{\beta}_{HML,p,j} HML_{j,[1,D]} - \widehat{\beta}_{UMD,p,j} UMD_{j,[1,D]} \end{aligned} \tag{3}$$

where, [1,D] stands for the accumulated daily period from day 1 to D.

Figures 3 and 4 present the results for the NYSE and NASDAQ, respectively.[25] For each exchange, I present the results of the full information portfolios (denoted as Full) and their three portfolios (denoted as Size1-Size3). Importantly, for each day of the 100 accumulated days, I calculate the average across all events. The significance level is calculated based on the standard errors of these averages. Similarly, for each day, I also calculate Bootstrap standard errors, based on draws from the coefficient set. For brevity's sake, I present only the results for HR's measure, where the results for Amihud's measure are qualitatively similar. Starting with the NYSE's "Full" portfolio, Graph A presents a negative pattern, indicating that the price of the illiquid stocks dropped more, relative to the liquid stocks. The pattern across the 100 days indicates that the pick is around day 50 with a negative return of -1.5%, followed by a reversal pattern. The confidence intervals plotted around the graphs (for both the *t*-Statistic and the Bootstrap *t*-Statistic) indicate that the results are marginally significant at the 5% level, but significant at the 10% level. A possible explanation is that the pattern is different across the size groups. To test this conjecture, I analyze the three size portfolios. Indeed, Graphs B.1-B.3 point out different price patterns. Size1 (the smallest) portfolios are highly significant. The negative return reaches roughly -4.5% at the pick, followed by a reversal pattern. Contrary to Size1, the results for Size2 and Size3, are not significant, and seem to be around 0. The results for the NASDAQ are stronger and more significant than the NYSE, for the full information portfolio and the three size

[25] The purpose of the daily accumulated estimation is to present the evolvement of the price pattern. Presenting the results in a table will limit the information.

portfolios. This is consistent with the fact that the NASDAQ is less liquid than the NYSE (see, for example, the levels of the liquidity measures presented in Graph B of Figure2 around September 2008). Here, for both the full information and size portfolios, we can observe negative significant results, followed by a reversal pattern. The order of magnitude is decreasing, from Size1 to Size3, which is a result of the stocks' liquidity levels.

4.3 Quick summary of the strategies' findings

Overall, the portfolio analysis indicates that the illiquid stock price drops, relative to the liquid stock price. Importantly, the price differences seem to revert later on. The price differences can stem from two possible channels: (i) A change in the liquidity valuation; without any indication of specific excessive trade in the illiquid stocks, the price of the illiquid stocks can drop because investors demand compensation for holding these illiquid assets. (ii) "Flights" from illiquid stocks by some group of investors may exert pressure on the illiquid stock prices.

The next section investigates a possible change in the share holdings. Section 7 will discuss the possible explanations in more details.

5 Analysis of the Changes in Share Holdings during the Events

Can we identify a group of investors who change their holding positions toward more liquid stocks? The intuition behind such groups of investors can be found in theoretical works, such as those of Vayanos (2004) (henceforth, "Vayanos") and, Brunnermeier and Pedersen (2009) (henceforth, "BP"). Each suggests a different group of investors.[26] Due to data limitations, I focus my analysis on institutional investors' share holding and, in particular, mutual

[26]Vayanos (2004) models the behavior of fund managers who face customer withdrawals. Brunnermeier and Pedersen (2009) model the behavior of arbitrageurs who face financial constraints. In Vayanos's model, in times of high volatility, the probability of customer withdrawals is higher. Due to stock-specific transaction costs, withdrawals are costly to the fund manager. Thus, when volatility increases, the frequency of withdrawals increases, and fund managers are less willing to hold illiquid stocks. In the BP model, arbitrageurs face financial constraints in the form of margin requirements. In times of high volatility, financiers set higher margin requirements. These requirements are higher for illiquid stocks, which also have higher volatility. As a result, illiquid stocks are more costly to hold, because they will earn less return per margin. In both models, the outcome is that the illiquid stocks will be less preferable.

fund holdings. The analysis will be conducted using Fama-MacBeth style cross-sectional regressions.

5.1 The Set of Pre-Event Standardized Explanatory Variables

Let us first consider the next set of explanatory variables, which will also be used in the subsequent analyses: (i) End of month market capitalization, which captures the size effect. This insures that the liquidity estimates are distinct from size. (ii) Three momentum variables similar to those in Brennan, Chordia, and Subrahmanyam (1998). Specifically, Ret23, Ret46 and Ret712, are the accumulated return of months *m*-3 to month *m*-2, *m*-6 to month *m*-4 and *m*-12 to month *m*-7, respectively. (iii) Dividend yield calculated as the sum of cash dividends (per share) during the last twelve months, divided by the end of the last month's price. As Amihud (2002) explains, this variable helps capture the value premium and possible tax effects. (iv) Idiosyncratic standard deviation, estimated by a daily frequency EGARCH (1,1) model. This helps to capture the most recent idiosyncratic risk effect. For details about the estimation of this EGARCH model, see Appendix B. (v) the logarithm of book-to-market to account for the value premium, estimated as in Fama-French (1992) with Pontiff and Woodgate's (2008) approach to missing values.[27] (vi) Systematic risk loadings, estimated for each stock using the previous 60 months, with at least 36 available months using Eq.2.

For each of the months during each event, all of the explanatory variables are estimated at the end of month *m*-1, which is the pre-event month. As mentioned in Section 3, the paper's goal is to infer the effect of liquidity from all of the events. As seen in Appendix A, the events are spread over time from 1986 to 2008. During this time, the explanatory variables, and specifically the liquidity variables, have changed. To maintain the same meaning over time, I normalize the explanatory variables according to their standard deviation, and run the Fama-MacBeth style

[27] As in Pontiff and Woodgate (2008), first stocks with negative or missing values of book-to-market get the value of 0. Thus, the book-to-market variable includes stocks with a logarithm of the positive book-to-market and stocks with zero values. Then a dummy variable (BMdum) takes the value of 1, whenever the book-to-market exists and is positive; and otherwise, takes a value of 0. Finally, in the regressions, both the dummy and the book-to-market variable are included.

cross-sectional regressions on the standardized explanatory variables. Thus, the coefficient presents the effect of 1 standard deviation on the dependent variable.

5.2 Changes in Share Holdings

5.2.1 Changes in Stock Turnover

The analysis of the change in the share holdings starts with the analysis of the change in the stocks' turnover. The change in turnover can give an indication of whether illiquid stocks experience an increase in their trade activity, relative to the liquid stocks. Specifically, for each month *m* in event *j*, the change in turnover is measured as the monthly share turnover minus the pre-event six-month average of the share turnover, divided by the pre-event six-month average of the share turnover. Specifically, the cross-sectional regressions estimated by,

$$TurnoverCng_{i,j,m} = const_{j,m} + \sum_{c=1}^{C} \hat{\delta}_{c,j,m} Z_{c,i,j} + \hat{\gamma}_{j,m} LIQ_{i,j} + \varepsilon_{i,j,m} \tag{4}$$

where $Z_{i,j}$ is the full set of control variables (including the risk loadings) and LIQ_j is the liquidity variable of interest.

Table 3 presents the results for both exchanges and liquidity measures. Let us first consider Amihud's measure. For both exchanges, the coefficient is positive and significant, indicating that illiquid stocks face a higher increase in their turnover, relative to liquid stocks. For example, the coefficient for month 0 (the event month) is 0.057 (0.041) for the NYSE (NASDAQ), indicating that 1 standard deviation increases the turnover by 5.7% (4.1%). Furthermore, the increase in turnover is not confined only to the event month. The increase in turnover stays at the same level in months 1 and 2 and reverts back to the pre-event level only in month 3. The results for HR are weaker and basically hold only for the NASDAQ.

5.2.2 Changes in Share Holdings

The most interesting aspect is to identify a group of investors that may change their share holdings of illiquid stocks, relative to liquid stocks. Relying on Vayanos's intuition, a natural group for such analysis is that of mutual fund investors. Mutual funds roughly hold about one-third, on average, of total institutional holdings. Thus, they are a significant part of institutional holdings.[28] Although Thompson's S34 file (institutional holdings) include the type codes of the different institutional investors, based on WRDS notes, these codes have incurred significant errors since 1998, and so cannot be used in my main analysis.[29] To overcome this issue, I use both data sets to create the next two groups of investors: From the S12 file (mutual fund holdings), for each stock i and quarter q, I calculate the aggregate share holdings of the mutual funds (henceforth, "MF"). This is done by summing the holdings of all the funds in the same share.[30] From the S34 (institutional holdings) file, for each stock i and quarter q, I first calculate the aggregate institutional holding. Then, to calculate the institutional investor holding which are not mutual funds, I subtract the aggregate mutual fund holdings from the aggregate institutional holdings. I refer to this group as "other institutional" (henceforth, "OINST"). Then, for each of the groups, the change in the holdings is estimated as in Sias, Starks and Titman (2006). That is, for each quarter from March 1986 through December 2008, which contain the financial crisis events, I compute the quarterly change in the fraction of shares held, as the difference between the aggregate shares held by each group, at the beginning and end of the quarter from the firm's outstanding shares (henceforth, "CngFrac").

To estimate the contribution of the liquidity variables to the change in the share holdings, using the same explanatory variables as in Eq.4, I estimate the next cross-sectional regression for each group separately,[31]

[28] As mentioned in Section 3, the data of the mutual fund investors' holdings appear in two separate files: The S12 file, which contains only the mutual fund holdings with a breakdown at the fund manager level's holdings (FUNDNO). The S34 files, which include the holdings of all institutional investors, such as banks, insurance companies, investment companies, independent investment advisors, and other endowments, such as pension funds, universality endowments and foundations. In this file, the breakdown is at the institution manager level (MGRNO), which cannot be matched to the fund manager's identifying numbers.

[29] The type-codes used in the S34 dataset are: 1-banks, 2-insurance companies, 3-investment companies, 4-investment advisors, 5-other.

[30] As mentioned in Frazzini and Lamont (2008), while the SEC requires mutual funds to disclose their holdings on a semi-annual basis, approximately 60% of funds additionally report quarterly holdings. Similar to their methodology, for each fund and each quarter, I calculate the holding of fund i in stock j, based on the latest available holdings data.

[31] Note that due to the calculation of MF and OINST, each group has the exact cross-section of stocks.

$$CngFrac_{i,j,q} = const_{j,q} + \sum_{c=1}^{C} \hat{\delta}_{c,j,q} Z_{c,i,j} + \hat{\gamma}_{j,q} LIQ_{i,j} + \varepsilon_{i,j,q} \tag{5}$$

Table 4 presents the results for both exchanges and liquidity measures. Consider HR's measure. Both exchanges present negative and significant coefficients with similar magnitudes regarding the mutual fund group (MF). For example, the NASDAQ coefficient is -0.50 with a *t*-Statistic of 4.38, which indicates that an increase of 1 standard deviation decreases the holdings in illiquid stock by -0.50%. The coefficient of the OINST group is positive for both exchanges, although it appears to be larger and more significant on the NASDAQ. The difference between the coefficients for the groups is significant for both exchanges. The results for Amihud's measure are not significant for the NYSE and significant for the NASDAQ, consistent with the fact that the NASDAQ is less liquid than the NYSE. Overall, the results indicate that the MF group decreases their holding in illiquid stocks, while the other institutions increase their holdings.

Finally, the results presented in Table 4 may be consistent with longer horizon investors providing liquidity to the short horizon investors. As a result, the longer horizon investors earn from liquidity provision.[32] To test this conjecture, in non-tabulated results, I analyze the institutional manager portfolio's turnover, which is defined for simplicity as the absolute change in the portfolio value during the quarters. Consistent with this conjecture, I find that the asset turnover of the mutual fund group is almost double that of the other institutional group.[33]

5.3 Quick Summary of Section 5

Are the changes in the holding sufficient to influence to the price pattern observed in the previous section? The results indicate that the change in the shares of illiquid stocks is 0.4%-0.5% for 1 std. change in the liquidity measures. To determent if the change is "large" enough, a possible direction is to estimate the turnover of the illiquid stocks during these quarters. Sorting

[32] For liquidity provision, see Saar, Bloomfield and O'Hara (2005), Saar and Hasbrouck (2009).

[33] Over the period 1980-2008, I estimate the time series average of the quarter cross-sectional average of the fund/institution manager assets' turnover. For example, the asset turnover of the mutual fund managers is 0.225 on average, while the estimated portfolio turnover of the insurance companies (Type-code 2) is 0.128 on average.

the stocks into quintiles based on Amihud's liquidity measures, the monthly turnover of the most illiquid (liquid) quintile during the crises is around 3% (32%), with an average of 13.2%. So, the change in shares can reach 15% of the monthly turnover, and 3.5% on average. Importantly, Coval and Stafford (2007) find that 2% of average volume can have a significant effect on stock prices, so the presented share changes can be economically significant.

6 Analysis at the Fund Level

In Section 4, we observed that illiquid stock prices drop more, relative to liquid stocks. Then in Section 5, we observed that, on aggregate, mutual funds tend to decrease their holdings of illiquid stocks compared to liquid stocks, while other institutional investors increase their holdings. In this section, I investigate the drivers behind the mutual funds' aggregate outcome. Specifically, I examine whether the aggregate result is based on a strategic decision made by the fund managers or a result of some other external reason.

6.1 Cross-sectional regressions of fund level trade activity

To address this question, I analyze the actual fund manager's buy and sell trading decisions. During the entire analysis of this section, I analyze only funds that satisfy the following three conditions: (i) appear on the merged CRSP Survivor-Bias Free Mutual Fund Database and Thomson Reuters CDA/Spectrum Mutual Fund Holdings Database (S12); (ii) have at least 50 stocks; (iii) contain a change in their portfolio during the event quarters.

I analyze the fund managers' buy and sell activity over the same financial crisis quarters that were analyzed in the previous section. For each fund, I have the portfolio of the equity holdings at the beginning and end of the quarter; which enables me to calculate the change in the holdings during the quarter. Using the change in shares and the share prices, a measure for trade activity is constructed. First, to create a meaningful comparison across the funds, the funds' trade activity in each stock is normalized by the fund's total trade volume in the quarter; specifically, the trade activity termed as "Sell" if given by,

$$Sell_{i,j,q} = \frac{DollarTrade_{i,j,q}}{\sum_{i=b}^{B} | DollarBuy_{j,q} | + \sum_{i=s}^{S} | DollarSell_{j,q} |} \tag{6}$$

where, in the numerator the *DollarTrade* is the change in share times the price at the end of the quarter. In the denominator, we have the absolute value of the buy and sell activity, which reflects the total dollar volume of the fund trades over the quarter. By using the end of month prices, the implicit assumption is that the trades are carried out at the end of the period. Then, based on the Sell component, I consider two measures that take into account a deviation from a benchmark.[34] These measures are given by,

$$CapBmkSell_{i,j,q} = Sell_{i,j,q} - Sign_{(B+S)} * CapBmk_{i,j,q} \tag{7.1}$$

$$CapBrkRetSell_{i,j,q} = Sell_{i,j,q} - Sign_{(B+S)} * CapBmkRet_{i,j,q} \tag{7.2}$$

where, $Sign_{(B+S)}$ gets the value of 1 (-1) if the total fund portfolio activity is positive (negative). $CapBmk_{i,j,q}$ is the dollar asset value portion of stock *i* from the total dollar asset value of the fund portfolio at the end of the previous quarter. Similarly, $CapBmkRet_{i,j,q}$ is the dollar asset value portion of stock *i* from the total dollar asset value of the fund portfolio, adjusted for the returns over the quarter.

After the benchmarked measures are constructed, the next stage is to estimate the fund manager's decision based on the same set of explanatory variables and the liquidity measure of interest as in Eq.4. Specifically, for each fund manager, I estimate the following cross-sectional equations,

$$CapBmkSell_{i,j,q} = const_{j,q} + \sum_{c=1}^{C} \hat{\delta}_{c,j,q} Z_{c,i,j} + \hat{\gamma}_{j,q} LIQ_{i,j} + \varepsilon_{i,j,q} \tag{8.1}$$

$$CapBmkRetSell_{i,j,q} = const_{j,q} + \sum_{c=1}^{C} \hat{\delta}_{c,j,q} Z_{c,i,j} + \hat{\gamma}_{j,q} LIQ_{i,j} + \varepsilon_{i,j,q} \tag{8.2}$$

As in the estimation of the previous cross-sectional regressions, the explanatory variables must have the same meaning across the funds. To achieve this, I normalize the explanatory

[34] An example of such flow measures can be found in Frazzini and Lamont (2008), who generally measure investors' sentiment by flows info funds, which exceed the expected flows into the fund according to proportional inflows (benchmark).

variables by their standard deviation at the fund level. As a result, the coefficients present the effect of 1 standard deviation at the fund level, and can be averaged across the funds. Additionally, I calculate the effect of the average level of liquidity on the dependent variable. This is done by multiplying the estimated coefficient by the average liquidity of the fund.

Table 5 presents the results of the fund level cross-sectional regressions. There are 6,386 fund level regressions over the 10 event quarters. Panel A presents the distribution of the liquidity coefficients based on the estimation of Eq.8.1 and Eq.8.2, for Amihud and HR's measures. Overall, it seems that the distribution is symmetric; there is almost an equal number of positive and negative coefficients. Moreover, the number of the significant coefficient at the 10% level is around 10% (13%) for HR's (Amihud's) measure, and at the 5% level is around 5.5% (8.4%) for HR's (Amihud's) measure. Importantly, the coefficients are divided almost evenly between the positive and negative coefficients, indicating that the distribution can be an outcome of a random sample. As regards robustness, the distribution of the coefficients under logistic regressions, which assigns a value of 1 for a negative measure and a value of 0 for a positive measure, has an even stronger indication of being random.[35] Panel B of Table 5 indicates that the amount of coefficients at the 10% (5%) level are, on average, 7.5% (4.2%) and again symmetric between the positive and negative outcomes.[36] Finally, Panel C of Table 5 presents the time series average of these coefficients. Specifically, for each event, I calculate the cross-sectional average of the coefficients in that event. Then, the time series average across the events is calculated. The averages of the coefficients are negative, significant for HR's measure, and insignificant for Amihud's measure. Importantly, the economic significance of the liquidity measures on the trade activity seems negligible. The effect of 1 standard deviation (average) is around -0.05% (-0.02%), which indicates that the selling of the illiquid stocks is not different than what was expected by the benchmark.

[35] The logistic estimation provides a non-parametric test because there is no meaning to the differences in magnitude. To be consistent with Panel A of Table 5, a positive (negative) coefficient on the liquidity variable, which means a higher (lower) probability for negative differences, is multiplied by -1.

[36] Barras Scaillet and Wermers (2010) (henceforth,"BSW") have a formal method to evaluate the distribution of the coefficient. In their "false discovery method" the distribution, which is not symmetric, is a mixture of three fund populations: zero alpha funds, skilled funds, and unskilled funds. Contrary to BSW Figure 1 example, the fund coefficients distribution seems to be symmetric. Thus, further analysis was not conducted.

6.2 Panel regression of the trade activity on stock level and fund level explanatory variables

Overall, the results suggest that the fund decision can be a result of a fund level effect, rather than a stock level effect. To test this hypothesis, I explore the fund activity by running a panel regression. Importantly, in the panel estimation, I can include both stock and fund explanatory variables. Thus, I am able to explore the variations resulting from both the stock determinants and the fund determinants.

Consider the next fund level explanatory variables: (i) number of stocks of the fund portfolio; (ii) the logarithm of the fund portfolio's market-cap at the beginning of the quarter; (iii) the average liquidity of the fund portfolio, measured by the average of the stock's liquidity; (iv) the fund's normalized flow, calculated based on the total net assets (*TNA*) between the quarters and the fund returns, available from the CRSP Survivor-Bias Free Mutual Fund Database. Specifically, for each month *m* in quarter *q*, the monthly normalized flow of fund *f*, is given by the next equation,[37]

$$FundMonNormFlow_{j,q,m} = (TNA_{j,q,m} - (1 + R_{j,q,m})TNA_{j,q,m-1} - MRG_{j,q,m}) / TNA_{j,q,m-1} \quad (9)$$

where $TNA_{j,q,m}$ ($TNA_{j,q,m-1}$) is the total net assets of the fund at the end (beginning) of the month, $R_{j,q,m}$ is the fund's monthly return and $MRG_{j,q,m}$ is the increase in the fund's TNA, due to mergers. Normalization by the fund's TNA is needed to compare between the funds. Next, to get a quarterly estimate, the quarterly flow is the average of the normalized monthly flows. The monthly calculation yields a more accurate estimate about the dynamics of the fund capital over the quarter. On average, a fund that has early outflows over the quarters will have a higher average.[38]

As discussed above, the purpose of the panel estimation is to capture the difference in the trade activity *of the same share* by different funds. Therefore, I estimate the panel regression

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[37] As in Frazzini and Lamont (2008) and others, the flow calculation takes into account the increase in the total net assets (TNA), due to mergers within the period of calculation.

[38] For simplicity, consider two funds (A and B) with zero return over the quarter. Both funds end the quarter with 70% of their TNA. Fund A had the outflow in the last month of the quarter, and fund B had an equal outflow of 10%. The quarterly calculation for both funds will be (100-30)/100=30%, but the average of the monthly calculation will be, 10% (11.2%) for fund A (B).

with two suggested dependent variables. The first is $Sell_{i,f,j,q}$, which is the normalized sell of the share as in Eq.6. The second is $CngFrac_{i,f,j,q}$, which is the change in the shares from the outstanding shares as in Eq.5. Specifically, I consider the following equations,

$$Sell_{i,f,j,q} = const_{j,q} + \sum_{c=1}^{C} \hat{\delta}_{c,j,q} Z_{c,i,j} + \hat{\gamma}_{j,q} LIQ_{i,j} + \sum_{k=1}^{K} \hat{\theta}_{k,j,q} F_{k,f,j} + \varepsilon_{i,f,j,q} \tag{10.1}$$

$$CngFrac_{i,f,j,q} = const_{j,q} + \sum_{c=1}^{C} \hat{\delta}_{c,j,q} Z_{c,i,j} + \hat{\gamma}_{j,q} LIQ_{i,j} + \sum_{k=1}^{K} \hat{\theta}_{k,j,q} F_{k,f,j} + \varepsilon_{i,f,j,q} \tag{10.2}$$

where Z is the set of the stock level explanatory variables that contains the same explanatory variables used in Eq.4, and F is the set of the fund level explanatory variables discussed above.

Panel A (B) of Table 6 presents the results of Eq.10.1 (10.2). For brevity's sake, from the stock level explanatory variables, the table presents only the stock liquidity variable. To avoid an estimation of a three-dimensional panel (stock *i* fund *j* and time *t*), I estimate the panel of stocks and funds for each event, and then take the time series average of the estimated coefficients. Panel A indicates that both stock liquidity measures are not significant. By contrast, the fund's quarterly normalized flow (*FundQrtNormFlow*) is positive and highly significant. The positive coefficients indicate that for stock *i*, a fund that experiences larger outflows will have a larger sell. The other fund control doesn't have a particular pattern. Panel B presents similar results; the stock liquidity variables are not significant, while the fund's flow variable is strongly significant. Consider for example the change in shares; the effect of 1 standard deviation of the fund flows on the change in shares is 0.56%. Importantly, recall that the aggregate change in holding, due to liquidity, is around 0.4%-0.5%. Overall, the panel results indicate that the fund flows are the main driver for the observed sell activity.

6.3 Cross-sectional regressions of the fund flows and fund returns

The analysis in Subsection 5.2 shows that mutual funds, on aggregate, reduce their holdings of illiquid stocks. Furthermore, Subsection 6.2 provides evidence that the fund outflows seem to be the main driver behind the change in shares. Further analysis is needed to link the fund outflows and the reduction in the aggregate holding of illiquid stocks. Continuing with this point, the goal in this Subsection is to provide evidence that funds with less liquid stocks face higher outflows. Moreover, if investors are affected by fund performance, providing evidence indicating that funds with less liquid stocks also have lower returns can help explain the reason behind investors' withdrawal decisions.

In detail, I estimate the monthly cross-sectional regressions of the fund monthly normalized flows (estimated using Eq.9), and the fund monthly returns on a set of explanatory variables. The monthly fund data is available only from 1991; thus, the analysis includes the events during the period of 1991-2008. The set of explanatory variables is comprised of two parts: Set1 includes the logarithm of the fund portfolio's market-cap, the fund number of stocks, and the fund investment objective dummies. Set2 includes the stock level explanatory variables that are used in the estimation of Eq.4. Moreover, to transform these stock level explanatory variables into a fund level explanatory variable, I calculate for each explanatory variable the proportional market-cap weighted average over the stocks in each fund portfolio. Specifically, I consider the following equations,

$$FundMonNormFlow_{f,j,m} = const_{j,m} + \sum_{k1=1}^{Set1} \hat{\theta}_{k1,j,m} Set1_{k1,f,j} + \sum_{k2=1}^{Set2} \hat{\theta}_{k2,j,m} Set2_{k2,f,j} + \varepsilon_{f,j,m} \quad (11.1)$$

$$FundRet_{f,j,m} = const_{j,m} + \sum_{k1=1}^{Set1} \hat{\theta}_{k1,j,m} Set1_{k1,f,j} + \sum_{k2=1}^{Set2} \hat{\theta}_{k2,j,m} Set2_{k2,f,j} + \varepsilon_{f,j,m} \quad (11.2)$$

Table 7 presents the results of the cross-sectional regressions, starting with the fund normalized monthly flow in Panel A and continuing with the fund monthly returns in Panel B. For brevity's sake, I present only the results for the liquidity measures. The analysis includes two specifications. "RISK", which includes only the risk variables from Set2 and the liquidity variables of interest, and "FULL" which includes all of the explanatory variables from Set2 (including the liquidity variables of interest). The months considered in the analysis are months 0, 1 and 2 - the event month and the subsequent two months, respectively. Let us first consider the results of Panel A. The results of Period 0 and Period 1 indicate that funds with less liquid stocks indeed face higher outflows. Both liquidity measures in both specifications are negative and significant. Consider, for example, the results of HR: a change of 1 standard deviation affects the flows by -1.00% over the period. Thus, Panel A provides evidence which indicates that the aggregate reduction in the illiquid share holdings is a result of fund outflows. Next, to better understand investors' withdrawal decisions, Panel B analyzes the fund monthly returns. The results in Panel B indicate that funds with less liquid stocks also have lower returns. The results for Period 0 are significant for both measures and specifications. The results for Period 1 are significant for the HR measure, but only marginally significant for Amihud's measure. Consider again the HR measure: a 1 standard deviation change in the measure affects the return (alpha return) by -3.00% (-1.40%) over the period. Overall, the results presented in Table 7 link the aggregate holding results and the fund outflows. Moreover, the results indicate that investors are affected by fund performance and withdraw money from the funds; this, in turn, further affects fund performance and withdrawals. Thus, the effect is not confined only to the month of event, but stretches out over the subsequent months.

7 Discussion

This paper documents negative price differences between illiquid and liquid stocks, in the three months following the beginning of the crises. Furthermore, these differences revert during the subsequent three months, during which market liquidity improves. What are the possible drivers behind these price differences?

The observed price differences may result solely from changes in the preference for holding illiquid stocks. In other words, without specific changes in the holding positions of illiquid stocks, the price of illiquid stocks can change to reflect investors' changes in preference. Following this argument, the changes in the pricing of liquidity, due to preference changes in the holding of illiquid stocks, can explain the observed price differences.

The liquidity literature includes both, liquidity as a characteristic of the stock and liquidity as a systematic risk factor. Consider first Amihud and Mendelson's (1986) theoretical framework, which studies the aspect of liquidity as a characteristic of the stock. The change in the liquidity cost, as well as the change in the investors' investment horizon (due to the change in the economic environment), can drive the observed change in prices. The systematic liquidity literature is also consistent with the observed changes in stock pricess. In this literature (e.g., Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka and Korajczyk (2008), among others), stocks which are "liquidity sensitive" are compensated over time because they are expected to perform poorly in periods of crisis.

The other possibility is the existence of temporary price pressure in illiquid stock prices. Studies, such as those of Coval and Stafford (2007) and Cella, Ellul and Giannatti (2010), indicate that flows can have an effect on individual stock prices. Moreover, studies such as those of Edelen and Warner (2001), Goetzmann and Massa (2003), and Ben-Rephael, Kandel and Wohl (2010) indicate that flows can even effect broad indices. Indeed, this paper finds that mutual funds sell illiquid stocks during these periods, as a result of their investors' outflows. Thus, it seems that fund managers are forced to trade. As seen in Section 5.2.2, the magnitude of these forced sales can be quite large, and affect the illiquid stock prices. Moreover, the magnitude of the change in the illiquid stock holdings, presented in this paper, may be downward biased, due to the quarterly resolution of the data. In addition, there might be other traders in the market, who can affect stock prices through their trades, such as arbitrageurs who need to unwind their illiquid positions (Shleifer and Vishny (1997) and Brunnermeier and Pedersen (2009)).

Still, this paper studies unique crisis periods; thus, the observed trades by the mutual funds can somewhat reflect the preferences for holding illiquid stocks. That is to say, the trades do not directly affect the stock prices, but merely reflect the information gathered in the market. Since it is unlikely that mutual fund investors take stock liquidity information into account when making decisions, it is reasonable to assume that these outflows exert price pressure on the illiquid stock prices. Thus, a possible price pressure seems plausible.[39]

8 Conclusion

This paper examines flight-to-liquidity in the equity markets during the period of 1986-2008, using 10 periods of financial crisis defined by a positive jump in the VIX measure.

[39] On that subject, Cella, Ellul and Giannatti (2010) find that during the 2008 financial crisis, shorter horizon investors amplified the negative shocks. Moreover, they find that investors trade not only because of valuation beliefs, but also because of unanticipated changes of the assets under management.

Analyzing both stock prices and share holdings, this paper finds that: illiquid stocks experience larger price declines, relative to liquid stocks, in the three months **following** the beginning of the crises; for example, the four-factor alpha return difference between illiquid and liquid stocks accumulates to -2% (-4%) for the NYSE (NASDAQ),over these months. Importantly, these price differences are temporary and revert back over the subsequent three months. Next, the paper finds that mutual funds, as a group, reduce their holdings of illiquid stocks, while other institutional investors increase their holdings of illiquid stocks. This is a result of larger customer withdrawals from funds with less liquid stocks, rather than a result of the trading activity of fund managers. Moreover, funds with less liquid stocks experience lower returns, which can explain mutual fund customer withdrawal decisions. Overall, the price differences followed by a reversal can be explained by changes in the pricing of liquidity; however, this mutual fund activity may suggest that these price changes are partially due to temporary price pressure.

Appendix A – List of the Financial Crisis Events

Table A reports the list of the financial crisis events analyzed in the paper, based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. *VXO-Jump* is the difference between the end of the month and the end of the previous month VXO levels. *VXO-Pick-Level* is the maximum level of the VXO, during the event period. *Jump-in-%* is the percentage of the jump from the pre-jump VXO level. *MrkRet* is the return of the CRSP value weighted index.

Event	Year	Month	VXO-Jump	VXO-Pick-Level	Jump-in-%	MrkRet
1	1987	10	39.0	61.4	174%	-22.5%
2	1990	8	9.2	30.6	43%	-9.2%
3	1997	10	10.2	34.5	42%	-3.5%
4	1998	8	22.1	48.3	84%	-15.8%
5	2000	11	6.9	32.9	27%	-10.3%
6	2001	2	6.7	33.8	25%	-9.9%
7	2001	9	7.3	35.3	26%	-9.2%
8	2002	9	8.8	44.6	24%	-10.0%
9	2007	7	8.5	25.2	51%	-3.2%
10	2008	9	21.9	61.4	56%	-9.8%

Appendix B – Estimation of the EGARCH (1,1) Model

Idiosyncratic volatility used as an explanatory variable in this paper is estimated based on an EGARCH (1,1) model (henceforth, "EGARCH"). The EGARCH is estimated based on daily frequency. For each stock *i* and time of estimation *t*, I apply the EGARCH based on the residual from a regression of the logarithm of the excess return on the Fama-French factors (MktRf, SMB, and HML). Then, based on the EGARCH estimated parameters, and known data, I forecast the expected volatility for the next month, based on future daily forecasts.

More specifically, for each stock in the sample and each time of estimation, the EGARCH parameters are estimated based on 5 years of daily data; hence insuring the accuracy of the estimation. Using Hamilton's (1994, p. 668) Eq.21.2.7 notations, the EGARCH equations are given by,

$$ExRet_{i,t} = \alpha_i + \beta_{MktRf,i} MktRf_t + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \varepsilon_t,$$
$$\varepsilon_{it} \sim N(0, h_{it}) \qquad \text{(B1)}$$

$$log(h_{i,t}) = \{k + \phi_1 log(h_{i,t-1}) + \theta_1[\gamma(\frac{r_{t-1}}{\sqrt{h_{t-1}}}) + |\frac{r_{t-1}}{\sqrt{h_{t-1}}}| - E|\frac{r_{t-1}}{\sqrt{h_{t-1}}}|]\} \qquad \text{(B2)}$$

where h_{it} is the conditioned variance of stock *i* at time *t*.

After the parameters are estimated, I forecast the expected variance h_{it} for each of the subsequent 22 days using Equation B2. Then, the expected volatility for the next month is given by,

$$ExpMonVol = \sqrt{\sum_{s=1}^{22} \widehat{h_{t+s}}} \qquad \text{(B3)}$$

Appendix C – Robustness and Extensions

In this Appendix, I add to the results presented in the paper in two ways. First, I incorporate the market volatility risk factor, as suggested by Ang, Hodrick, Xing, and Zhang (2006) (henceforth, "AHXZ") and Vayanos (2004). Next, I extend the price analysis, by estimating trading strategies with two systematic liquidity measures.

C.1 Market Volatility Risk Factor

AHXZ find that the market volatility is a priced risk factor. As was shown in Section 3 the market volatility increases during these periods. If investors are compensated for the sensitivity of the stocks to aggregate market risk (loadings on the risk factor), it is important to test whether the results hold after adjusting the stock returns to this risk. Hence, when the stocks' alpha returns are estimated, I add the market volatility factor, constructed as in AHXZ. Specifically, the daily accumulated alpha return is now given by,

$$\begin{aligned} AlphaRet_{p,j,[1,D]} &= \left(RET_{p,j,[1,D]} - Rf_{j,[1,D]}\right) - \widehat{\beta}_{MktRf,p,j} MktRf_{j,[1,D]} - \widehat{\beta}_{SMB,p,j} SMB_{j,[1,D]} \\ &\quad - \widehat{\beta}_{HML,p,j} HML_{j,[1,D]} - \widehat{\beta}_{UMD,p,j} UMD_{j,[1,D]} - \widehat{\beta}_{FVIX,p,j} FVIX_{j,[1,D]} \end{aligned} \tag{C}$$

where FVIX is the mimicking aggregate volatility factor, estimated exactly as in AHZX.[40] The results are qualitatively similar to the results presented in Table 2 and Figures 3 and 4.

C.2 Systematic Liquidity Measures

Next, I estimate the price patterns based on liquidity trading strategies as in Section 4. Specifically, I use two systematic liquidity measures, both of which capture the sensitivity of the stock return to innovations in the market liquidity, as in Pastor and Stambaugh (2003)

[40] As in AHXZ, for each month I use all stocks with at least 17 trading days in the month. The only exception is September 2001, where there were only 15 trading days. First, the "bases assets" are constructed. For each month, using AHXZ's Eq.3, I estimate the loadings on the daily VXO differences. Based on these loadings, 5 portfolios are constructed. Following Breeden, Gibbons, and Litzenberger (1989) and Lamont (2001), (AHXZ Eq.4), I estimate the weights on these 5 basses assets (zero investment portfolios). Having these weights, I construct the monthly FVIX based on the weights' estimates and the bases assets' monthly returns. My estimation yields similar results to those of AHXZ. The daily (monthly) correlation between the daily FVIX and VXOdiff is 0.93 (0.70).

(henceforth, “PS”).[41] I use both Amihud and HR’s measures as the basis for the innovations in market liquidity. As in PS, I calculate the market liquidity as the average of the stocks’ liquidity in the sample. Because the average across the sample is taken, and the most recent information is needed for calculating the liquidity risk factor, I use Amihud and HR’s measures, which are estimated based on the last available month. Furthermore, market liquidity is highly persistent. As in PS, I apply the AR (2) model to the market liquidity series and take the residuals from this regression to capture the innovation in the market liquidity. Furthermore, to avoid an in-sample outcome, the estimation of the regression for each month is conducted based on the available known information at the time of the (rolling) estimation Figure C.1 depicts the innovations in the market liquidity based on the monthly HR measure (Acharya and Pedersen (2005) present a similar graph for the Amihud-based innovations). As can be seen, the high picks in the measure are related to the familiar crisis periods, such as the 1987, 2001 and 2008 events.

After the series of the market liquidity innovations (the liquidity risk factor) are constructed, I calculate the loadings on the liquidity risk factor. As in PS, I estimate a regression of the stock excess return on the Fama-French factors and the market liquidity factor. Similar to the estimation of Eq.2, I require 60 months with at least 36 months for the estimation. I term the Amihud- (HR-) based systematic liquidity measure as ASB (HRSB).[42] Because these measures are measures of illiquidity, a stock with a high (low) loading on the liquidity factor should earn lower (higher) return ex-ante. This is because in bad times, when market illiquidity increases, these stocks are expected to perform well (poorly).

Figure C.2 presents the results of ASB and HRSB liquidity-based trading strategies. Similar to the previous strategies, I control for size and construct long-short portfolios. To present graphs that are consistent to the graphs presented in Section 4, I need to hold the stocks with the lowest loadings (ex-ante earn higher return) in long positions and the stocks with the highest loadings (ex-ante earn lower return) in short positions. Graph A presents the results for the NYSE. Consistent with the results presented in Figure 3, both systematic liquidity measures

[41] Acharya and Pedersen (2005) postulate four possible relations between the stock return, market return, innovation to market liquidity, and stock liquidity. In this section, I focus on the relation between the stock return and market liquidity.

[42] Acharya and Pedersen (2005) show that the Amihud-based measure is a risk factor. The HR-based measure was not presented in previous studies. In a non-reported result, I check that the HRSB measure is actually a systematic liquidity priced factor. Similar to AHXZ (2006), I run a time series regression of a top minus bottom portfolio, based on a pre-HRSB loading that is rebalanced annually, on the Fama-French-Carhart factors and get a significant negative alpha, as expected.

present a negative price pattern, which is then followed by a reversal. The magnitude of the negative price pattern seems qualitatively similar to previous results, but interestingly the reversal seems stronger. Graph B presents the results for the NASDAQ. ASB doesn't seem to have a negative price pattern, but HRSB presents negative and significant price patterns. Overall, the systematic liquidity measures present consistent results with the results found in Section 4. Importantly, they provide stronger evidence of a price reversal.

Figure C.1
Standardized Innovations in HR's Market Liquidity Measure
The figure depicts the standardized innovation in the market liquidity, over the period 1970-2008. The market liquidity is calculated for each month, based on HR's (2009) monthly measure. As in Pastor and Stambaugh (2003), innovations in the market liquidity are based on AR2's model of market liquidity, where the innovations are the residuals from this regression. For each month, the regression is run based only on known previous information (rolling regression). The standardization is then performed based on the residual series' standard deviation.

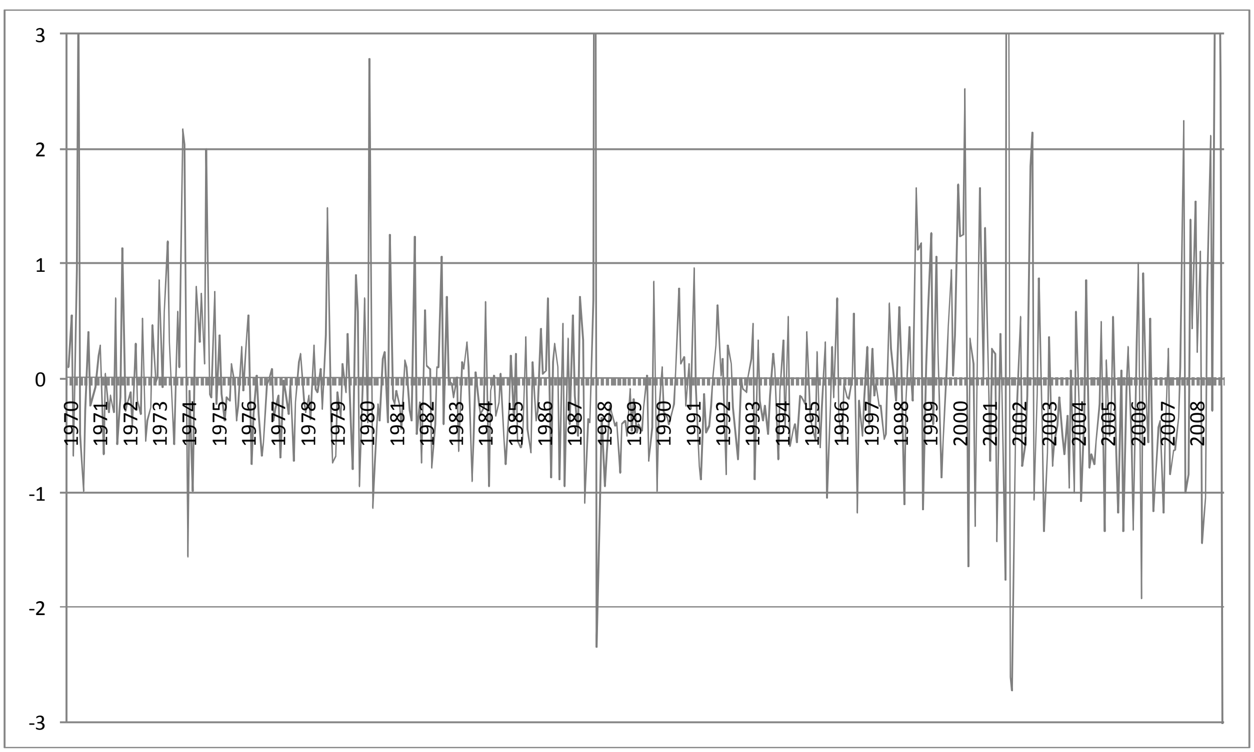
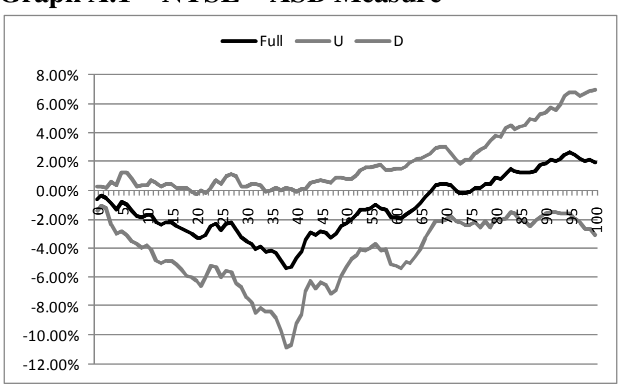


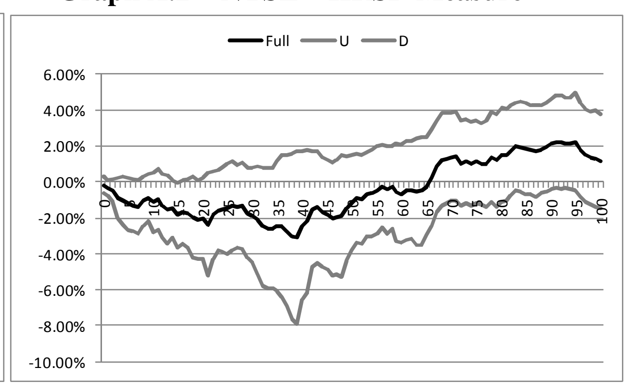
Figure C.2
Systematic Liquidity-based Trading Strategies — Pre-sorted by Size

The figure depicts the accumulated daily alpha returns of liquidity-based trading strategies controlled for size, based on two systematic liquidity measures, using the sample of common stocks traded on the NYSE and NASDAQ during periods of financial crisis. The first systematic liquidity measure is based on Amihud's measure (ASB), and the second is based on HR's measure (HRSB). As in Pastor and Stambaugh (2003), both measures are estimated as the loadings on the stock return on the innovation to market liquidity. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. For each of the 10 events (denoted as month 0), I sort the stocks in our sample into three size groups, based on the pre-event size (market-cap at month m-1). Sizes 1 to 3 refer to the smallest-to-largest size groups. Within each size group, I sort the stocks into five illiquidity quintiles, based on the pre-event systematic liquidity measure (month m-1). Then, three long-short liquidity-based trading portfolios are formed, one for each size group. The portfolios are long in the bottom quintile, which consists of the lowest loading stocks and short in the top quintile, which consists of the highest loadings stocks. The bottom quintile portfolio assigns equal weight to the lowest loadings stocks; the top quintile portfolio assigns equal weight to the highest loadings stocks. The portfolios are not rebalanced during the event. Finally, I construct a portfolio which assigns equal weight to all three sizes of trading strategies portfolios. I term this portfolio "Full information portfolio." The portfolios' alpha returns are calculated as in Brennan, Chordia, and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001). Specifically, the accumulated daily out-of-sample alpha is given by Eq.3, for the accumulated 100 trading days after the pick of the event. To present the results, for each accumulated day from day 0 up to day 100, the cross-sectional average of all events is taken. The significance of these cross-sectional averages is calculated based on the standard deviation of the events average. In each of the presented graphs, the black line represents the cross-sectional average, accompanied by two gray lines which represent the 5% confidence intervals (denoted by U and D). All graphs present the results of the full information portfolio.

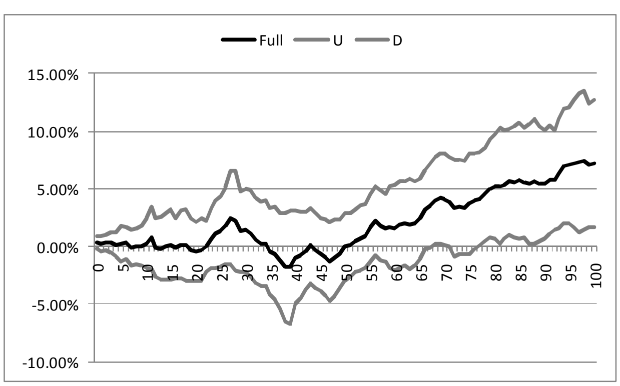
Graph A.1 – NYSE – ASB Measure



Graph A.2 – NYSE – HRSB Measure



Graph B.1 – NASDAQ – ASB Measure



Graph B.2 – NASDAQ – HRSB Measure

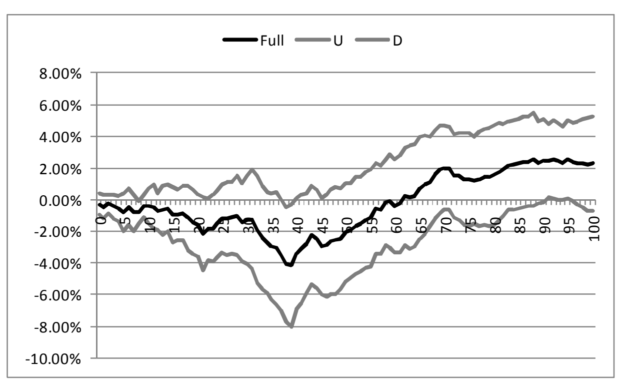


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Table 1
Summary Statistics of Market Liquidity and Volatility

The table reports the time-series average of the market liquidity and market volatility during periods of financial crisis. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. Panel A reports the average of the changes in the market liquidity, using the sample of common stocks traded on the NYSE and NASDAQ. Months 0, 1, 2, and 3 are the crisis months (0) and the subsequent three months, respectively. *MrkCngAmihud* is the change in the market liquidity from the pre-event month, based on Amihud's illiquidity measure. *Amihud* in turn, is Amihud's (2002) illiquidity measure adjusted for inflation presented in December 2008 prices, calculated based on daily data over the month. The market liquidity, in turn, is the cross-sectional average of the stock's liquidity measure. *MrkCngHR* is the change in *HR's* market liquidity from the pre-event month, based on Hasbrouck's (2009) measure. *HR,* in turn, is Roll's (1984) measure of the effective bid-ask spread obtained using a Gibbs estimator, and calculated based on daily data over the month. Panel B reports the average of the changes in the market volatility estimated using the VXO measure. Months -1, 0, and 1 are the 1 month pre-crisis, month of crisis, and 1 month post-crisis, respectively. *VXOdiff* is the difference between the VXO levels at the end of the month and the end of the previous month. *t*-Statistics, and Bootstrap *t*-Statistic (BS) are reported below the averages.

Panel A – Changes in Market Liquidity

	NYSE				NASDAQ			
Measure	0	1	2	3	0	1	2	3
MrkCngAmihud	0.35	0.65	0.68	0.72	0.19	0.46	0.82	0.74
t-Statistic	1.82	2.22	2.53	2.3	1.64	2.69	2.64	2.04
BS *t*-Statistic	1.91	2.35	2.66	2.45	1.74	2.89	2.62	2.18
MrkCngHR	0.15	0.51	0.37	0.33	0.16	0.40	0.36	0.33
t-Statistic	1.49	2.62	2.31	1.81	1.53	2.63	2.28	1.65
BS *t*-Statistic	1.59	2.74	2.46	1.92	1.61	2.76	2.42	1.74

Panel B – Changes in Market Volatility

Measure	-1	0	1
VXODiff	1.3	13.0	-5.7
t-Statistic	1.27	4.25	-2.47
BS *t*-Statistic	1.34	4.38	-2.57

Table 2
Top-Minus-Bottom Liquidity-based Trading Strategies

The table presents results from liquidity-based trading strategies, based on Amihud and HR's liquidity measure, using the sample of common stocks traded on the NYSE and NASDAQ during periods of financial crisis. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. For each of the 10 events (denoted as month 0), I sort the stocks in my sample into ten liquidity deciles, based on the pre-event illiquidity measure (month m-1). Then, I construct a portfolio that is long in the top decile, which consists of the most illiquid stocks and short in the bottom decile, which consists of the most liquid stocks. The top decile portfolio assigns equal weight to the most illiquid stocks; the bottom decile portfolio assigns equal weight to the most liquid stocks. The portfolios are not rebalanced during the event. The portfolios' alpha returns are calculated as in Brennan, Chordia, and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001). Specifically, the monthly out-of-sample alpha is given by Eq.2. *Period1* is the average of the monthly alpha returns over the three-month period from month 1 up to month 3. *Period2* is the average of the alpha returns over the three-month period from month 4 up to month 6. *Amihud* is Amihud's (2002) illiquidity measure adjusted for inflation presented in December 2008 prices, calculated based on daily data over the last three months. *HR* is Hasbrouck's (2009) measure, which is Roll's (1984) measure of the effective bid-ask spread obtained using a Gibbs estimator, calculated based on daily data over the last three months. T-stat is the *t*-Statistic of the averages.

Panel A – NYSE

Measure	Period1	T-stat	Period2	T-stat
Amihud	-1.66%	-3.54	0.72%	2.07
HR	-1.74%	-2.69	1.85%	3.78

Panel B – NASDAQ

Measure	Period1	T-stat	Period2	T-stat
Amihud	-3.22%	-3.30	1.95%	2.19
HR	-3.18%	-3.15	1.12%	1.78

Table 3
Cross-Sectional Regressions of Change in Turnover

The table presents the average of the coefficients from monthly cross-sectional regressions of stock change in turnover on Amihud and HR's illiquidity measures and other explanatory variables (Eq.4), using the sample of common stocks traded on the NYSE and NASDAQ during periods of financial crisis. To conserve space, the control variables are not reported. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. For each of the 10 events, cross-sectional regressions are estimated for each of the four months from the event month (denoted as month 0). For all the months, the explanatory variables are calculated based on the information known at month *m*-1 (pre-event). 0, 1, 2, and 3 are the event month and the subsequent three months, respectively. Change in turnover is calculated as the monthly share turnover minus the pre-event six-month average of the share turnover, divided by the pre-event six-month average of the share turnover. *Amihud* is Amihud's (2002) illiquidity measure adjusted for inflation presented in December 2008 prices, calculated based on daily data over the last three months. *HR* is Hasbrouck's (2009) measure, which is Roll's (1984) measure of the effective bid-ask spread obtained using a Gibbs estimator, calculated based on daily data over the last three months. *Coef* is the average of Amihud and HR's standardized measure coefficients over the period, where all explanatory variables are normalized by their standard deviation. The standardization transforms the coefficients to present the effect of 1 std. *t*-Statistics and Bootstrap *t*-Statistic (BS) are reported below the averages.

	NYSE				NASDAQ			
Measures	0	1	2	3	0	1	2	3
Amihud								
Coef	0.057	0.056	0.049	-0.029	0.041	0.065	0.040	-0.012
t-Statistic	3.69	3.48	2.44	-1.10	3.80	5.31	2.13	-0.40
BS t-statistic	3.89	3.7	2.6	-1.2	4.03	5.70	2.39	-0.45
HR								
Coef	-0.019	-0.020	-0.006	-0.015	0.014	0.050	0.032	0.000
t-Statistic	-1.74	-1.64	-0.41	-1.00	0.98	2.60	1.35	0.04
BS t-statistic	-1.89	-1.76	-0.44	-1.07	1.04	2.75	1.46	0.02

Table 4
Cross-Sectional Regressions of Aggregate Change in Share

The table presents results from quarterly cross-sectional regressions of stock aggregate change in shares on Amihud and HR's illiquidity measures and other explanatory variables (Eq.5), using the sample of common stocks traded on the NYSE and NASDAQ during periods of financial crisis. To conserve space, the control variables are not reported. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. For each of the 10 quarters of events, cross-sectional regressions are estimated. For all quarters, the explanatory variables are calculated based on the information known at the end of the previous quarter. Aggregate change in shares is calculated as in Sias, Stark and Titman (2006) as the difference between the aggregate shares held at the beginning and end of the quarter from the firm's outstanding shares. *MF* is the aggregate change in shares of the mutual fund institutional investors based on Thompson CDA/Spectrum mutual fund holdings (S12) database. *OINST* is the aggregate change in share holdings of the institutional investors based on Thompson CDA/Spectrum institutional holdings (S34) database net of the MF holdings. *Amihud* is Amihud's (2002) illiquidity measure adjusted for inflation presented in December 2008 prices, calculated based on daily data over the last three months. *HR* is Hasbrouck's (2009) measure, which is Roll's (1984) measure of the effective bid-ask spread obtained using a Gibbs estimator, calculated based on daily data over the last three months. Coef is the average of Amihud and HR's standardized measure coefficients over the period, where all explanatory variables are normalized by their standard deviation. The standardization transforms the coefficients to present the effect of 1 std. *Diff* is the difference between the MF and OINST coefficient averages. *t*-Statistics and Bootstrap *t*-Statistic (BS) are reported below the averages.

Panel A – NYSE

Measure	MF	OINST	Diff
Amihud			
Coef	0.06%	-0.09%	0.15%
t-Statistic	0.23	-0.24	0.49
BS *t*-Statistic	0.53	-0.27	0.51
HR			
Coef	-0.41%	0.23%	-0.64%
t-Statistic	-2.67	1.37	-2.30
BS *t*-Statistic	-2.39	1.46	-2.49

Panel B – NASDAQ

Measure	MF	OINST	Diff
Amihud			
Coef	-0.40%	0.70%	-1.10%
t-Statistic	-2.13	2.14	-2.20
BS *t*-Statistic	-2.29	2.30	-2.33
HR			
Coef	-0.50%	0.66%	-1.16%
t-Statistic	-4.59	3.10	-3.75
BS *t*-Statistic	-4.38	3.35	-3.66

Table 5
Cross-Sectional Regressions of the Fund Manager's Trading Activity

The table presents results from the quarterly fund level cross-sectional regressions of the fund manager's trading activity (Eq.7.1 and Eq.7.2) on Amihud and HR's illiquidity measures and other explanatory variables (Eq.8.1 and Eq.8.2), using the sample of common stocks traded on the NYSE and NASDAQ during periods of financial crisis. To conserve space, the control variables are not reported. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. The sample of funds is based on the merged CRSP's Survivor-Bias Free Mutual Fund Database and Thomson Reuters CDA/Spectrum Mutual Fund Holdings Database (S12), merged by WRDS's "MFlink" based on Wermers (2000) methodology, a total of 6,386 funds quarters. The trade activity is defined by the next two stages: First the buy or sell of each stock in the fund manager's portfolio during the quarter is defined as the dollar value of trade divided by the total dollar volume of trade (Eq.6). Then *CapBmkSell* and *CapBmkRetSell* are the buy or sell trades adjusted for the stock dollar asset share from the total portfolio at the beginning of the quarter, and adjusted for the return over the quarter, respectively (Eq.7.1 and Eq.7.2). *Amihud* is Amihud's (2002) illiquidity measure adjusted for inflation presented in December 2008 prices, calculated based on daily data over the last three months. *HR* is Hasbrouck's (2009) measure, which is Roll's (1984) measure of the effective bid-ask spread obtained using a Gibbs estimator, calculated based on daily data over the last three months. Panel A presents the distribution of the 6,386 cross-sectional coefficients. "All Coef" presents the percent of negative (Neg) and positive (Pos) coefficients. "Coef at 10% (5%) level" presents the percent of negative (Neg) and positive (Pos) coefficients with an absolute *t*-Statistic bigger than 1.64 (1.96). Panel B presents the distribution from the fund's logistic estimation, which assigns a value of 1 for a negative measure and a value of 0 for a positive measure. To be consistent with Panel A, a positive (negative) coefficient on the liquidity variable, which means higher (lower) probability for a negative difference, is multiplied by -1. Panel C presents the averages from the 6,386 cross-sectional coefficient estimates. *Coef* is the average of Amihud and HR's standardized measure coefficients over the period, where all explanatory variables are normalized by their standard deviation at the fund level. The standardization transforms the coefficients to present the effect of 1 standard deviation. *AveLiq* is the average of the average effect of liquidity, which is calculated according to the product of the monthly liquidity coefficient and the monthly liquidity average. Specifically, for each event the cross-sectional average is calculated across the funds' estimates, after which the time-series average is calculated over the 10 event averages. T-stat is the *t*-Statistic of the time-series average.

Panel A – Distribution of the Coefficients

	All Coef		Coef at 10% level		Coef at 5% level	
Measures	Neg	Pos	Neg	Pos	Neg	Pos
CapBmkSell						
Amihud	52.3%	47.7%	6.8%	6.1%	4.2%	4.4%
HR	50.7%	49.3%	5.5%	4.7%	3.2%	2.7%
CapBmkRetSell						
Amihud	52.1%	47.9%	6.5%	6.0%	3.9%	4.2%
HR	50.0%	50.0%	5.2%	4.6%	2.9%	2.5%

Panel B – Distribution of Logistic Regression Coefficients

Measures	All Coef Neg	All Coef Pos	Coef at 10% level Neg	Coef at 10% level Pos	Coef at 5% level Neg	Coef at 5% level Pos
CapBmkSell						
Amihud	51.6%	48.4%	4.8%	3.5%	2.7%	2.1%
HR	50.4%	49.6%	3.2%	3.2%	1.5%	1.7%
CapBmkRetSell						
Amihud	52.5%	47.5%	5.1%	4.0%	3.0%	2.5%
HR	49.5%	50.5%	3.0%	3.3%	1.5%	1.9%

Panel C – Coefficient Averages

Measures	Coef	T-stat	AveLiq	T-stat
CapBmkSell				
Amihud	-0.07%	-1.15	-0.02%	-1.20
HR	-0.02%	-2.22	-0.03%	-1.76
CapBmkRetSell				
Amihud	-0.08%	-1.13	-0.02%	-1.17
HR	-0.02%	-2.39	-0.03%	-1.88

Table 6
Panel Regressions of the Fund Manager's Trading Activity
The table presents results from the quarterly panel regression of the fund manager's trade activity on stock level and fund level explanatory variables (Eq.10.1 and Eq.10.2), using the sample of common stocks traded on the NYSE and NASDAQ during periods of financial crisis. To conserve space, only the stock liquidity variables and the fund level variables are reported. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. The sample of funds is based on the merged CRSP's Survivor-Bias Free Mutual Fund Database and Thomson Reuters CDA/Spectrum Mutual Fund Holdings Database (S12), merged by WRDS's "MFlink" based on Wermers's (2000) methodology, a total of 6,386 funds. The panel regression of stock *i* and fund *j*, is estimated event by event, after which the time-series average of the coefficients' estimates is calculated. *Amihud* is Amihud's (2002) illiquidity measure adjusted for inflation presented in December 2008 prices, calculated based on daily data over the last three months. *HR* is Hasbrouck's (2009) measure, which is Roll's (1984) measure of the effective bid-ask spread obtained using a Gibbs estimator, calculated based on daily data over the last three months. Panel A presents the results of the trade activity as a dependent variable (Eq.10.1). Panel B presents the result for the change in shares as a dependent variable (Eq.10.2). *Stock Liquidity* is the stock liquidity measure. *Fund liquidity* is the average of the stocks' liquidity in the fund portfolio. *FundAssets* is the number of stocks in the fund portfolio. *FundLnBgnCap* is the logarithm of the fund portfolio market-cap in millions (US dollars). *FundQrtNormFlow* is the fund average's normalized flow over the quarter (Eq.9). *Coef* is the average of the 10 event panel coefficients. The stock level explanatory variables are normalized by their standard deviation. The standardization transforms the coefficients to present the effect of 1 std. T-stat is the *t*-Statistic of the events average.

Panel A – Panel of Trade Activity

	Amihud		HR	
Variables	Coef	T-stat	Coef	T-stat
Stock Level Controls	YES		YES	
Stock Liquidity	-0.001	-0.98	0.000	-1.11
Fund Liquidity	0.002	1.47	0.000	-0.18
FundAssets	0.000	-1.76	0.000	-1.32
FundLnBgnCap	0.000	0.59	0.000	0.71
FundQrtNormFlow	0.045	10.33	0.045	10.54

Panel B – Panel of Share Activity

	Amihud		HR	
Variables	Coef	T-stat	Coef	T-stat
Stock Level Controls	YES		YES	
Stock Liquidity	-0.013	-1.00	-0.002	-1.26
Fund Liquidity	0.065	1.85	0.010	0.86
FundAssets	0.000	-1.44	0.000	-1.38
FundLnBgnCap	0.002	1.74	0.002	1.84
FundQrtFlow	0.145	6.45	0.144	6.36

Table 7

Cross-Sectional Regressions of the Fund Flows and Returns

The table presents results from the monthly cross-sectional regressions of the fund flows and fund returns on a set of explanatory variables (Eq.11.1 and Eq.11.2), using the sample of common stocks traded on the NYSE and NASDAQ during periods of financial crisis. The monthly fund data is available only from 1991; thus, the analysis includes the events during the period of 1991-2008. To conserve space, only the fund liquidity variables are reported. The sample of funds is based on the merged CRSP's Survivor-Bias Free Mutual Fund Database and Thomson Reuters CDA/Spectrum Mutual Fund Holdings Database (S12), merged by WRDS's "MFlink", based on Wermers's (2000) methodology. For all of the months, the explanatory variables are calculated based on the information known at month *m*-1 (pre-event). Moreover, the explanatory variables are normalized by their standard deviation; the standardization transforms the coefficients to present the effect of 1 standard deviation. The fund explanatory variables include two sets of variables. Set1 includes the number of stocks in the fund portfolio (*FundAssets*), the logarithm of the fund portfolio market-cap in millions of dollars (*FundLnBgnCap*), and the fund investment objective dummies (*IOD*). Set2 includes the stock level explanatory variables that are used in the estimation of Eq.4. To transform the stock level variables into a fund level explanatory variable, the proportional market-cap weighted average is calculated over the stocks in each fund portfolio. 0, 1, and 2 are the event month and the subsequent two months, respectively. RISK is the specification that uses only the risk explanatory variables from Set2. FULL is the specification that uses all the explanatory variables from Set2. Panel A reports the results from the monthly cross-sectional regression of the fund flows (Eq. 11.1). Panel B reports the results from the monthly cross-sectional regression of the fund returns (Eq. 11.2). The fund monthly flows are estimated using Eq.9. Amihud (HR) is the time-series average of Amihud's (HR's) coefficient from the monthly cross-sectional regressions. BS *t*-Statistic is the Bootstrap *t*-Statistic.

Panel A – Cross-Sectional Regressions of the Monthly Fund Flows

	RISK			FULL		
Period	0	1	2	0	1	2
Amihud	-0.33	-0.62	-0.60	-0.49	-0.48	-0.24
BS *t* -Statistic	-1.74	-2.06	-1.62	-3.39	-2.31	-0.40
HR	-0.02	-0.02	-0.03	-0.02	-0.02	-0.02
BS *t* -Statistic	-2.01	-3.20	-1.99	-2.01	-2.35	-0.86

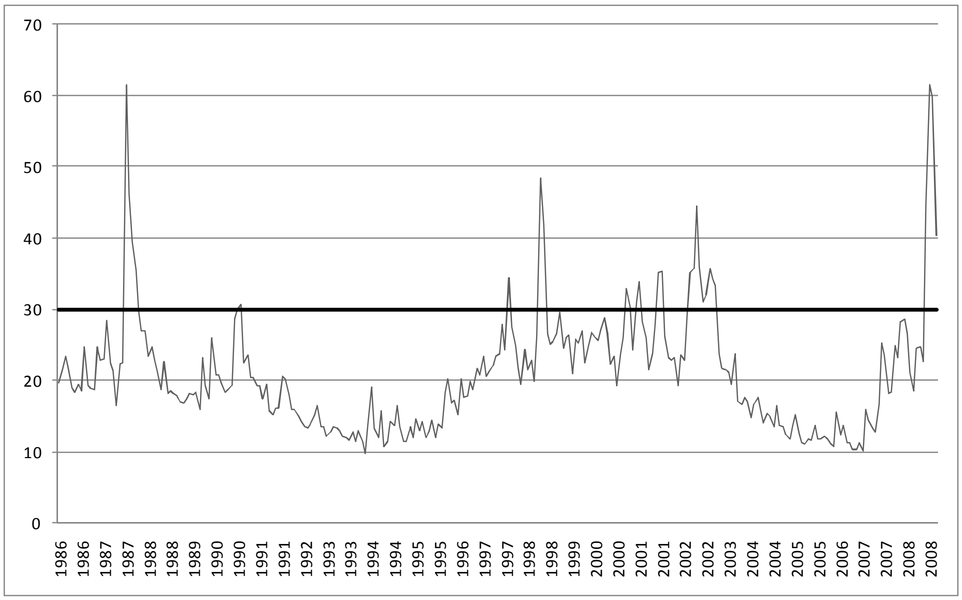
Panel B – Cross-Sectional Regressions of the Monthly Fund Returns

	RISK			FULL		
Period	0	1	2	0	1	2
Amihud	-0.62	-0.38	-0.13	-0.43	0.02	-0.27
BS *t* -Statistic	-2.43	-2.38	-0.39	-1.81	0.02	-0.54
HR	-0.05	-0.02	0.03	-0.04	-0.02	0.01
BS *t* -Statistic	-3.52	-1.55	3.08	-3.83	-1.96	1.21

Figure 1
Market Volatility and Market Returns

The figure depicts the market volatility and market return over the period 1986-2008. Graph A depicts the market return using end of month levels of the VXO measure, where the VXO is the implied volatility of the S&P100 index options. The black solid line is at the level of 30. Graph B depicts the monthly market returns using the CRSP value weighted index. The black solid line is at the level of -9%.

Graph A – VXO measure



Graph B – CRSP Value Weighted Index Returns

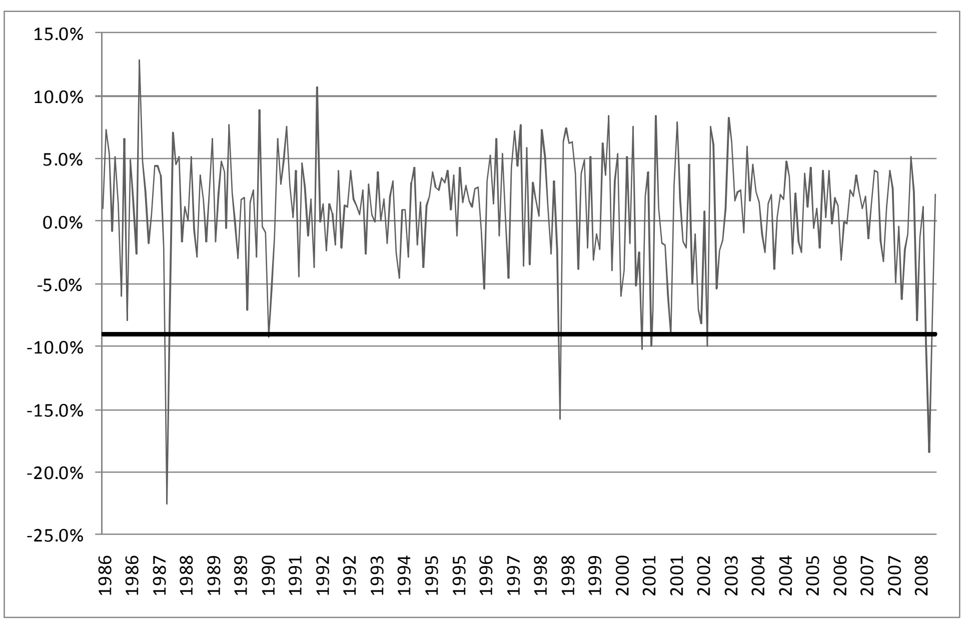
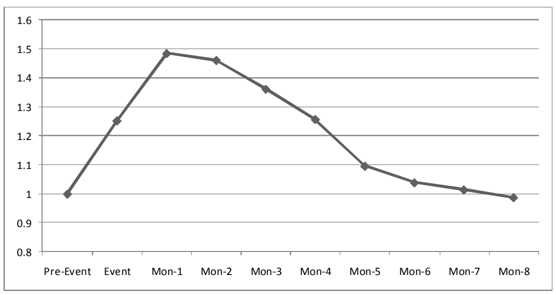


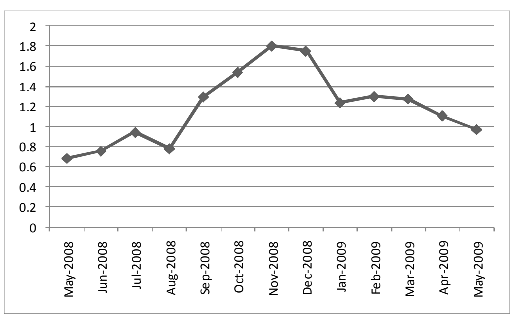
Figure 2
NYSE and NASDAQ Liquidity around Periods of Financial Crisis

The figure depicts the evolvement of NYSE and NASDAQ liquidity, during the months around periods of financial crisis. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. The NYSE and NASDAQ monthly liquidity is estimated by the monthly average of the CRSP end of day half bid-ask spread quotes (HBAS) in %. The daily HBAS, in turn, is the cross-sectional average of the stocks' HBAS used in my sample. Graph A presents the average of NASDAQ liquidity over all the crises, starting from the Pre-Event month which is normalized to be 1, through the event month and the subsequent 8 months, excluding 2007. Pre-Event liquidity levels are taken from 3 months before the event month. Graph B presents results from 2008 crises for both the NYSE and NASDAQ.

Graph A – NASDAQ Normalized Measure



Graph B.1 – NASDAQ, September 2008



Graph B.2 – NYSE, September 2008

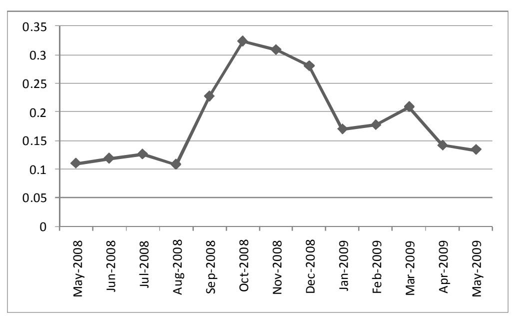
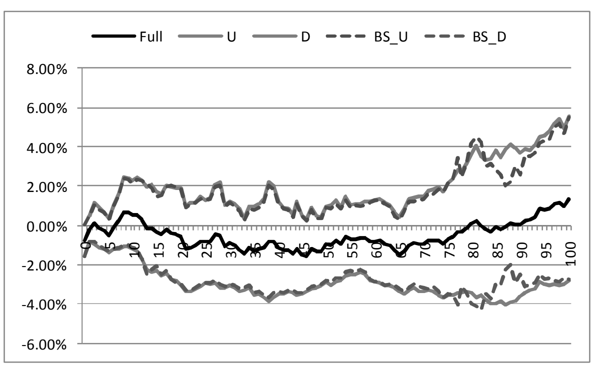


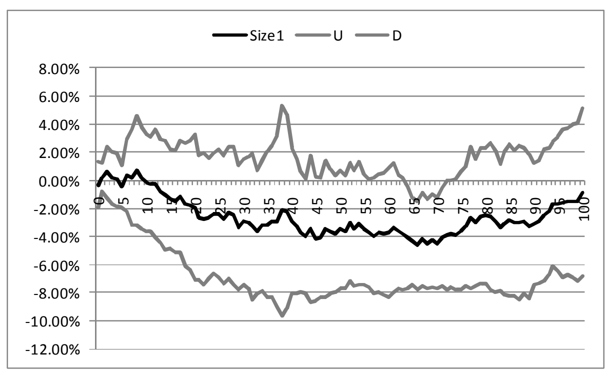
Figure 3 - NYSE Liquidity-based Trading Strategies ─ Pre-sorted by Size

The figure depicts the accumulated daily alpha returns of *HR's* liquidity-based trading strategies, controlled for size, using the sample of common stocks traded on the NYSE during periods of financial crisis. *HR* is Hasbrouck's (2009) measure, which is Roll's (1984) measure of the effective bid-ask spread obtained using a Gibbs estimator, calculated based on daily data over the last three months. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. For each of the 10 events (denoted as month 0), I sort the stocks in my sample into three size groups, based on the pre-event size (market-cap at month m-1). Sizes 1 to 3 refer to the smallest-to-largest size groups. Within each size group, I sort the stocks into five liquidity quintiles, based on HR's pre-event illiquidity measure (month m-1). Then, three long-short liquidity-based trading portfolios are formed, one for each size group. The portfolios are long in the top quintile, which consists of the most illiquid stocks and short in the bottom quintile, which consists of the most liquid stocks. The top quintile portfolio assigns equal weight to the most illiquid stocks; the bottom quintile portfolio assigns equal weight to the most liquid stocks. The portfolios are not rebalanced during the event. I also construct a portfolio which assigns equal weight to all three sizees of trading strategies portfolios. I term this portfolio "Full information portfolio" or "Full." The portfolios' alpha returns are calculated as in Brennan, Chordia, and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001). Specifically, the accumulated daily out-of-sample alpha is given by Eq.3, for the accumulated 100 trading days after the event. Finally, for each accumulated day from day 1 up to day 100, the cross-sectional average of all events is taken. The significance of these cross-sectional averages is calculated based on the standard deviation of the events average. In each of the presented graphs, the black line represents the cross-sectional average, accompanied by two gray lines which represent the 5% confidence intervals (denoted by U and D). Graph B1 also includes the 5% Bootstrapped confidence intervals (BS_U and BS_D broken lines). Graph A presents the results of the full information portfolio. Graphs B.1 to B.3 present the results for Size1 to Size3 portfolios.

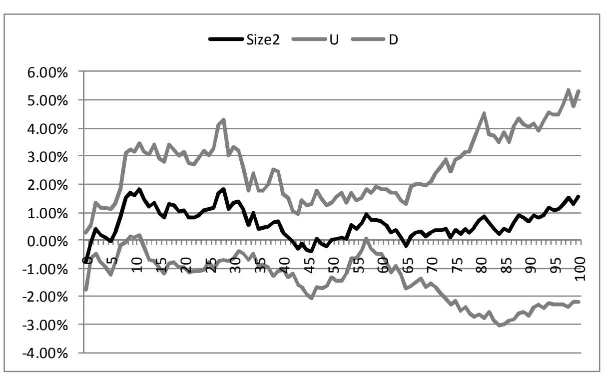
Graph A – Full Information Portfolio



Graph B.1 – Size1 Portfolio



Graph B.2 – Size2 Portfolio



Graph B.3 – Size3 Portfolio

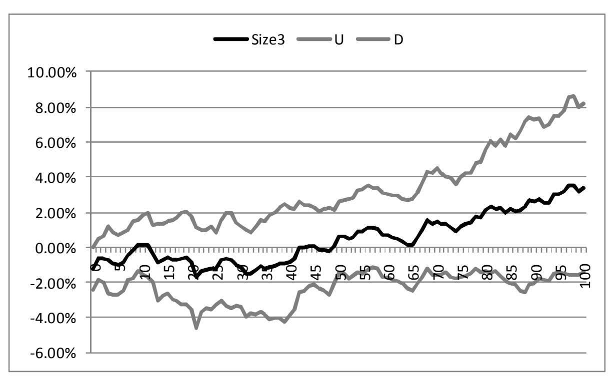
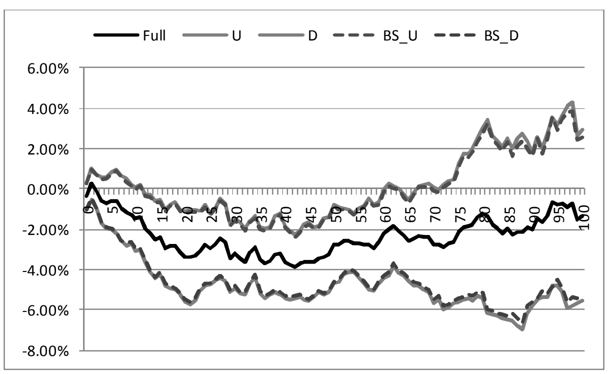


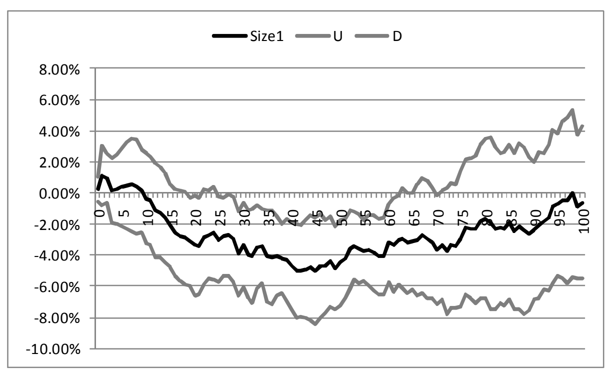
Figure 4 - NASDAQ Liquidity-based Trading Strategies — Pre-sorted by Size

The figure depicts the accumulated daily alpha returns of *HR's* liquidity-based trading strategies controlled for size, using the sample of common stocks traded on the NASDAQ during periods of financial crisis. *HR* is Hasbrouck's (2009) measure, which is Roll's (1984) measure of the effective bid-ask spread obtained using a Gibbs estimator, calculated based on daily data over the last three months. Specifically, ten monthly periods of financial crisis are chosen based on the VXO measure during the period 1986-2008, where the VXO is the implied volatility of the S&P100 index options. For each of the 10 events (denoted as month 0), I sort the stocks in my sample into three size groups, based on the pre-event size (market-cap at month m-1). Sizes 1 to 3 refer to the smallest-to-largest size groups. Within each size group, I sort the stocks into five liquidity quintiles, based on HR's pre-event illiquidity measure (month m-1). Then, three long-short liquidity-based trading portfolios are formed, one for each size group. The portfolios are long in the top quintile, which consists of the most illiquid stocks and short in the bottom quintile, which consists of the most liquid stocks. The top quintile portfolio assigns equal weight to the most illiquid stocks; the bottom quintile portfolio assigns equal weight to the most liquid stocks. The portfolios are not rebalanced during the event. I also construct a portfolio which assigns equal weight to all three sizes of trading strategies portfolios. I term this portfolio "Full information portfolio" or "Full." The portfolios' alpha returns are calculated as in Brennan, Chordia, and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001). Specifically, the accumulated daily out-of-sample alpha is given by Eq.3, for the accumulated 100 trading days after the pick of the event. Finally, for each accumulated day from day 1 up to day 100, the cross-sectional average of all events is taken. The significance of these cross-sectional averages is calculated based on the standard deviation of the events average. In each of the presented graphs, the black line represents the cross-sectional average, accompanied by two gray lines which represent the 5% confidence intervals (denoted by U and D). Graph B1 also includes the 5% Bootstrapped confidence intervals (BS_U and BS_D dashed lines). Graph A presents the results of the full information portfolio. Graphs B.1 to B.3 present the results for Size1 to Size3 portfolios.

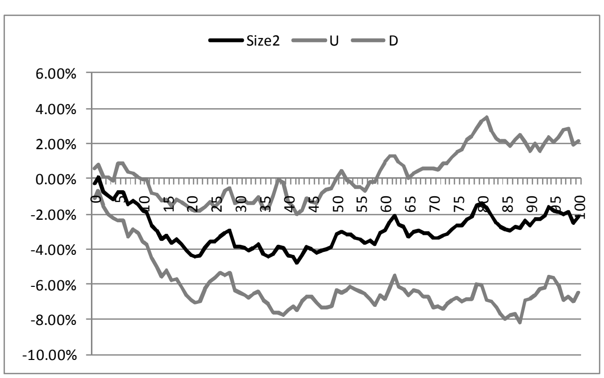
Graph A – Full Information Portfolio



Graph B.1 – Size1 Portfolio



Graph B.2 – Size2 Portfolio



Graph B.3 – Size3 Portfolio