The liquidity management of institutional investors and the pricing of liquidity risk

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Contents

Introduction

This PhD thesis studies how mutual funds and hedge funds manage their liquidity and reduce trading costs, and the pricing of liquidity level and liquidity risk in financial markets. The liquidity level of an asset is generally defined as the ease with which it can be traded, and it is usually measured by trading costs. Liquidity risk originates from the time variation of trading costs. Investors dislike liquidity risk, especially because tradings costs typically increase during market downturns. If institutional investors such as mutual funds and hedge funds care about liquidity level and liquidity risk of assets, they should incorporate them into their trading strategies, and therefore liquidity level and liquidity risk should be priced in financial market. In this introduction, I will summarize the contents of each chapter of this dissertation.

Chapter 1 documents the trading behavior of actively managed equity mutual funds from the perspective of their trading cost management. There are many theoretical predictions on how should investors trade to reduce trading costs. For example, Scholes (2000), Duffie and Ziegler (2003) and Brown, Carlin, and Lobo (2010), suggest that financial institutions that have urgent liquidity needs should sell liquid assets first in order to reduce the trading costs. Garleanu and Pedersen (2013) recommend that investors "trade gradually towards the aim" in order to reduce price impact costs. However, there is little empirical evidence to support those claims, and there is still uncertainty regarding the extent to which institutional investors actually care about trading costs, and what they actually do to reduce them. In this paper, I attempt to address this knowledge gap by looking directly at the trading behavior of mutual funds.

Consistent with those predictions, I present three main findings. Firstly, mutual funds trade more liquid stocks than illiquid stocks when there are large fund flows. Secondly, these mutual funds spread their trades over stocks, especially for outflow-driven sales. Finally, they also spread their flow-driven trades over time and use cash buffers. In addition, the fact that mutual funds spread trades over stocks and time is consistent with the claim that total trading costs in dollar are increasing and convex in trading amount, and it is also consistent with the key assumption in Berk and Green (2004) that costs are increasing and convex in fund size.

Chapter 2 is a joint work with Joost Driessen. It analyzes what size for the liquidity risk premium can be justified theoretically. Like other systematic risks (e.g. market risk), liquidity risk is another systematic risk that should be priced in financial market. Recent empirical work documents large liquidity risk premiums in stock markets. Several articles document substantial liquidity risk premiums in realized returns (for example Pastor and Stambaugh 2003), while other work finds that is difficult to disentangle the liquidity risk premium from the direct effect of transaction costs on prices, sometimes called the liquidity level premium (Acharya and Pedersen 2005). In addition, the liquidity risk factors are often correlated with other risk factors, such as market risk, volatility risk and the Fama-French (1993) size factor. This makes it nontrivial to empirically pin down the liquidity risk premium.

In this chapter we therefore add to the debate on the liquidity risk premium by analyzing what size for the liquidity risk premium can be justified theoretically. We calculate the liquidity risk premiums demanded by large investors by solving a dynamic portfolio choice problem with stochastic price impact of trading, CRRA utility and a time-varying investment opportunity set. We find that, even with high trading-cost rates and substantial trading motives, the theoretically demanded liquidity risk premium is negligible, less than 3 basis points per year. Assuming forced selling during market downturn enlarges the liquidity risk premium to maximally 20 basis points per year, which is well below existing empirical estimates of the liquidity risk premium.

Chapter 3 studies how hedge funds adjusted their holdings of liquid and illiquid stocks before, during and after the 2008 financial crisis. Among all types of investors, hedge funds might be the group of investors that care most about their liquidity management. It is because clients of hedge funds are mainly sophisticated institutional investors which react quickly to market changes. Moreover, the use of leverage and short positions makes hedge funds more sensitive to fund outflows than other investors. Yet there is no empirical work on how hedge funds manage the liquidity of their portfolios dynamically around crisis periods.

In this chapter, I find that hedge funds sold more liquid than illiquid stocks at the peak of the crisis, and they repurchased a large amount of liquid stocks during the upturn but continued to sell illiquid stocks. Consistently, hedge funds' portfolio composition shows a delayed "flight to liquidity": the proportion of hedge funds' liquid stock holdings decreased slightly at the peak of the crisis and then increased substantially to a highest level ever since 2007. This result confirms the prediction in Scholes (2000) that institutional investors should sell liquid stocks first during a crisis and build a "liquidity cushion" for future liquidity needs later. For comparison, I show that pension funds have a nearly constant portfolio composition of liquid versus illiquid stocks through the entire crisis.

Summarizing, Chapter 1 and 3 of this dissertation show institutional investors such as mutual funds and hedge funds actually care about trading costs, and the ways they trade to reduce trading costs are in accordance with existing theoretical predictions. Consistently, Chapter 2 shows under the standard portfolio choice framework, trading costs (liquidity level) have a direct and significant effect on stock prices. However, time variation in trading costs (liquidity risk) does not. Nonstandard assumptions are necessary in order to have a chance at generating larger liquidity risk premiums.

Chapter 1

Trading Cost Management of Mutual Funds

1.1. Introduction

Since Constantinides (1986), theories on portfolio choice with trading costs have developed rapidly. Recent works, such as Scholes (2000), Duffie and Ziegler (2003) and Brown, Carlin, and Lobo (2010), have suggested that financial institutions that have urgent liquidity needs should sell liquid assets first in order to reduce the trading costs. Garleanu and Pedersen (2013) recommend that investors "trade gradually towards the aim" in order to reduce price impact costs. However, there is little empirical evidence to support those claims, and there is still uncertainty regarding the extent to which institutional investors actually care about trading costs, and what they actually do to reduce them. In this paper, I attempt to address this knowledge gap by looking directly at the trading behavior of mutual funds. I conduct this analysis using the holding data of mutual funds and find that trading-cost-management behavior exists and is consistent with theoretical predictions. Specifically, using quarterly holding data of mutual funds from 1980 to 2009, I investigate how actively managed equity mutual funds trade in order to reduce trading costs and the price impact of trades.

The trading strategy is always a joint decision of maximizing the profits and minimizing the trading costs, and usually the trading motives[1] are not observable in publicly available data[2]. Therefore, the biggest challenge of this study is to identify the trading cost management from other trading motives. In this paper, I use fund flows for this identification. Firstly, it is because fund flows are observable, which can be calculated as the changes of total net assets (TNA) adjusted by fund returns from the data. Secondly,

[1] Such as active trades for active investment strategies, passive rebalancing for stock price fluctuations, investment for diversification etc.

[2] The signals used by mutual funds for their investment strategies are highly confidential.

mutual funds are forced to trade when there are large fund flows.[3] In this paper, I define the trades caused by fund flows as flow-driven trades. Thirdly, fund flows are largely exogenous to their investment strategies.[4] Fourthly, price-impact costs play a crucial role for flow-driven trades since the size of flow-driven trades is usually very large. Flow-driven trades account for about 28% of all trading activities of active mutual funds, and the total amount of flow-driven trades every year is about 100% of their total net assets. Therefore, I focus my analysis on flow-driven trades.

I find evidence for three aspects of trading-cost-management behavior predicted by theories,

(1) They trade more liquid stocks than illiquid stocks when there are large fund flows;

(2) They spread their flow-driven trades over stocks (trade more stocks) to reduce price impact of trades;

(3) They use cash buffers to spread their flow-driven trades over time.

I do both portfolio analysis and regression analysis for each of these. For the portfolio analysis, I sort all fund-quarter observations into deciles based on their quarterly fund flows. I find that, firstly, mutual funds trade relatively more liquid stocks in their portfolios when they face large fund flows. Secondly, rather than scaling up or down their portfolio proportionally, most mutual funds only trade a small number of stocks when facing small fund flows. They trade more stocks when facing larger fund flows to reduce the price impact of trades, but they still trade only a fraction of stocks in their portfolios (about 50% to 60%) when facing extremely large fund flows. Thirdly, they have less stock holdings and more cash buffers when there are inflows and more stock holdings and less cash buffers when there are outflows.

Then, I do regression analysis using both fund level data and fund-stock level holding data. Firstly, using fund level data, I study the relation between the average liquidity

[3]When there are large inflows, they have to gradually increase their holdings, otherwise they will underperform; and when there are large outflows, they have to sell to fulfill the redemption.

[4]Fund flows depend largely on the liquidity shocks faced by investors of mutual funds, which are exogenous to the investment strategies of mutual funds. Recent mutual fund literature documents strong flow-performance sensitivity (e.g. Sirri and Tufano 1998, Jain and Wu 2000, Huang, Wei and Yang 2007, Ivkovic and Weisbenner 2009, etc.), which shows strong correlation between fund flows and realized returns of mutual funds. Although the expected returns of mutual funds' investment strategies have some predictability to their realized returns, the realized returns of mutual funds are still largely random because of their exposures to both market shocks and shocks on individual assets. Thus even the flows introduced by fund performance are largely exogenous to their investment strategies.

of stocks traded and the size of fund flows. I find that the average liquidity of stocks sold increases with the magnitude of fund outflows, and the average liquidity of stock bought increases with the magnitude of fund inflows. This tendency is stronger for outflow-driven sales than inflow-driven purchases since outflow-driven sales are usually more urgent than inflow-driven purchases. Consistently, the analysis using fund-stock-level holding data shows that the flow-driven trade is on average 10% larger for a stock 1 standard deviation more liquid across individual stocks.

Secondly, I investigate the relation between the number of stocks traded and the size of flow-driven trades to study mutual funds' spreading of trades over stocks. If mutual funds simply scale up or down their portfolios proportionally for fund flows as most existing portfolio choice theories describe, they should trade all stocks in their portfolios. Instead, I find mutual funds trade only a fraction of stocks in their portfolios (about 50% to 60% at most) even when facing extremely large fund flows. It might because there are fixed trading costs for trading each stock, and mutual funds' tendency to trade relatively liquid stocks in their portfolios. Then, following Edelen (1999), I do a two-step regression to estimate the relation between the number of stocks traded and the size of flow-driven trades. In the first step, I regress the total dollar trading amount on fund flows to measure the size of flow-driven trades. In the second step, I regress the number of stocks traded on this measure of flow-driven trades. The result shows that a 1% increase of outflow-driven sales on average leads to a 1% increase of the number of stocks sold, and a 1% increase of inflow-driven purchases leads to about 0.7% increase of the number of stocks bought on average. Mutual funds indeed trade substantially more stocks for larger flow-driven trades, and they trade even more stocks for outflow-driven sales than inflow-driven purchases. Moreover, I show that across mutual funds, the average amount sold per stock sold does not increase with the total dollar amount of the outflow-driven sales, which is in accordance with the prediction that mutual funds trade more stocks to have a smaller trading amount on each stock and thus reduce the overall price impact of trades.

Thirdly, I study the effect of flows on stock holdings and cash holdings over time. Specifically, I regress the changes of stock holdings on current and lagged flows. The result shows that the effect of flows on stock holdings lasts about a year. Instead of digesting all the flows in the same quarter, mutual funds on average delay about 13% of their flow-driven trades to the 3 quarters followed. They spread their flow-driven trades over time. Consistently, the effect of flows on cash holdings also lasts about a year. In addition, I find that large funds and small-cap funds spread their flow-driven trades over time more than small funds and large-cap funds do, and mutual funds on average spread outflow-driven sales over time more than they spread inflow-driven purchases. Since large funds and small-cap funds face larger price impact of trades than small funds and large-cap funds, and outflow-driven sales have larger price impacts than inflow-driven purchases, these results are in accordance with the conjecture that the price impact of trades is the hidden cause of the spreading of trades.

Finally, I do a rolling-window analysis to check the robustness of my findings in each sub-period, and document a time trend of mutual funds' trading-cost-management behavior. All findings are robust in all sub-periods, and mutual fund spread their trades over time less as the stock market becomes more liquid in the past decades. Moreover, I find stronger evidence of trading cost management for unexpected flow-driven trades than expected flow-driven trades, which fits well with the prediction that mutual funds prepare in advance for the expected flow-driven trades and therefore rely less on the other trading-cost-management behavior.

This paper contributes to four threads of literature. Firstly, as mentioned at the beginning of this paper, it provides direct empirical evidences to the theoretical literature on the portfolio choice with trading costs, which has developed rapidly in the previous decade. There are only few empirical papers documenting trading-cost-management behavior of funds, and their analyses are limited to the liquidity of the stocks traded during the crisis period. For example, Ben_David, Franzoni and Moussawi (2012) show that hedge funds sold more liquid stocks than illiquid stocks at the peak of 2008 financial crisis; Manconi, Massa, and Yasuda (2012) document that in August 2007, mutual funds sold liquid securities first; and Ben-Rephael (2014) finds that mutual funds, on aggregate, reduce their holdings of illiquid stocks during crisis periods. Different from these papers, my analysis covers three different aspects of trading cost management using the complete sample for both crisis periods and non-crisis periods. From the perspective of dynamic portfolio liquidity management, Huang (2015) and Rzeznik (2015) show mutual funds adjust their portfolio liquidity dynamically in response to the changes in market volatility. Rather than focusing on the relation between portfolio liquidity and market condition, my paper pins down this analysis to the trading cost management of flow-driven trades, and enriches this analysis to the number of stocks traded and the time length of trades as well. Therefore, this paper does a more thorough and complete comparison between real-world trading behavior of mutual funds and the predictions in theories of portfolio choice with trading costs. To my best knowledge, this paper is the first one documenting that mutual funds spread their trades over stocks (trade more stocks) to reduce price impact of trades.

Secondly, this paper complements the growing literature documenting large price impact of flow-driven trades. Coval and Stafford (2007) document large price impacts on the stocks facing large aggregate flow-driven trades. Lou (2012) further documents that those price impacts are highly time persistent because fund flows are highly persistent. Lou (2012) assumes mutual funds simply scale up or down their portfolios proportionally when facing large fund flows. I complement their results by showing that mutual funds actually adjust their trading behavior from many aspects to reduce the price impact of their flow-driven trades.

Thirdly, it contributes to the thread of literature that studies the reason why fund size erodes fund performance. The mainstream explanation is that high price impact costs of large funds erode their returns and impede the flexibility of their investments. Chen, Hong, Huang and Kubic (2004) is the first paper which documents this “diseconomies of scale”. They show that this size effect is most pronounced for funds that play small-cap stocks, and thus they argue trading cost is an important reason why size erodes performance. Following Chen, Hong, Huang and Kubic (2004), some papers further verify the role of trading cost in this size effect: Yan (2008) measures portfolio liquidity of mutual funds and finds that this size effect is stronger for less liquid portfolios as well as high-turnover funds; Pollet and Wilson (2008) find that large funds and small-cap funds diversify their portfolios in response to fund inflow. Greater diversification, especially for small-cap funds, is associated with better performance. However, the diversification of their portfolios is not a direct measure of their trading-cost-management behavior. In this paper, I document the trading-cost-management behavior of mutual funds directly. The behavior of mutual funds to reduce price impact of trades confirms that price impact costs of large trades are indeed a big concern to mutual funds and therefore has the potential to erode fund performance. Consistent with their findings, I also find some evidence that large funds and small-cap funds manage their price impact costs more than small funds and large-cap funds do. In short, the behavior to reduce price impact costs documented in this paper further supports the believe that the price impact of trades is the main driving factor of the "diseconomies of scale" in mutual funds.

Last but not least, this paper also contributes to the thread of literature that shows flow-driven trades (liquidity-motivated trades) erode fund performance. It is marked by the groundbreaking paper Edelen (1999), which reports a statistically significant indirect cost in the form of a negative relation between a fund's abnormal return and investor flows. The existence of trading-cost-management behavior on flow-driven trades indicates that high trading costs of flow-driven trades is (at least one of) the hidden cause of this negative relation.

The organization of the paper is as follow. Section 2 outlines the data and liquidity measure used in this paper. Section 3 lists the hypotheses. Section 4 documents the empirical evidences of the three aspects of trading-cost-management behavior: 4.1 for the "trading of liquid versus illiquid stocks"; 4.2 for the "spreading of trades over stocks"; and 4.3 for the "spreading of trades over time". In each subsection, I provide evidence using both portfolio analysis and regression analysis. In addition, 4.4 documents the time trend of mutual funds trading-cost-management behavior, and 4.5 compares the trading-cost-management behavior for unexpected fund flows and expected fund flows. Section 5 concludes.

1.2. Data

I derive the basic information of mutual funds from the CRSP Mutual Fund files, and the quarterly stock holdings for each fund manager from Thomson Reuters CDA/Spectrum Holdings Database. These two mutual fund databases have been used extensively in the literature, for example, Wermers (2000), Pollet and Wilson (2008), Lou (2012), Petajisto (2013) etc.. I merge these two mutual funds datasets using the "active share" data provided on Petajisto's data page[5]. It provides the mapping between CRSP and Thomson-Reuters U.S. equity mutual fund identifiers using a common and unique fund identifier, Wharton Financial Institution Center Number (WFICN). As in Petajisto (2013), my

[5]Petajisto's data page: http://www.petajisto.net/data.html.

merger of these two datasets includes funds with an objective code as "aggressive growth, growth, growth and income, equity income, growth with current income, income, long-term growth, maximum capital gains, small capitalization growth, unclassified or missing" and at least 70% equity holdings on average. The period of the data is from 1980 to the end of the third quarter of 2009, which is limited by the data available on Petajisto's data page. In addition, information of individual stocks comes from the CRSP stock files.

Moreover, to eliminate the apparent data error, I require the ratio of the stock holdings to total net assets (TNA) to be between 0.6 and 1.2, and the TNAs reported by CDA/Spectrum and CRSP do not differ by more than a factor of two ($0.5 < TNA^{CRSP}/TNA^{CDA} < 2$). This procedure is similar to those in Coval and Stafford (2007) and Lou (2012).

Following prior literature (e.g., Chen etc. 2004, Alexander, Cicci and Gibson 2007, Coval and Stafford 2007), I estimate fund flows using the CRSP series of monthly TNA and returns. The net flow of funds to mutual fund i during month t is defined as

$$FLOW_{i,t} = TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t}) \tag{1.1}$$

$$flow_{i,t} = \frac{FLOW_{i,t}}{TNA_{i,t-1}} \tag{1.2}$$

Where $TNA_{i,t}$ is the CRSP TNA value for fund i at the end of month t, and $R_{i,t}$ is the monthly return for fund i over month t. I sum monthly flows for all share classes belonging to a common fund to compute the total fund monthly flow. In order to match with the quarterly holdings data, I sum monthly flows over the quarter to calculate quarterly flows. Most of my analysis uses the percentage flow which is the dollar value of fund flow $FLOW_{i,t}$ as a percentage of beginning of period TNA, $TNA_{i,t-1}$, as equation (1.2) shows. Following Coval and Stafford (2007), I only keep the flows between -50% and 200% to eliminate all the extreme data.

To measure the stock liquidity, I use the ILLIQ measure proposed in Amihud (2002), which is widely used in liquidity literature in the previous decade. Specifically, for each stock in each quarter t, I calculate its ILLIQ values using its daily data in the past year. As shown in equation (1.3), ILLIQ value for stock j, in year y, $ILLIQ_{j,y}$, is calculated as the past year average of the absolute value of the daily return, $|R_{j,y,d}|$, divided by the daily dollar trading volume, $VOLD_{j,y,d}$. $D_{j,y}$ is the total number of trading days for stock j in year y. I use annually average ILLIQ to smooth the fluctuations of ILLIQ values over time, since my analysis relies on the dispersion of stock's liquidity level in cross section rather than its time variation. For Nasdaq, following Atkins and Dyl (1997) and Massa and Phalippou (2005), I divide the trading volume by 2 to account for inter-dealers trading. Finally, I winsorize the past-year ILLIQ at 1% level every quarter to reduce the influence of outliers. Following Amihud (2002), I use the natural logarithm of ILLIQ, lnILLIQ, instead of ILLIQ to make sure that the regression results are not driven by the extremely large ILLIQ values of small stocks, which have values of liquidity measures substantially larger than that of liquid stocks.

$$ILLIQ_{j,y} = \frac{1}{D_{j,y}} \sum_{t=1}^{D_{j,y}} \frac{|R_{j,y,d}|}{VOLD_{j,y,d}} \tag{1.3}$$

Table 1.1 reports the summary statistics for the merged data from CRSP and Thomson Reuters CDA databases at the end of each year from 1980 to 2008. Consistent with previous literature, the number of mutual funds in my sample increased substantially in 1990s, from 293 in 1990 to 1115 in 2000, and dropped slightly in the 2008 financial crisis. Number of fund families, average fund TNA and combined fund TNA all follow the same trend. Average percentage stock holdings ranges from 69.7% to 95.7%, which is in accordance with my sorting criteria for equity mutual funds. Average cash holding ranges from 3.1% to 8.6%. It is worth noting that the sum of stock holdings and cash holdings is close but not exactly equals to 100%, which indicates the equity mutual funds in my sample also hold small amount of other assets such as government and corporate bonds etc.

[Insert Table 1.1 about here]

In addition, I construct the flow deciles to study the trading behavior of mutual funds when there are large flows. In each quarter from 1980 q1 to 2009 q3, I sort mutual funds into flow deciles according to their net flows in this quarter. Decile 1 for the funds with the largest outflows, and decile 10 for those with largest inflows. Fund flows are measured as a percentage of beginning-of-quarter TNA as shown in equation (1.2). There are about 7300 fund-quarter observations for each flow decile.

Table 1.2 presents the average fund characteristics and trading behavior of mutual funds by flow deciles. Panel A reports the fund characteristics. It shows that the dispersion of fund flows is substantial, from -13.7% for flow decile 1 to 34.8% for decile 10; the average dollar flows also follows our sorting criteria; change of stock holdings are mostly positive (except for flow decile 1) and increases with the fund flows deciles; quarterly returns are higher on average for fund-quarter observations with inflows than for those with outflow; funds with large inflows/outflows are smaller on average; "Average Holding/TNA (%)" decreases with the increase of inflows, and "Average Cash/TNA (%)" increases with the increase of inflows (cash serves as a liquidity cushion). Panel B reports the fund trading behavior by flow deciles. It shows that consistent with our intuition, "Fraction of Positions Expended" decreases with outflow and increases with inflow; "Fraction of Positions Reduced" increases with outflow and decreases with inflow; and "Fraction of Positions Eliminated" decreases with inflow. There are more positions expended than reduced during inflow periods, and more positions reduced than expended during outflow periods.

[Insert Table 1.2 about here]

1.3. Hypotheses

In this section, I am going to establish the hypotheses of mutual funds' trading-cost-management behavior. There are mainly three types of trading costs in stock market:

Fixed Trading Cost: fixed dollar amount is charged for each trade on each stock;

Proportional Trading Cost: fixed proportion of the dollar amount traded is charged;

Quadratic Trading Cost (price impact cost): the dollar trading cost increases quadratically with the dollar trading amount.

To mutual funds, the fixed trading cost is mostly in the form of human capital for executing and monitoring the trades on each individual stock. Fixed brokerage fee per trade is common for small trades, but not for large trades made by mutual funds. The proportional trading cost is a very common form of explicit trading costs for mutual funds. For example, brokerage fees are usually charged as a percentage of the trading amount. The quadratic trading cost is the implicit trading cost introduced by the price impact of trades. Many papers (e.g. Chan and Lakonishok 1995, Keim and Madhavan 1997) document a price impact of trade increasing with the trading amount. Since the dollar trading costs introduced by the price impact is the product of the price impact and the trading amount, the dollar trading cost increases more than linearly (quadratically) with the trading amount.

In this paper, I test the hypotheses of funds' trading-cost-management behavior from three aspects:

(1) The trading of liquid stocks versus illiquid stocks;

(2) The spreading of trades over stocks (trade more stocks);

(3) The spreading of trades over time.

I firstly establish the benchmark of my tests. If there is no trading cost, or mutual funds do not manage their trading costs, they respond to fund inflows/outflows by simply scaling up/down their portfolios proportionally and instantly. So we have

Benchmark: *Mutual funds scale up/down their portfolios proportionally and instantly when facing fund inflows and outflows.*

To reduce trading costs and the price impact of trades, mutual funds are supposed to trade more liquid stocks than illiquid stocks to fulfill the outflows or digest the inflows. Therefore, we have

Hypothesis 1: *Mutual funds trade more liquid stocks than illiquid stocks for flow-driven trades.*

H_0 : *The average liquidity of stocks sold/bought does not change with outflows/inflows.*

H_1 : *The average liquidity of stocks sold/bought increases with outflows/inflows.*

To test this hypothesis, I regress the average ILLIQ values of all stocks sold/bought by each fund on its outflows/inflows, and test whether the coefficients of fund outflows/inflows (β_1 in regression 1.4 & 1.5 in next section) are significantly different from 0. To further pin down this analysis to fund-stock level, I also test

H_0 : *The changes of holdings caused by fund flows are proportional for liquid stocks and illiquid stocks.*

H_1 : *The changes of holdings caused by fund flows are larger for liquid stocks than illiquid stocks.*

Here I regress the changes of holdings of each stock held by each fund on its fund flows and the interaction term of fund flows and stock ILLIQ values, and test whether the coefficient of this interaction term (γ_3 for $flow_{i,t} \times lnILLIQ_{j,t-1}$, in regression 1.6 in next section) is significantly negative.

If there is fixed trading cost for trading each stock, it is too costly to trade all the stocks in the portfolio every time they face fund flows. So for each stock, they are supposed to weight the fixed trading cost with the cost of not trading it. It will make them trade only a proportion of stocks in their portfolios when facing fund flows, especially when facing small fund flows.

Hypothesis 2: *Mutual funds trade only a proportion of stocks in their portfolios when facing fund flows.*

H_0 : *The number of stocks sold/bought equals the total number of stocks in the portfolio when there are fund outflows/inflows.*

H_1 : *The number of stocks sold/bought is smaller than the total number of stocks in the portfolio when there are fund outflows/inflows.*

When mutual funds face a large fund flow, the price impact cost becomes a more primary concern to them than fixed trading cost. To reduce the price impact cost, mutual funds can either trade more stocks (with smaller trading amount in each stock) or spread their trades over time (with smaller trading amount at each time point). Thus we have

Hypothesis 3: *Mutual funds spread their flow-driven trades over stocks (trade more stocks) for large fund flows.*

H_0 : *The number of stocks sold/bought does not increase with the total dollar amount of outflow-driven sales/inflow-driven purchases.*

H_1 : *The number of stocks sold/bought increases with the total dollar amount of outflow-driven sales/inflow-driven purchases.*

I regress the number of stocks sold/bought on the total dollar amount of outflow-driven sales/inflow-driven purchases (estimated from a first-step regression of trades on flows), and test whether the coefficients of outflow-driven sales and inflow-driven purchases (β_1 in regression 1.12 & 1.13 in next section) are significantly positive.

Hypothesis 4: *Mutual funds spread their flow-driven trades over time.*

H_0 : *The changes of stock holdings are not correlated with the past fund flows.*

H_1 : *The changes of stock holdings are positively correlated with the past fund flows.*

I regress the changes of stock holdings on the current and lagged fund flows, and test whether the coefficients of current and lagged fund flows (β_c, $c = 1, 2, ..., 6$, in regression 1.15 in next section) are significantly positive.

Theoretically, Garleanu and Pedersen (2013) recommend investors to "trade gradually towards the aim" and "aim in front the target", which share the spirit of my prediction that they should "spread their trades over time". Empirically, Huang (2015) finds that mutual funds increase their cash holdings when expected market volatility is high, which is consistent with my later finding that mutual funds use cash buffers to spread the flow-driven trades over time.

Moreover, Hypothesis 3 & 4 are well in accordance with the empirical evidence of the price impact of trades documented in previous literature, and supplement the thread of literature which argues that the size of mutual fund erodes performance. Since Chen, Hong, Huang and Kubic (2004) first documents this effect, papers in this thread consistently agree that the trading cost is the primary driver of this *"diseconomies of scale"*. Chen, Hong, Huang and Kubic (2004) document that fund size erodes the performance of small-cap funds more; Yan (2008) extends this analysis and find that this effect is more pronounced for funds with less liquid portfolios and more trading motives; Pollet and Wilson (2008) show funds holding larger number of stocks perform better and this effect is also larger for small-cap funds; more directly, Edelen, Evans and Kadlec (2007) test the effect of trading costs on fund performance and find that relative trade size subsumes fund size in regressions of fund returns.

Then the most direct question is which type of trading costs has the potential to cause the *"diseconomies of scale"*? Fixed trading cost leads to a *"economies of scale"* instead of *"diseconomies of scale"* since the fixed trading cost does not increase with the fund size.

Proportional trading cost is corresponding to *"constant economies of scale"*. Therefore, the quadratic trading cost (price-impact cost) is the only type of trading cost that has the potential to generate *"diseconomies of scale"*. More strictly, the necessary condition for a type of trading cost to generate the *"diseconomies of scale"* is that it is increasing and convex in the size of trade. This statement is consistent with a key assumption in Berk and Green (2004) that, "Costs are increasing and convex in the amount of funds under active management", which is indispensable for their model to get the *"diseconomies of scale"* as a crucial implication. Moreover, many papers document the empirical evidence that in stock market, the price impact of trades indeed increases with the trade size (e.g. Chan and Lakonishok 1995, Keim and Madhavan 1997). To sum up, all those evidence mentioned above consistently indicate that trading costs increase more than proportionally to the trade size.

If trading costs are increasing and convex in trade size, sophisticated mutual funds are supposed to split their trades to reduce the average trade size and thus reduce the price impact costs[6]. Theoretically, mutual funds can do it in two ways:

(1) Spread trades over stocks (trade more stocks) to reduce the trade size on each stock;

(2) Split large trades to small trade packages and spread it over time[7];

Papers, such as Chan and Lakonishok (1995), document that institutional investors indeed broke up their large trades to smaller trade packages to reduce price impact. To my best knowledge, there is no paper documenting that investors trade more stocks to reduce the total trading costs. The most related paper is Pollet and Wilson (2008), which shows mutual funds increase the number of stocks in their portfolios in response to fund inflows, and those funds holding more stocks on average perform better. Different from Pollet and Wilson (2008), I investigate directly the relation between the total trading amount and the number of stocks traded, and focus on outflow periods more than inflow periods. In Pollet and Wilson (2008), the increase of the number of stocks in their portfolios might be caused by the additional money put into those new profitable

[6]Different from quadratic trading cost, fixed trading cost gives investor incentive to trade less stocks rather than more; and if trading costs are proportional to trade size, investors will be indifferent between trading small number of stocks and large number of stocks. For example, if the proportional trading cost is 3%, the trading cost is always \$3 whatever you trade \$100 of 1 stock or 2 stocks with \$50 each.

[7]Consistent with this conjecture, Garleanu and Pedersen (2013) recommend investors to "trade gradually towards the aim" and "aim in front of the target" to reduce the price impact cost.

investment opportunities. My result documents directly their spreading of trades over stocks. Besides, since the number of stocks held is the upper limit of the number of stocks can be sold, the pricing effect documented in Pollet and Wilson (2008) might be partially driven by the trading costs saved by spreading the trades over stocks.

Finally, mutual funds are also expected to manage the price impact of outflow-driven sales more than inflow-driven purchases. Because outflow-driven sales caused by redemption are more urgent and inelastic than inflow-driven purchases, outflow-driven sales face larger price impact costs than inflow-driven purchases (as documented in Coval and Stafford 2007). In addition, outflow-driven sales are close to purely liquidity-motivated, while inflow-driven purchases are to a certain extent information based (Chan and Lakonishok 1993, Keim and Madhavan 1996). It also makes trading cost management a higher priority for outflow-driven sales than for inflow-driven purchases. So we have

Hypothesis 5: *Mutual funds manage the trading costs of outflow-driven sales more than those of inflow-driven purchases.*

H_0 : *All three aspects of trading-cost-management behavior (Hypothesis 1, 3 &4) are the same (or less prominent) for outflow-driven sales than inflow-driven purchases.*

H_1 : *All three aspects of trading-cost-management behavior (Hypothesis 1, 3 &4) are more prominent for outflow-driven sales than inflow-driven purchases.*

1.4. Trading-cost-management behavior on flow-driven trades

Here I test the hypotheses for each aspect of trading cost management in a separate subsection.

1.4.1. Trading of liquid stocks vs. illiquid stocks

When facing large fund flows, mutual funds have the incentive to trade more liquid stocks than illiquid stocks to reduce the trading costs and the price impact of trades. In this subsection, I test the ***Hypothesis 1*** using both fund-level data and fund-stock-level holding data.

Portfolio analysis for the trading of liquid stocks vs. illiquid stocks

Figure 1.1 plots the average liquidity of stocks sold (relative to the portfolio liquidity) across outflow deciles. We see the curve for the illiquidity (the natural logarithm of ILLIQ) of stocks sold decreases monotonically from 0.27 for flow decile 6 to 0.07 for flow decile 1 (largest fund outflows), which means the stocks sold by mutual funds when facing large fund outflows are 20% more liquid (the price impact of trades is 20% smaller) on average than those sold during normal time. Consistently, Figure 1.2 shows the illiquidity of stocks bought decreases from 0.27 for flow decile 6 to 0.19 for flow decile 10 (largest fund inflows), which means the stocks bought by mutual funds when facing large fund inflows are 8% more liquid (the price impact of trades is 8% smaller) on average than those bought during normal time. These two patterns strongly support the *Hypothesis 1*. Besides, the different results for outflow-driven sales and inflow-driven purchases also indicate that mutual funds manage the trading costs of outflow-driven trades more than that of inflow-driven purchases, and thus also supports the *Hypothesis 5*.

[Insert Figure 1.1 about here]

[Insert Figure 1.2 about here]

Column 6 & 7 in Table 1.3 report the average natural logarithm of ILLIQ (lnILLIQ) of stocks sold/bought relative to the average lnILLIQ of all stocks in funds' portfolios plotted in Figure 1.1 and 1.2. Consistent with the plots, column 6 shows a clear increasing trend across flow deciles, and column 7 shows a clear decreasing trend. In addition, the fact that all values in column 6 and 7 are positive indicates that, for the trades of mutual funds' active investment strategies, they trade more illiquid stocks than liquid stocks. It is because small and illiquid stocks usually have more arbitrage opportunities than large and liquid stocks do.

Besides, as shown in column 3, the average portfolio illiquidity shows a hump shape across flow deciles. It is higher for funds with more extreme inflows or outflows than funds with only moderate fund flows. This hump shape indicates that stocks held by funds with more extreme inflows or outflows are on average less liquid than funds with moderate fund flows. It is probably because small-cap funds are on average more likely to experience large fund flows than large-cap funds do. Since stocks sold or bought by mutual funds are on average more liquid if the stocks held by them are more liquid, column 4 and 5 follow the same pattern.

[Insert Table 1.3 about here]

Fund-level regression

To provide formal statistical evidence, I analyze whether mutual funds sold (bought) more liquid stocks than illiquid stocks when there are larger outflows (inflows) using fund level data. Specifically, I regress the average lnILLIQ values of all stocks sold/bought on the fund flows as a percentage of TNA, controlling for the average lnILLIQ values of all stocks in their portfolio, equation (1.4) for stocks sold and equation (1.5) for stocks bought. The dollar weighted average lnILLIQ of all stocks sold/bought/held are calculated separately in each quarter t for each fund i. Since I focus on the flow-driven trades only, I use the outflow samples only for regression (1.4) to study the effect of outflows on average lnILLIQ values of stocks sold, and inflow samples only for regression (1.5) for the effect of inflows on stocks bought.

$$lnILLIQ\_sold_{i,t} = \alpha_0 + \beta_1 * flow_{i,t} + \gamma_2 * lnILLIQ\_held_{i,t} + \varepsilon_{i,t} \tag{1.4}$$

$$lnILLIQ\_bought_{i,t} = \alpha_0 + \beta_1 * flow_{i,t} + \gamma_2 * lnILLIQ\_held_{i,t} + \varepsilon_{i,t} \tag{1.5}$$

Both quarter and fund fixed effects are added and the standard errors are clustered at the fund level. Similar results are derived when standard errors are clustered at the quarter level.

[Insert Table 1.4 about here]

Table 1.4 shows that the coefficient of fund flow is significantly positive for the regression of outflow-driven sales (0.30 with a t statistic of 5.73), which means the average liquidity of all stocks sold is 3% higher (the price impact of sales is 3% smaller) for an outflow about 10% of TNA larger. This positive coefficient is consistent with the positive slope in Figure 1.1. Since I control for both fund and quarter fixed effects in regression (1.4), the economic effect estimated here is smaller than that estimated in the portfolio analysis in previous subsection, and thus this estimate can be seen as a lower bound of this effect. The coefficient of fund flow is significantly negative for the regression of inflow-driven purchases (-0.16 with a t statistic of 7.60), which means the average liquidity of all stocks bought is 1.6% higher (the price impact of purchases is 1.6% smaller) for an inflow about 10% of TNA larger. This negative coefficient is also consistent with the negative slope in Figure 1.2.

This result is consistent with the findings in Ben_David, Franzoni and Moussawi (2012) and Manconi, Massa, and Yasuda (2010). Ben_David, Franzoni and Moussawi (2012) find that hedge funds sold more liquid stocks than illiquid stocks at the peak of 2008 financial crisis to reduce the trading costs, and Manconi, Massa, and Yasuda (2010) document that in August 2007, mutual funds sold liquid securities first for the same reason. Besides, the regression result further supports *Hypothesis 5* by showing mutual funds' tendency to trade liquid stocks for large fund flows is stronger for outflow samples (0.30) than inflow samples (-0.16).

Fund-stock-level regression

In the fund-level analysis, I have documented robust evidence that during the periods with large fund flows, the stocks traded by mutual funds are on average more liquid than stocks traded during normal periods. However, we still do not know whether mutual funds trade liquid stocks more than simply scaling up/down their portfolios proportionally for fund flows. In this subsection, I analyze the holding data of liquid stocks and illiquid stocks at the fund-stock level to answer this question. I find clear evidence that mutual funds trade liquid stocks more than simply scaling up/down their portfolios proportionally for fund flows. The regression is as below,

$$trade_{i,j,t} = \alpha_0 + \beta_1 flow_{i,t} + \gamma_2 X + \gamma_3 flow_{i,t} X + \beta_4 lnHolding_{i,j,t-1} + \varepsilon_{i,t} \tag{1.6}$$

The dependent variable, $trade_{i,j,t} = \frac{shares_{i,j,t} - shares_{i,j,t-1}}{shares_{i,j,t-1}}$, is the changes of number of shares of stock j held by fund i in quarter t as a percentage of the number of shares of stock j held by fund i at the beginning quarter t. The main independent variable is the fund flows as a percentage of fund TNA $flow_{i,t}$. If mutual funds digest all their flows in the same quarter and keep their portfolio weight exactly the same as before, β_1 should equal to 1. X is a set of variables that reflect trading costs. I include the measure of stock liquidity $lnILLIQ_{j,t-1}$ for each stock j; stock ownership, $own_{i,j,t-1}$, shares of stock j held by fund i as a percentage of total shares of stock j outstanding in the market; and also the portfolio-weighted $lnILLIQ$ and average ownership share ($lnILLIQ\_held_{i,t}$ and $own_{i,t-1}$). In addition, I include their interaction terms with the fund outflows to the right side of the equation to study how funds trade liquid and illiquid stocks differently for flow-driven trades. If mutual funds indeed trade the relatively illiquid stocks less (or funds with relatively illiquid portfolios trade less) for fund flows, all values in vector γ_3 should be negative. To separate the results of inflow-driven purchases and outflow-driven sales, I analyze inflow samples and outflow samples separately. Both quarter and fund fixed effects are added and the standard errors are clustered at the fund level.[8] Since the dependent variable $trade_{i,j,t}$ strongly depends on fund j's initial holdings of stock i, if the initial holding of stock i equals zero (or is very small), $trade_{i,j,t}$ would be infinite (or extremely large) even with only a slight increase in holding, which adds noise to the regression results. Thus I eliminate all fund-stock observations with initial holdings, $holding_{i,j,t-1}$, smaller than 0.2% of the fund TNA. It leaves us about half of the sample. In addition, I add the natural logarithm of dollar initial holdings, $lnHolding_{i,j,t-1}$ as a control variable.

[Insert Table 1.5 about here]

The results in Table 1.5 show that the coefficients of the interaction term of fund flow and stock illiquidity $flow_{i,t} \times lnILLIQ_{j,t-1}$ are significantly negative (0.02 for all four settings). Consistent with the prediction of Hypothesis 1, the holdings of liquid stocks change more with fund flows than the holdings of illiquid stocks. Given the standard deviation of $lnILLIQ_{j,t}$ is 2.7 across individual stocks, a flow of 1% of fund TNA leads to 0.054% more changes of holdings for a 1 standard deviation more liquid stock (in addition to a change of 0.5% holdings on average), which means mutual funds trade a stock 10.8% more for fund flows if it becomes 1 standard deviation more liquid. Besides, I find weak evidence that funds trade the stocks they hold a lot (high $own_{i,j,t-1}$) less. The coefficient of the interaction term of fund flow and stock ownership $flow_{i,t} \times own_{i,j,t-1}$ is negative in 3 out of 4 settings but mostly insignificant. It is worth noting that in

[8] I also include the stock-quarter fixed effects for robustness check, all the main results stay the same.

settings "Outflow (2)" and "Inflow (2)", the coefficients of the interaction term of fund flows and portfolio-weighted average lnILLIQ, $flow_{i,t} \times lnILLIQ\_held_{i,t}$, are both not significant, while the coefficients of interaction term of fund flow and stock illiquidity $flow_{i,t} \times lnILLIQ_{j,t-1}$ are always significantly negative. It tells us the truth is indeed that funds on average trade relatively liquid stocks in their portfolios more for fund flows, rather than funds which hold more liquid stocks trade more for fund flows. To sum up, the results of fund-stock-level analysis confirm the previous finding that mutual funds trade more liquid than illiquid stocks for flow-driven trades to reduce trading costs.

Besides, Table 1.5 show that the coefficient β_1 of outflow sample is significantly positive, which is 0.56 for setting âOutflow (2)â. It means 1% more of fund outflows on average leads to 0.56% more sales of each position in the same quarter. Similarly, the coefficient β_1 of inflow sample shows that 1% more of fund inflows on average leads to 0.42% more purchases of each position in the same quarter. The fact that the β_1 is smaller than 1 for both inflow and outflow samples indicates that fund only digest part of their fund flows into the portfolio in the same quarter. One thing worth noting is that I only include large stocks holdings (>0.2% of fund TNA) into the regression analysis, so the result for small holdings and the entire sample can be different.

1.4.2. The spreading of trades over stocks

If there is fixed trading cost of trading each stock, it is costly for mutual funds to simply scale up or down their portfolios for fund flows and trade all stocks in their portfolios. So they might choose to trade only a fraction of their stocks in their portfolios when the fund flows are small (*Hypothesis 2*). When fund flows become larger, mutual funds are expected to trade more stocks (spread trades over stocks) to reduce the average price impact of trades, even though they need to pay more fixed costs for trading more stocks (*Hypothesis 3*).

Portfolio analysis for the spreading of trades over stocks

Before testing those hypotheses formally using regressions, first I document the trading behavior of mutual funds by flow deciles. Figure 1.3, Figure 1.4 and Table 1.6 report the total trading amount, average trading amount for each stock traded and number of stocks traded by fund flow deciles, for sales and purchases separately. All of them show that mutual funds trade only a fraction of stocks in their portfolios even when facing extremely large fund flows, and they trade more stocks when flows are larger.

Column 3 of Table 1.6 reports the percentage of holdings sold,

$$\overline{sold}_{i,t} = \frac{\sum_{i,t} Sold_{i,t}}{\sum_{i,t} Holding_{i,t-1}} (= \overline{sold}_{i,j,t} = \frac{\sum_{i,j,t} Sold_{i,j,t}}{\sum_{i,j,t} Holding_{i,j,t-1}}) \tag{1.7}$$

$\overline{sold}_{i,t}$ is the average dollar amount of stocks sold as a percentage of stock holdings at the beginning of the quarter. $Sold_{i,t}$ is the dollar amount of stock holdings sold by fund i in quarter t, and $Holding_{i,t-1}$ is the dollar amount of all stock holdings of fund i at the end of quarter $t-1$. The weighted average is used, and this average value is the same across fund-quarter observations as across all fund-quarter-stock observations. $\overline{sold}_{i,t}$, the amount sold, increases monotonically with the fund outflows, from -11.7% of total holdings for flow decile 5 (with an average outflow of -1.1%) to -20.6% of total holdings for flow decile 1 (with an average outflow of -12.2%). Correspondingly, we could see the orange curve of Figure 1.3 decreases with the fund outflows roughly in the same speed.

Column 4 of Table 1.6 reports the percentage of holdings sold per stock sold,

$$\overline{sold}_{i,j,t}(sold_{i,j,t} < 0) = \frac{\sum_{i,j,t} Sold_{i,j,t}}{\sum_{i,j,t} Holding_{i,j,t-1}}, s.t. Sold_{i,j,t} < 0 \tag{1.8}$$

$\overline{sold}_{i,j,t}(sold_{i,j,t} < 0)$ is similar to the percentage of holdings sold, $\overline{sold}_{i,j,t}$, mentioned above but includes only those fund-quarter-stock observations with a negative change of holdings in quarter t. $Sold_{i,j,t}$ is the dollar amount of stock j sold by fund i in quarter t, and $Holding_{i,j,t-1}$ is the dollar amount of stock j held by fund i at the end of quarter $t-1$.

Column 5 of Table 1.6 reports the number of stocks sold as a percentage of the number of stocks in the portfolio,

$$\overline{\#sold}_{i,t} = \frac{\sum_{i,t} \#Sold_{i,t}}{\sum_{i,t} \#Held_{i,t}} \tag{1.9}$$

$\overline{\#sold}_{i,t}$ is the average number of stocks sold as a percentage of total number of stocks in the portfolio across all fund-quarter observations. $\#Sold_{i,t}$ is the number of stocks sold by fund i in quarter t, and $\#Held_{i,t}$ is the number of stocks in fund i's portfolio in quarter t. Column 5 shows the number of stocks sold, $\overline{\#sold}_{i,t}$, increases monotonically with fund outflows, from 30.3% of the number of stocks in the portfolio (for flow decile 5) to 52.1% of the number of stocks in the portfolio (for flow decile 1). It never goes to 100% (If the *Null Hypothesis* is true, the number of stocks sold should always be 100% of the number of stocks in the portfolio). Therefore, this result confirms *Hypothesis 2* and indicates fixed trading cost play an important role at mutual funds trading behavior, at least for flow-driven trades.

More interestingly, while the number of stocks sold, $\overline{\#sold}_{i,t}$, increases substantially with fund outflows, the percentage of holdings sold per stocks sold, $\overline{sold}_{i,j,t}(sold_{i,j,t} < 0)$, increases only slightly from 31.0% (for flow decile 5) to 32.5% (for flow decile 1), and such increase is not monotonic. The percentage of holdings sold per stock sold for flow decile 3 and 4 are 30.1% and 30.5% respectively, even lower than the 31.0% for flow decile 5. Consistently, Figure 1.3 shows the blue curve (number of stocks sold) increases substantially with fund outflows, while the green curve (average amount sold per stock sold) does not change. These evidence suggest that when mutual funds need to release more stock holdings to fulfill larger fund outflows, they balance the price impact costs and the fixed trading costs. Consistent with *Hypothesis 3*, they sell more stocks to reduce the average price impact of trades even though they need to pay more fixed costs for that.

[Insert Figure 1.3 about here]

[Insert Figure 1.4 about here]

Different from outflow-driven sales, columns 7 and 8 of Table 1.6 (corresponding to the orange curve and blue curve in Figure 1.4) show that both the number of stocks bought, $\overline{\#bought}_{i,t}$, and the percentage of holdings bought per stock bought, $\overline{bought}_{i,j,t}$ ($bought_{i,j,t} > 0$), increase substantially with fund inflows. It means that when mutual funds need to increase their stock holdings to digest fund inflows, they buy more stocks and more shares of each stock at the same time. It supports the *Hypothesis 5*. They spread outflow-driven sales over stocks more than inflow-driven purchases.

[Insert Table 1.6 about here]

Regression analysis for the spreading of trades over stocks

Here I test *Hypothesis 3* formally by studying the relation between the number of stocks traded and the size of flow-driven trades through regression analysis. If mutual funds manage the price impact of their flow-driven trades by trading more stocks, the number of stocks traded should increase with the size of flow-driven trades.

To distinguish the flow-driven trades from non-flow-driven trades, Edelen (1999) does a two-step regression. In the first step, he regresses the trades on fund flows and uses the fitted part as a proxy of flow-driven trades. In the second step, he uses this proxy to study the relation between flow-driven trades and fund performance. Following the same methodology, in the first step, I regress the natural logarithm of total dollar amount sold $lnSold_{i,t}$ on the natural logarithm of outflows $lnOutflow_{i,t}$, and the natural logarithm of total dollar amount bought $lnBought_{i,t}$ on the natural logarithm of inflows $lnInflow_{i,t}$.

$$lnSold_{i,t} = \alpha_0 + \beta_1 lnOutflow_{i,t} + \varepsilon_{i,t} \tag{1.10}$$

$$lnBought_{i,t} = \alpha_0 + \beta_1 lnInflow_{i,t} + \varepsilon_{i,t} \tag{1.11}$$

I use the fitted part of regression (1.10), $\widehat{lnSold}_{i,t} = \widehat{\alpha_0} + \widehat{\beta}_1 lnOutflow_{i,t}$, as a proxy of outflow-driven sales, and the fitted part of regression (1.11), $\widehat{lnBought}_{i,t} = \widehat{\alpha_0} + \widehat{\beta}_1 lnInflow_{i,t}$, as a proxy of inflow-driven purchases.

Then I regress the natural logarithm of the number of stocks sold (bought), $ln\#Sold_{i,t}$ ($ln\#Bought_{i,t}$), on the proxy of outflow-driven sales $\widehat{lnSold}_{i,t}$ (inflow-driven purchases $\widehat{lnBought}_{i,t}$). The coefficient on $\widehat{lnSold}_{i,t}$ ($\widehat{lnBought}_{i,t}$) measures how much mutual funds spread their flow-driven trades over stocks to reduce the price impact of trades. If the *Null Hypothesis, "mutual funds simply scale up/down their portfolios proportionally when facing fund flows"*, is true, this coefficient should equal to 0 since the number of stocks traded does not increase with the size of flow-driven trades. While if mutual funds trade off the price impact costs against the fixed trading costs and choose to trade more stocks when facing larger fund flows, this coefficient should be significantly positive. In addition, to see whether the spreading of flow-driven trades is stronger for large funds, small-cap funds and large trades, I add the indicators for large funds, $High\_TNA_{i,t-1}$, large-cap funds, $Large\_Cap_{i,t-1}$, large trades, $Large\_Trade_{i,t}$, and their interaction terms with the proxy for outflow-driven sales (inflow-driven purchases), $\widehat{lnSold}_{i,t}$ ($\widehat{lnBought}_{i,t}$), into the regression. Those indicators equal 1 if they are larger than the median, zero otherwise. I do the regression for outflow-driven sales (equation 1.12) using outflow sample only, and the regression for inflow-driven purchases (equation 1.13) using inflow sample only. Both fund and quarter fixed effects are added, and the standard errors are clustered at the fund level. The regressions are as follow,

$$\begin{aligned} ln\#Sold_{i,t} &= \alpha_0 + \beta_1 \widehat{lnSold}_{i,t} + \beta_2 \widehat{lnSold}_{i,t} \times High\_TNA_{i,t-1} \\ &+ \beta_3 \widehat{lnSold}_{i,t} \times Large\_Cap_{i,t-1} + \beta_4 \widehat{lnSold}_{i,t} \times Large\_Trade_{i,t} \\ &+ \beta_5 High\_TNA_{i,t-1} + \beta_6 Large\_Cap_{i,t-1} + \beta_7 Large\_Trade_{i,t} \\ &+ \beta_8 ln\#Held_{i,t} + \beta_9 lnTNA_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{1.12}$$

$$\begin{aligned} ln\#Bought_{i,t} &= \alpha_0 + \beta_1 \widehat{lnBought}_{i,t} + \beta_2 \widehat{lnBought}_{i,t} \times High\_TNA_{i,t-1} \\ &+ \beta_3 \widehat{lnBought}_{i,t} \times Large\_Cap_{i,t-1} + \beta_4 \widehat{lnBought}_{i,t} \times Large\_Trade_{i,t} \\ &+ \beta_5 High\_TNA_{i,t-1} + \beta_6 Large\_Cap_{i,t-1} + \beta_7 Large\_Trade_{i,t} \\ &+ \beta_8 ln\#Held_{i,t} + \beta_9 lnTNA_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{1.13}$$

Moreover, I also document the relation between the number of stocks traded and the size all trades (including both flow-driven trades and non-flow-driven trades) for comparison. Since non-flow-driven trades usually concentrate on a small number of investment opportunities, the increase of number of stocks traded with the increase of trade size should be smaller for non-flow-driven trades than flow-driven trades. So I redo the regression (1.12) and (1.13) using the natural logarithm of total dollar amount of sales $lnSold_{i,t}$ and purchases $lnBought_{i,t}$, instead of the proxies of flow-driven trades $\widehat{lnSold}_{i,t}$ and $\widehat{lnBought}_{i,t}$, as main independent variables. In this case, the coefficients of $lnSold_{i,t}$ and $lnBought_{i,t}$ measure how much the number of stocks traded increases with the trade size for flow-driven trades and non-flow-driven trades on average.

[Insert Table 1.7 about here]

Column "outflow (1) Flow-driven" in Panel A of Table 1.7 reports the result of regression (1.12) for the outflow-driven sales. It shows the coefficient of $\widehat{lnSold}_{i,t}$ is as large as 0.97 with a t statistic about 50, which means 1% increase in the dollar amount of outflow-driven sales leads to about 1% increase in the number of stocks sold on average. More interestingly, the fact that 1:1 increase of outflow-driven sales and number of stocks sold indicates that the average dollar amount of outflow-driven sales for each stock sold (=total dollar amount of outflow-driven sales/total number of stocks sold) does not increase with outflow-driven sales at all, which is consistent with the conjecture that mutual funds trade more stocks to reduce the average trading amount on each stock and thus reduce the average price impact of trades. Similarly, Column "inflow (1) Flow-driven" in Panel B reports that 1% increase in the total dollar amount inflow-driven purchases leads to 0.63% increase of the number of stocks bought on average, which is also substantial but smaller than the 0.97% for outflow-driven sales. These results strongly support *Hypothesis 3, "Mutual funds spread their flow-driven trades over stocks (trade more stocks) for large fund flows"*, and *Hypothesis 5*, *"Mutual funds manage the trading costs of outflow-driven sales more than those of inflow-driven purchases"* since mutual funds spread outflow-driven sales over stocks more than inflow-driven purchases when facing large fund flows.

Besides, column "outflow (2) Flow-driven" in Panel A shows the coefficient of the interaction term of outflow-driven sales and the indicator for large-cap funds, $lnSold_{i,t} \times Large\_Cap_{i,t-1}$, is negative and significant at 1% significance level. Since small-cap funds face larger price impact of trades than large-cap funds do, small-cap mutual funds spread the outflow-driven sales over stocks 5% more than large-cap funds do.

For the relation between the number of stocks traded and the size all trades (including both flow-driven trades and non-flow-driven trades), column "outflow(1)" in Panel A and "inflow(1)" in Panel B report that on average, 1% increase in the total dollar amount of all sales (purchases) leads to 0.53% (0.54%) increase in the number of stocks sold (bought), substantially smaller than the 0.97% for outflow-driven sales, and 0.63% for inflow-driven purchases, which is in accordance with the conjecture that different from flow-driven trades, non-flow-driven trades are limited by the small number of investment opportunities and can hardly be spread to large number of stocks.

To rule out the possibility that contemporary fund flows and the number of stocks traded are correlated with some omitted macroeconomics variables and time-varying fund investment styles, I also use the one-quarter lagged fund flows, instead of the concurrent fund flows, in the first step regression to identify the flow-driven trades. Since flows are persistent over time, lagged flows are positively correlated with the concurrent flows, and lagged flows are less correlated with the contemporary value of other variables. The results in Table 1.8 show that all those main results still hold under this setting.

[Insert Table 1.8 about here]

As shown above, the number of stocks sold increases about 1:1 with the dollar amount of the fund outflow-driven sales. It indicates that mutual funds spread their outflow-driven sales substantially over stocks. By doing that, they kept the trading amount of each position sold low to reduce the average price impact of sales. To perform a direct test that whether the average trading amount of each stock sold was actually kept at a low level by their spreading of flow-driven trades over stocks. I regress the dollar amount of each stock j sold by mutual fund i in quarter t , $lnSold_{i,j,t}$, on the total dollar amount of the fund outflow faced by fund i in quarter t, $lnOutflow_{i,t}$, directly. Only the stocks sold are included into this regression. If the spreading of flow-driven trades works, we are supposed to find a coefficient of $lnOutflow_{i,t}$ close to zero or even slightly negative. In addition, the interaction term of fund outflows with the indicators for large funds, large-cap funds and large trades are also included, and I also control for their initial holdings in each stock.

$$\begin{aligned} lnSold_{i,j,t} \quad = \quad & \alpha_0 + \beta_1 lnOutflow_{i,t} + \beta_2 lnOutflow_{i,t} \times High\_TNA_{i,t-1} \\ & +\beta_3 lnOutflow_{i,t} \times Large\_Cap_{i,t-1} + \beta_4 lnOutflow_{i,t} \times Large\_Trade_{i,t} \\ & +\beta_5 High\_TNA_{i,t-1} + \beta_6 Large\_Cap_{i,t-1} + \beta_7 Large\_Trade_{i,t} \\ & +\beta_8 lnHolding_{i,j,t-1} + \varepsilon_{i,t} \end{aligned} \tag{1.14}$$

[Insert Table 1.9 about here]

The results of Table 1.9 confirm our predictions that dollar amount sold per stock sold on average does not increase (or only increases slightly) with the fund outflows. Setting (1) and (3) report that when both quarter and fund fixed effects are included, 1% increase in fund outflows leads to only about 0.05%-0.15% increase in dollar amount sold per stock sold. Moreover, under setting (2) and (4), when only quarter fixed effects are included, 1% increase in fund outflows even leads to about 0.08%-0.23% decrease in dollar amount sold per stock sold. I find stronger evidence of the "spreading of outflow-driven sales over stocks" across funds than across time. One possible reason is that the number of stocks can be sold is limited by the number of stocks in their portfolios which is quite constant across time. However, the number of stocks in portfolio is quite different across funds, and the probability of facing large fund outflows could be one of the crucial determinants of it. The more likely they are going to face large fund outflows, the more stocks they want to hold to strengthen their ability to spread their outflow-driven sales over stocks. Therefore, a stronger evidence of the spreading of outflow-driven sales over stocks is observed than over time.

1.4.3. Spreading of trades over time

As we have discussed above, mutual funds are supposed to spread their flow-driven trades both over stocks and over time to reduce the average price impact of trades. In this subsection, I study how funds' stock holdings and cash holdings change with the concurrent and lagged fund flows, and test *Hypothesis 4*. If mutual funds spread their trades over time, there should be a positive correlation between fund flows and stock holdings.

[Insert Figure 1.5 about here]

Figure 1.5 plots the average stock holdings and cash holdings as a percentage of fund TNA for all flow deciles, as shown in columns 7 and 8 of Table 1.2. It shows that mutual funds on average have less stock holdings and more cash buffers when there are fund inflows, and more stock holdings and less cash buffers when there are fund outflows. The blue curve for the average stock holdings decreases monotonically with either the increase of fund inflows or the decrease of fund outflows (from 94.1% of total TNA for flow decile 1 to 92.1% of total TNA for flow decile 10). The red curve for cash holdings increases monotonically with either the increase of fund inflows or the decrease of fund outflows (from 4.7% of total TNA for flow decile 1 to 6.5% of total TNA for flow decile 10). This result strongly supports the *Hypothesis 4* against the *Null Hypothesis that mutual funds scale up/down their portfolios proportionally and instantly for fund flows*. If the *Null Hypothesis* is true, the weights of stock holdings and cash holdings should not change across flow deciles. Those changes indicate that mutual funds digest only part of their fund flows in the same quarter. The spreading of trades over time helps to both reduce the price impact of trades and cancel out current flows with future flows. Besides, the difference of cash holdings (or stock holdings) between flow decile 1 (extreme outflows) and 10 (extreme inflows) is about 2% of TNA, which means mutual funds on average use about 2% of TNA for this purpose.

Then I regress the changes of stock holdings (as % of TNA) on current and lagged flows (as % of TNA) to test *Hypothesis 4* formally. I also include the interaction terms of fund flows and the indicators for large funds, $High\_TNA_{i,t-1}$, and large-cap funds, $Large\_Cap_{i,t-1}$, to study whether large funds and small-cap funds spread their trades over time more than small funds and large-cap funds do. Current and lagged fund returns are added as control variables. Both quarter and fund fixed effects are included, and standard errors are clustered at the fund level. The regression is as below,

$$\begin{aligned}\Delta holding_{i,t} = {} & \alpha_0 + \textstyle\sum_{c=0}^{6} \beta_c flow_{i,t-c} + \sum_{c=0}^{6} \gamma_c flow_{i,t-c} \times High\_TNA_{i,t-c-1} \\ & + \textstyle\sum_{c=0}^{6} \delta_c flow_{i,t-c} \times Large\_Cap_{i,t-c-1} + \sum_{c=0}^{6} \vartheta_c High\_TNA_{i,t-c-1} \\ & + \textstyle\sum_{c=0}^{6} \phi_c Large\_Cap_{i,t-c-1} + \sum_{c=0}^{6} \theta_c Ret_{i,t-c} + \varepsilon_{i,t}\end{aligned} \tag{1.15}$$

[Insert Table 1.10 about here]

The result of setting (1) in Table 1.10 shows that mutual funds digest most of their fund flows in the same quarter (about 68%), 7%-9% in the next quarter, and 1%-2% each in the following two quarters[9]. The effects of fund flows on stock holdings last about a year. I include the interaction terms of fund flows and the indicator for large funds into the regression for setting (2) of Table 1.10, and the interaction terms for indicator of large-cap funds in setting (3). Panel A of Figure 1.6 plots the spreading of flow-driven trades over time for large funds and small funds separately based on the regression results in setting (2). It shows that large funds on average digest 3.7% less of their fund flows in the same quarter, and 3.6% more in the next quarter, than small funds do. Though these numbers are not always statistically significant, they are consistent with the prediction that large funds, facing larger price-impact costs, spread their trades over time more than small funds do. Besides, Panel B of Figure 1.6 plots the spreading of flow-driven trades

[9] We could notice that the sum of the the changes of holdings (68%+9%+2%+2%=81%) is smaller 100% of the fund flows. It is because, first, part of inflows and outflows offset each other over time and thus will not lead to changes of stock holdings; second, the stock holdings in Thomson Reuters database include long positions greater than 10,000 shares and $200,000 only, thus my estimates of changes of stock holdings are downward biased.

over time for large-cap funds and small-cap funds separately based on the regression result in setting (3) of Table 1.10. It shows that large-cap funds on average digest 5.8% more of their flow-driven trades in the same quarter, 2.5% less in the next quarter, and 3.4% less in the quarter after, than small-cap funds do. Similarly, though these numbers are also not always statistically significant, it supports the conjecture that small-cap funds, facing large price impact costs, spread their trades over time more than large-cap funds do. These results are consistent with the findings in Huang (2015), which shows the dynamic adjustment of cash buffer in volatile periods is more substantial for large funds and small-cap funds than small funds and large-cap funds.

In addition, I plot the spreading of flow-driven trades over time for outflow samples and inflow samples separately in Figure 1.7 . Consistent with *Hypothsis 5*, I find mutual funds spread their outflow-driven sales over time more than they spread inflow-driven purchases. They digest 63.3% inflows (versus 56.3% outflows) in the same quarter, and 7.6% inflows (versus 11.4%) outflows in the next quarter.

Next, I document how the changes of cash buffers depend on current and lagged flows. I use the first difference of cash holdings $\Delta cash_{i,t} = cash_{i,t} - cash_{i,t-1}$ as dependent variable and regress it on the concurrent and lagged fund flows, where the concurrent and lagged fund returns are controlled. The regression is as below:

$$\Delta cash_{i,t} = \alpha_0 + \sum_{c=0}^{6} \beta_c flow_{i,t-c} + \sum_{c=0}^{6} \theta_c Ret_{i,t-c} + \varepsilon_{i,t} \tag{1.16}$$

[Insert Table 1.11 about here]

Consistent with the findings on stock holdings, Table 1.11 shows the effects of flows on cash holdings also last about a year. Cash holdings are positively related with current flows and negatively related with past flows. Results of both setting (1) and (2) in Table 1.11 indicate that for 1% fund inflow (outflow), cash holdings of mutual fund on average increases (decreases) 0.02% of fund TNA in the same quarter, but it reverses 0.01% in the following quarter and 0.006% each in another two quarters followed. This result is consistent the effect of flows on stock holdings, and complements the findings in Huang (2015) that funds' cash holdings increase when there are fund inflows and decrease when there are fund outflows.

In addition, to compare my results with the findings in previous literature, I also study how fund flows affect the portfolio liquidity over time. To my best knowledge there are only two papers documenting how fund flows affect funds' portfolio liquidity dynamically. Huang (2015) shows that funds' cash holdings increase when there are fund inflows and decrease when there are fund outflows, and their portfolio liquidity follow the same pattern. Massa and Phalippou (2005) documents a sluggish adjustment in portfolio liquidity over time. If a fund increases its portfolio liquidity by 1% in a certain quarter, it keeps increasing portfolio liquidity over the next 2 quarters (0.5% the first quarter followed and 0.1% the second one). Later in this subsection, I will show that the sluggish adjustment in portfolio liquidity can be fully explained by the tendency to trade liquid stocks for flow-driven trades.

Similar to Huang (2015), I use the difference between the average ILLIQ values of stocks bought and stocks sold as a measure of the changes of portfolio liquidity caused by trades of mutual funds. But I do two adjustments. First, I use the natural logarithm of ILLIQ instead of ILLIQ as I do in Section 3.1; second, I use the dollar amount weighted average of $lnILLIQ$ instead of the equally weighted average to calculate the difference. It is to make sure that this measure is not solely driven by small trades. The expression of this measure is as below,

$$Trade\_lnILLIQ_{i,t} = \sum_{j} \frac{\Delta Held_{i,j,t} \times (lnILLIQ_{j,t-1} - lnILLIQ\_held_{i,t-1})}{\sum_k Held_{i,k,t}} \tag{1.17}$$

$Trade\_lnILLIQ_{i,t}$ is the measure of the change of portfolio liquidity in quarter t for fund i. $lnILLIQ_{j,t-1}$ is the natural logarithm of average ILLIQ value for stock j in the past year until quarter $t-1$, quarter $t-1$ included. $Bought_{i,j,t}$ is the dollar amount of stocks j bought by fund i in quarter t, $Sold_{i,j,t}$ is the dollar amount of stocks j sold by fund i in quarter t, and $Held_{i,k,t}$ is the dollar amount of stocks k held by fund i at the end of quarter t. A negative value of this measure indicates that mutual fund i bought more liquid than illiquid stocks in quarter t; and a positive values indicates the opposite.

I regress this measure of the changes of portfolio liquidity on contemporary and lagged fund flows and lagged changes of portfolio liquidity. Concurrent and lagged fund returns are added as control variables. Both fund and quarter fixed effects are included and the standard errors are clustered at the fund level. The regression is as below:

$$Trade\_lnILLIQ_{i,t} = \alpha_0 + \sum_{c=0}^{6} \beta_c flow_{i,t-c} + \sum_{c=1}^{6} \gamma_c Trade\_lnILLIQ_{i,t-c} + \sum_{c=0}^{6} \theta_c Ret_{i,t-c} + \varepsilon_{i,t} \quad (1.18)$$

[Insert Table 1.12 about here]

In Table 1.12, setting (1) shows that the coefficients of concurrent and the first three lagged fund flows are all significantly negative. It means mutual funds buy more liquid than illiquid stocks when there are fund inflows, and sell more liquid than illiquid stocks when there are fund outflows. Similar to previous results on stock holdings and cash holdings, this effect lasts about a year.

Setting (2) confirms the result documented in Massa and Phalippou (2005) that, lagged changes of portfolio liquidity correlate positively with current changes of portfolio liquidity. They interpret this finding as a sluggish adjustment in portfolio liquidity. However, my result in setting (3) shows that this effect can be completely explained by the effect of flows on the changes of portfolio liquidity. When concurrent and lagged fund flows are added to the right side of the regression, the persistency of $Trade\_lnILLIQ_{i,t}$ disappears completely. The coefficients of the lags of $Trade\_lnILLIQ_{i,t}$ even become negative, though not significant. It indicates that the portfolio liquidity may have the tendency to reverse back in the following quarters.

To sum up, these results show that to reduce the trading costs of flow-driven trades, mutual funds trade more liquid stocks than illiquid stocks. It makes the portfolio liquidity tilt temporarily towards liquid or illiquid stocks. Since mutual funds spread their flow-driven trades over time, the tilts of portfolio liquidity are also positively correlated over time. Therefore, the positive correlations of the changes of portfolio liquidity over time found in Massa and Phalippou (2005) seems caused by funds' spreading of flow-driven trades over time, instead of the sluggish adjustment of portfolio liquidity.

1.4.4. Time trend of trading-cost-management behaviors

Until now, I document mutual funds' average trading-cost-management behavior from 1980 to 2009. As we know, the liquidity of stock market has changed substantially in the past decades, and mutual funds is becoming more and more sophisticated over time at managing their trading costs. As a consequence, trading-cost-management behavior of mutual funds also varies over time.

In this subsection, I do a rolling-window analysis to investigate the time trend of mutual funds' trading cost management and check the robustness of my findings across different sub-periods. I choose a window size of 10 years and a step size of 1 year, and do the same analysis as before for all three aspects of trading cost management in each rolling window. The results in Table 1.13 show that my findings are robust for all 10-year sub-periods. In each column, all coefficients share the same sign and are similar in magnitude across all 10-year sub-periods.

In addition, I find that mutual funds spread their trades over time less as the stock market becomes more liquid in recent years. The last two columns in Table 1.13 show that mutual funds digest more fund flows in the same quarter and less in the following quarter as the stock market becomes more liquid in the past decades. As the stock market becomes more liquid, mutual funds worry less about the price impact of trades. Thus they have less incentives to spread their flow-driven trades over time and, instead, are more willing to adjust their portfolios according to fund flows immediately. To show this time trend more clearly, Figure 1.8 plots the results of the rolling-window analysis for mutual funds' spreading of flow-driven trades over time until the third quarter after the flow. Each bar in this figure stands for a 10-year sub-period. We could see mutual funds digest more and more of their fund flows in the same quarter (blue bars), from about 50% in 1980s and 90s to more than 70% in early 2000s. The fund flows digested in the second quarter (yellow bars) drop from 14% in 1980s to 6% in early 2000s. And the flow-driven trades in the third quarter (orange bars) almost vanish in 2000s. There is actually a decreasing trend of mutual funds' spreading of trades over time. And this change mainly happened around 2001, when the stock market became significantly more liquid[10]. Consistent with the fact that mutual funds are less worried about the trading costs of flow-driven trades, the cash buffers kept by mutual funds (the dark blue curve at the bottom) also decreases gradually over time, from 10% in 1980s to 3% in 2000s.

Besides, Table 1.13 shows that the time trend of the other two trading-cost-management

[10]The sudden increase of market liquidity can be partially attributed to the decimalization of stock market in 2001. Since then, security prices are quoted using a decimal format rather than fractions, such as one-fourth, one-eighth etc.

behaviors, trading more liquid stocks and spreading trades over stocks, are not monotonic. It is probably because unlike spreading trades over time, the other two aspects of trading-cost-management behavior require more skills, such as estimating the stock liquidity and selecting stocks. Both the stock market and mutual fund industry grew rapidly in the past decades. Since the increase of mutual funds' skills and the improvement of market liquidity happen simultaneously in this period, these two forces together lead to a non-monotonic time trend in the other two aspects of trading-cost-management behavior.

1.4.5. Trading-cost-management behavior for unexpected v.s. expected fund flows

Previous literature has largely documented that flows of mutual funds are highly predictable by lagged flows and past returns (e.g. Sirri and Tufano (1998), Coval and Stafford (2007), Huang, Wei and Yang (2007), Ivkovic and Weisbenner (2009), Lou (2012) etc.). If fund flows are predictable, mutual funds can adjust their holdings in advance to reduce the overall price impact of their flow-driven trades and rely less on the other aspects trading-cost-management behavior, such as trading more liquid stocks and spreading the trades over stocks. But if the fund flows are unpredictable, they have no other choice but to rely on those costly trading-cost-management behavior.

In this section, I firstly disentangle the expected and unexpected fund flows using the Fama-MacBeth regression, and secondly, study the difference between the trading-cost-management behavior of expected flow-driven trades and unexpected flow-driven trades.

To predict fund flows, I regress the current fund flows on the lagged fund flows and lagged fund returns within 2 years (until the 8th lag) as shown by regression 1.19.

$$flow_{i,t} = \alpha_0 + \sum_{c=1}^{8} \beta_c flow_{i,t-c} + \sum_{c=1}^{8} \theta_c Ret_{i,t-c} + \varepsilon_{i,t} \tag{1.19}$$

Table 1.14 reports the regression results of regression 1.19. I use both Fama-MacBeth regression and pooled OLS regression and report their results separately. Both regression results show substantial predictability in fund flows. The R^2 of Fama-MacBeth regression is about 0.11 and that of pooled OLS is about 0.21. The lagged flows are positive and significant until the 6th lag for Fama-MacBeth regression and until the 5th lag for pooled OLS regression, which means the time persistency of fund flows lasts more than a year. The effect of returns on flows also lasts more than a year. The lagged returns are positive and significant for the first 4 lags, the 6th lag and the 8th lag for Fama-MacBeth regression. Following Coval and Stafford (2007), I use the fitted part of Fama-MacBeth regression as the estimates of expected fund flows, and the unfitted part as the estimates of unexpected fund flows.

Then I do the same analysis as before for all three aspects of trading cost management[11], and for expected flow-driven trades and unexpected flow-driven trades separately. For each aspect of trading cost management, I also do the regressions for fund outflows and inflows separately. For the spreading of trades over time, only the coefficient of the concurrent flow is reported. Table 1.15 reports the results.

As it shows, I find significant evidence that mutual funds trade more liquid stocks than illiquid stocks for both unexpected inflows and outflows, but not for expected inflows or outflows. The sign of the coefficient is even opposite for expected inflows. The magnitudes of those coefficients consistently show that mutual funds spread unexpected flow-driven trades over stocks more than they spread expected flow-driven trades (1.224 versus 1.053 for unexpected outflows versus expected outflows, and 0.665 versus 0.572 for unexpected inflows versus expected inflows), even though mutual funds spread both unexpected flow-driven trades and expected flow-driven trades over stocks. More interestingly, I also find that mutual funds digest less of their expected fund flows in the same quarter than unexpected fund flows. They digest only 14.5% of expected outflows in the same quarter (compared with 38.9% of unexpected outflows), and 28.8% of expected inflows (compared with 59.5% of unexpected inflows). These results fit well with the conjecture that for expected fund flows, mutual funds prepare in advance to reduce the price impact of flow-driven trades in that quarter, and rely less on the other two aspects of trading-cost-management behavior, trading more liquid stocks and spreading the trades over stocks.

[11] As before, I do the regression (1.4) & (1.5) and report the coefficients of $flow_{i,t}$ for the trading of liquid stocks v.s. illiquid stocks. I report the second-step coefficient of $lnSold_{i,t}$ in regression (1.12) for outflow samples and the second-step coefficient of $lnBought_{i,t}$ in regression (1.13) for inflow samples for the spreading of trades over stocks. And I report the coefficient of contemporary flow $flow_{i,t}$ in regression (1.15) for the spreading of trades over time.

1.5. Conclusion

Previous literature of portfolio choice with trading costs (e.g. Scholes 2000, Duffie and Ziegler 2003, Garleanu and Pedersen 2013) indicates that investors should trade more liquid stocks than illiquid stocks, split their large trades, and use cash buffers to reduce the total trading costs. This paper studies the trading behavior of mutual funds from all these aspects of their trading cost management. I find clear empirical evidence that mutual funds trade more liquid than illiquid stocks when there are large fund flows; they spread their flow-driven trades over stocks to reduce the total price impact costs; and they also spread their flow-driven trades over time and use cash buffers. In addition, I find that large and small-cap funds spread their flow-driven trades over time more than small and large-cap funds do, and mutual funds manage their trading costs of outflow-driven sales more than those of inflow-driven purchases. These evidence strongly support the conjecture that fund size and flow-driven trades erode fund performance because of the large price impact of trades. Moreover, I document a time trend that mutual funds spread their flow-driven trades over time less as the stock market becomes more liquid, and I find more empirical evidence of trade cost management for unexpected flow-driven trades than expected flow-driven trades.

This paper shows the trading-cost-management behavior of mutual funds is consistent with existing theoretical predictions in most aspects, at least qualitatively. However, we still do not know whether their trading cost management is optimal quantitatively, and how much the trading-cost-management behavior contributes to fund performance and the efficiency of the stock market. It would be interesting to further quantify the optimal trading-cost-management behavior and their economic benefits to mutual funds and the stock market.

1.6. Appendix

Variables	Description
Holding-level Variables:	
$trade_{i,j,t}$	Change in shares held by fund i in stock j in quarter t as a percentage of shares held at the end of quarter $t-1$ (adjusted for stock split), winsorized at 99% level.
$own_{i,j,t-1}$	Fund i's ownership of stock j at the end of quarter $t-1$, which is calculated as shares held at the end of quarter $t-1$ as a percentage of total shares outstanding in the market.
$ILLIQ_{j,t-1}$	The past-year-average ILLIQ value for stock j, from $t-4$ to $t-1$. ILLIQ is a measure of stock liquidity proposed by Amihud.
$Holding_{i,j,t-1}$	Dollar amount of stock j held by fund i at the end of quarter $t-1$.
$Sold_{i,j,t}$	Dollar amount of stock j sold by fund i in quarter t, for positions sold only. (The value is set as missing if the position is bought or maintained; stock prices at the end of $t-1$ are used for the calculation)
$Bought_{i,j,t}$	Dollar amount of stock j bought by fund i in quarter t, for positions bought only. (The value is set as missing if the position is sold or maintained; stock prices at the end of $t-1$ are used for the calculation)
Fund-level Variables:	
$flow_{i,t}$	Net capital flow to fund i in quarter t as a percentage of the fund's total net assets at the end of the previous quarter.
$Flow_{i,t}$	Net dollar amount of capital flow to fund i in quarter t.
$\Delta holding_{i,t}$	Total dollar amount of changes of stock holdings for fund i in quarter t as a percentage of TNA. (stock prices and TNA at the end of $t-1$ are used for the calculation)

Continue...

Variables	Description
$Sold_{i,t}$	Total dollar amount of shares sold by fund i in quarter t (stock prices at the end of $t-1$ are used for the calculation)
$Bought_{i,t}$	Total dollar amount of shares bought by fund i in quarter t (stock prices at the end of $t-1$ are used for the calculation)
$Holding_{i,t-1}$	Total dollar amount of stock holdings held by fund i at the end of quarter $t-1$.
$\#Sold_{i,t}$	Total number of stocks sold by fund i in quarter t.
$\#Bought_{i,t}$	Total number of stocks bought by fund i in quarter t.
$\#Held_{i,t}$	Total number of stocks ever held by fund i either at the beginning or at the end of quarter t.
$\#sold_{i,t}$	$\#Sold_{i,t}$ as a percentage of $\#Held_{i,t}$.
$\#bought_{i,t}$	$\#Bought_{i,t}$ as a percentage of $\#Held_{i,t}$.
$own_{i,t-1}$	Portfolio-weighted average ownership share ($own_{i,j,t-1}$) for fund i.
$cash_{i,t}$	Cash holdings of fund i at the end of quarter t reported in CRSP as a percentage of stock holdings of fund i at the end of quarter t.
$lnILLIQ\_held_{i,t}$	Portfolio-weighted average of the ln value of past-year ILLIQ ($lnILLIQ_{j,t-1}$) for all stocks held by fund i in quarter t.
$lnILLIQ\_sold_{i,t}$	Dollar-weighted average of the ln value of past-year ILLIQ ($lnILLIQ_{j,t-1}$) for all stocks sold by fund i in quarter t.
$lnILLIQ\_bought_{i,t}$	Dollar-weighted average of the ln value of past-year ILLIQ ($lnILLIQ_{j,t-1}$) for all stocks bought by fund i in quarter t.
$TNA_{i,t-1}$	The TNA (total net asset) of fund i at the end of quarter $t-1$, in million \$.

Continue...	
Variables	Description
$High\_TNA_{i,t-1}$	An indicator variable that equals 1 if fund i's TNA is greater than the sample median at the end of quarter $t-1$, 0 otherwise.
$Large\_Cap_{i,t-1}$	An indicator variable that equals 1 if fund i's style (the portfolio-weighted mean market capitalization of stocks held) greater than the sample median at the end of quarter $t-1$, 0 otherwise.
$Large\_Trade_{i,t}$	An indicator variable that equals 1 if fund is total dollar amount sold/bought in quarter t is greater than the sample median, 0 otherwise.
$Ret_{i,t}$	Fund i's return in quarter t in excess of risk free rate.
$Outflow_{i,t}$	Dollar amount of capital outflows. $-Flow_{i,t}$ for fund-quarter observations with negative capital flow only. (The value is set as missing if capital flows are positive or zero)
$Inflow_{i,t}$	Dollar amount of capital inflows. $Flow_{i,t}$ for fund-quarter observations with positive capital flow only. (The value is set as missing if capital flows are negative or zero)

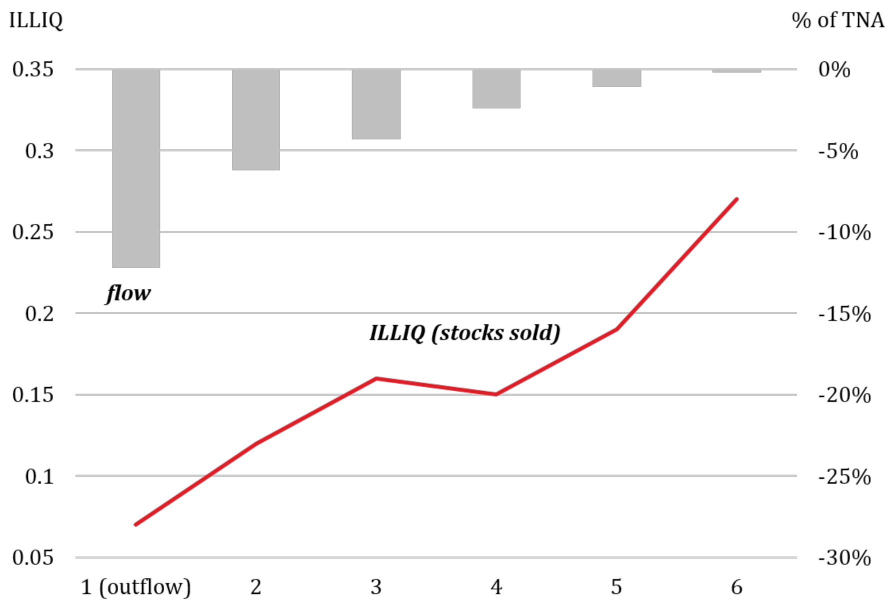


Figure 1.1: Stock Liquidity of Outflow-Driven Sales

This figure plots the average liquidity of stocks sold across outflow deciles. The red curve is for the average liquidity of stocks sold relative to the average liquidity of all stocks in the portfolio, and the gray bars are average fund outflows. The vertical axis on the left side is the average lnILLIQ value of stock sold relative to the average lnILLIQ value of all stocks in the portfolio, and the vertical axis on the right side is the fund outflows as a percentage of fund TNA. The horizontal axis denotes flow decile 1 (largest outflows) to 6. All averages are value-weighted.

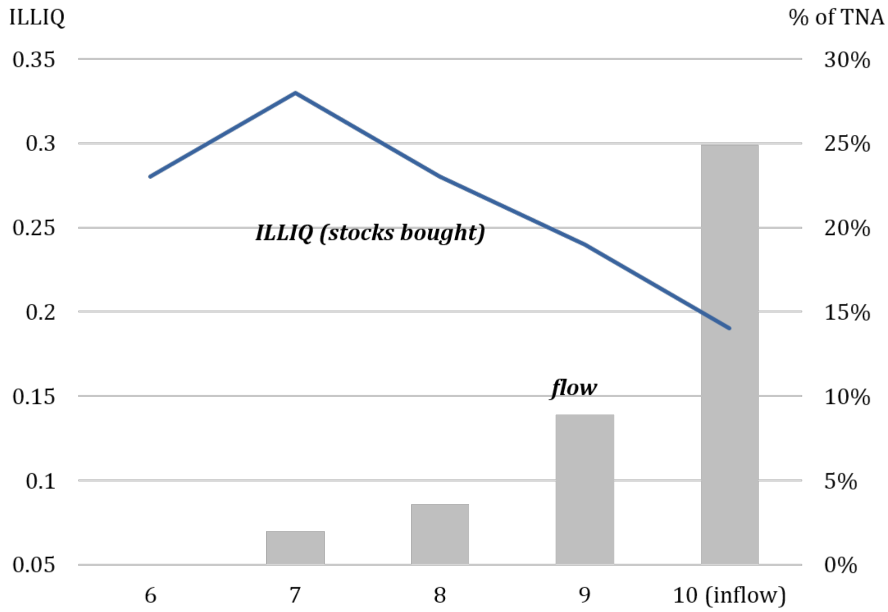


Figure 1.2: Stock Liquidity of Inflow-Driven Purchases

This figure plots the average liquidity of stocks bought across outflow deciles. The blue curve is for the average liquidity of stocks bought relative to the average liquidity of all stocks in the portfolio, and the gray bars are average fund inflows. The vertical axis on the left side is the average lnILLIQ value of stock bought relative to the average lnILLIQ value of all stocks in the portfolio, and the vertical axis on the right side is the fund inflows as a percentage of fund TNA. The horizontal axis denotes flow decile 6 to 10 (largest inflows). All averages are value-weighted.

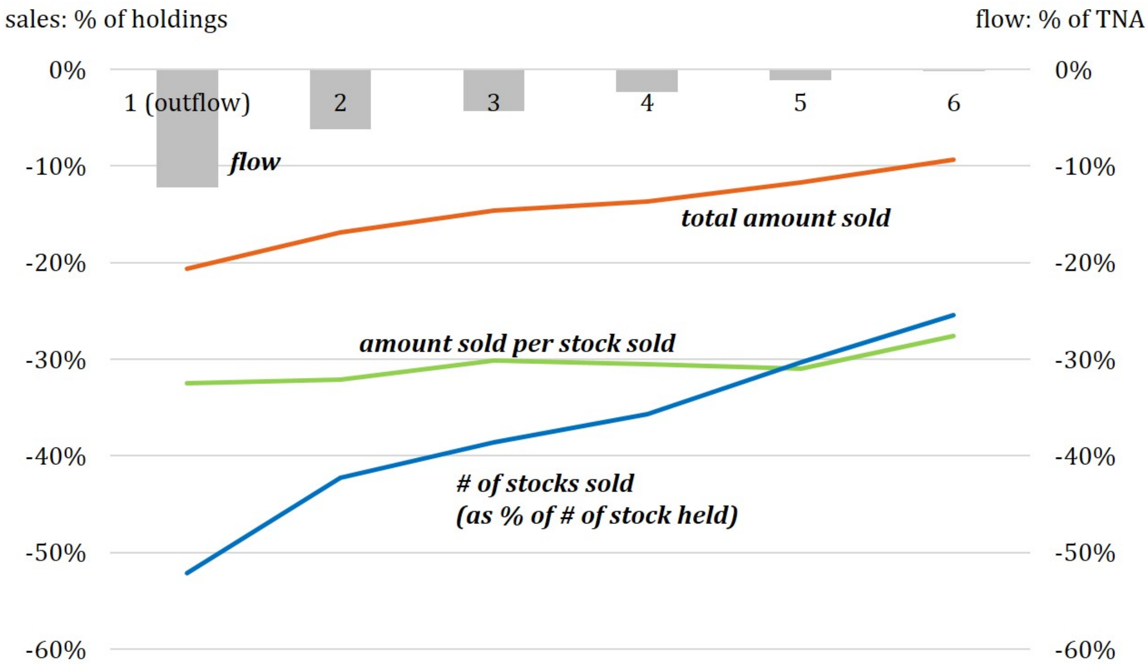


Figure 1.3: Spreading of Outflow-Driven Sales over Stocks

This figure plots the average total amount of stocks sold, amount sold per stock sold and number of stocks sold across flow deciles. The orange curve is for the average total amount sold as a percentage of the total holdings at the beginning of the quarter (equation 1.7); the green curve is for the average value of the amount sold per stock sold as a percentage of the initial holdings this stock (equation 1.8); and the blue curve is the number of stocks sold as a percentage of the total number of stocks even been held in this quarter (equation 1.9). The vertical axis on the left side is for the sales as a percentage of the holdings (for total amount, amount per stock sold and number of stocks), and the vertical axis on the right side is the level of fund flows. The horizontal axis denotes flow decile 1 (fund-quarter observations with the largest outflows) to 10 (with the largest inflows). Gray bars are the average fund flows of each flow decile. All averages are value-weighted.

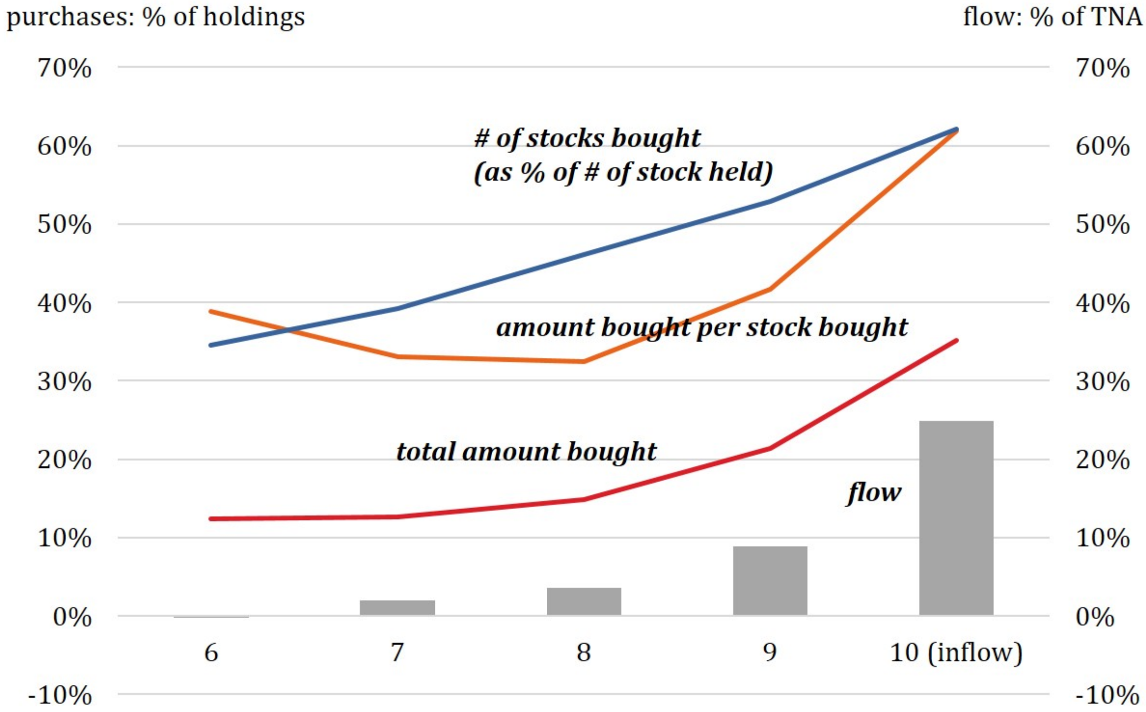


Figure 1.4: Spreading of Inflow-Driven Purchases over Stocks

This figure plots the average total amount of stocks bought, amount bought per stock bought and number of stocks bought across flow deciles. The red curve is for the average total amount bought as a percentage of the total holdings at the beginning of the quarter; the orange curve is for the average value of the amount bought per stock bought as a percentage of the initial holdings this stock; and the blue curve is the number of stocks bought as a percentage of the total number of stocks even been held in this quarter. The vertical axis on the left side is for the purchases as a percentage of the holdings (for total amount, amount per stock bought and number of stocks), and the vertical axis on the right side is the level of fund flows. The horizontal axis denotes flow decile 1 (fund-quarter observations with the largest outflows) to 10 (with the largest inflows). Gray bars are the average fund flows of each flow decile. All averages are value-weighted.

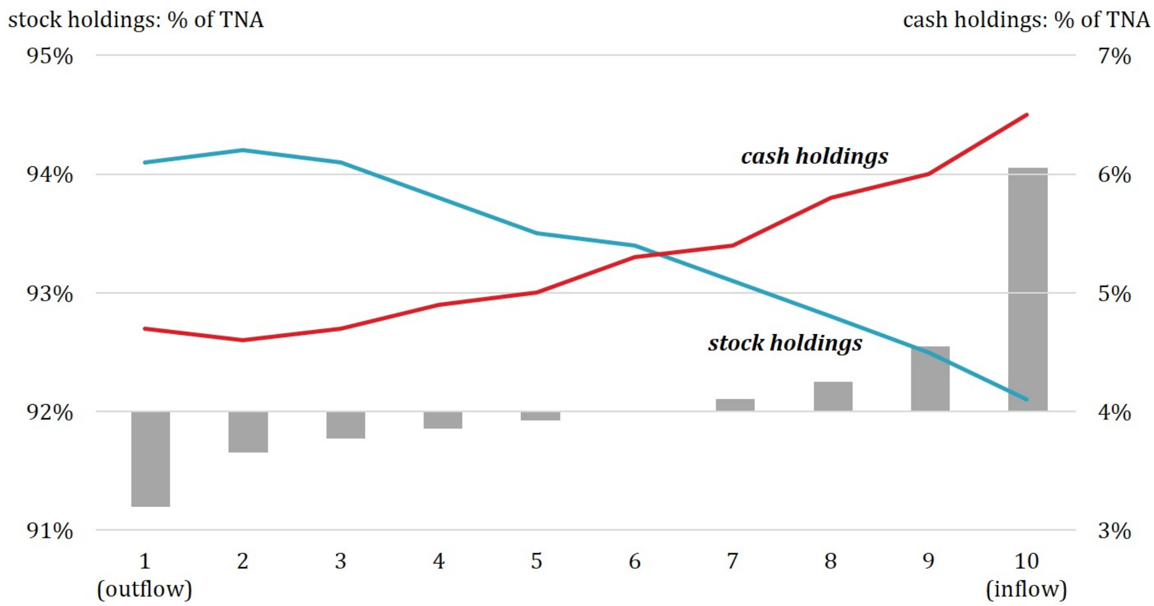


Figure 1.5: Stock Holdings and Cash Holdings across Flow Deciles

This figure plots the average stock holdings and cash holdings as a percentage of fund TNA (total net assets) across flow deciles. The blue curve and he vertical axis on the left side is for stock holdings; the red curve and the vertical axis on the right side is for cash holdings. The horizontal axis denotes flow decile 1 (fund-quarter observations with the largest outflows) to 10 (with the largest inflows). Gray bars are the average fund flows of each flow decile. Both averages are equally weighted.

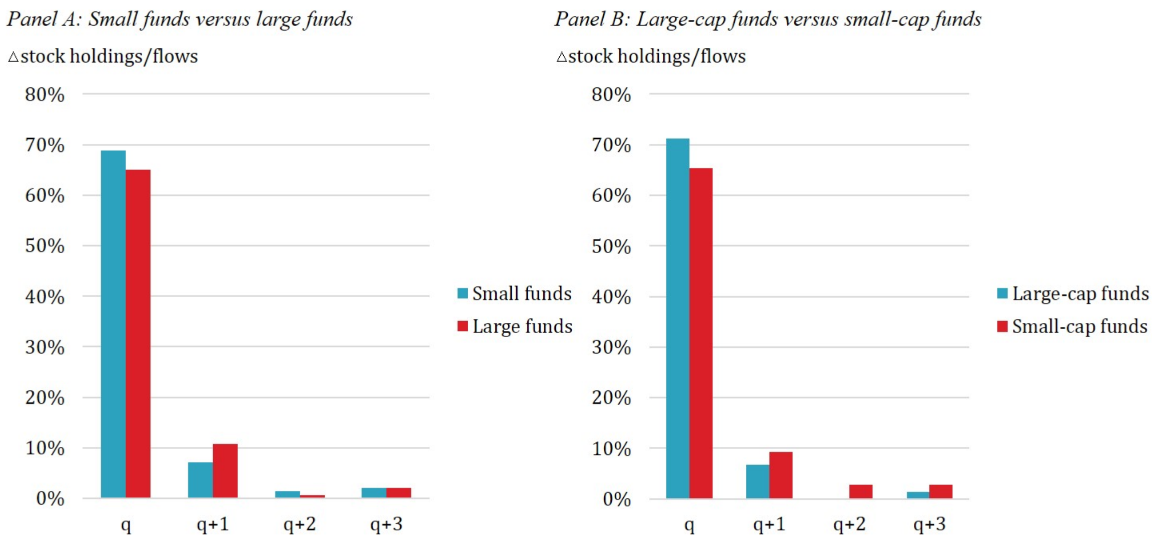


Figure 1.6: Spreading of Flow-Driven Trades over Time

This figure plots the effect of flows on stock holdings in the following year (4 quarterly observations). Panel A plots the change of total stocks holdings as a percentage of the fund flow for small funds (blue bars) and large funds (red bars) separately; Panel B plots it for large-cap funds (blue bars) and small-cap funds (red bars) separately. The horizontal axis denotes the time of the change of holdings relative to the time of fund flows, ‘q’ for the change of holdings the same quarter as the fund flows, ‘q+1’ for it in the next quarter, and ‘q+2’ ‘q+3’ for it in the second and third quarters after.

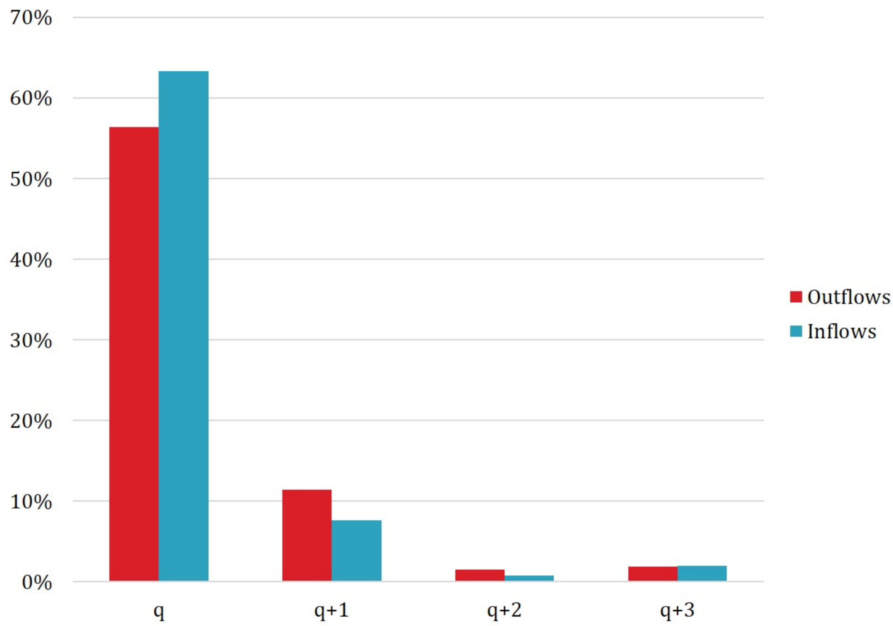


Figure 1.7: Spreading of Flow-Driven Trades over Time (Outflows v.s. Inflows)

This figure plots the effect of flows on stock holdings in the following year (4 quarterly observations) for inflow-driven purchases and outflow-driven sales separately. The changes of total stocks holdings are reported as a percentage of fund flows. The horizontal axis is the time of the change of holdings relative to the time of fund flows, 'q' for the change of holdings in the same quarter of the fund flow, 'q+1' for it in the next quarter, and 'q+2' 'q+3' for it in the second and third quarters after.

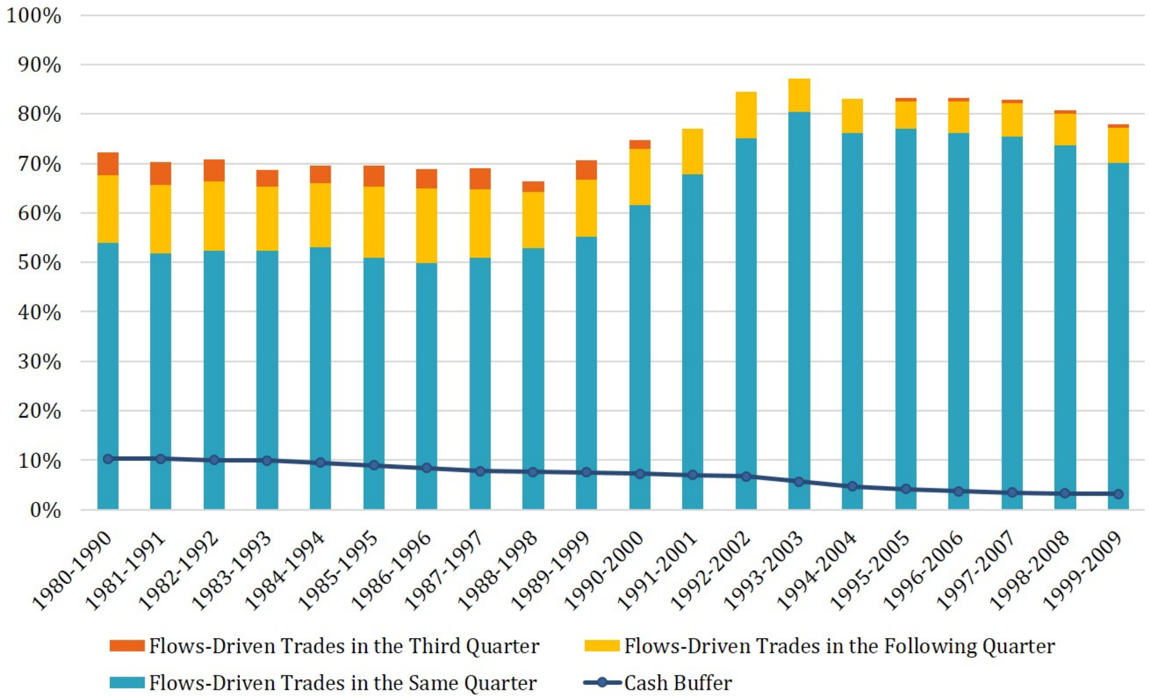


Figure 1.8: The Time Trend of The Spreading of Flow-Driven Trades over Time

This figure plots the results of a rolling-window analysis for mutual funds' spreading of flow-driven trades over time. Each bar in this figure stands for 10 years. The entire time periods is from 1980 to 2009 with 1 year each step. The blue bar shows the flow-driven trades in the same quarter of the fund flows. The yellow one is for the amount digested in the following quarter, and the orange one is for the third quarter. All of them are expressed as a percentage of the fund flows. The dark blue curve at the bottom of this figure plots the average cash buffer as a percentage of the fund TNA (total net assets).

Table 1.1: Summary Statistics for the Matched CDA-CRSP Sample

This table reports the summary statistics at the end of each year. Column "Year" is the year associated with the fund records. "Number of Matched Funds" reports the number of equity funds in the CRSP mutual fund database that match with records of equity holdings in the CDA/Spectrum mutual fund database in my sample. "Number of Fund Families" reports the number of fund families classified by management company abbreviations in CDA/Spectrum. "Mean Fund TNA ($mn)" reports the average size (average TNA in CRSP mutual fund database). "Combined TNA ($mn)" reports the combined assets under management for funds in the sample. "Average Stock Holding (%)" reports equity holdings as a percentage of fund TNA reported in CRSP. "Average Cash Holding (%)" reports cash holdings as a percentage of fund TNA reported in CRSP. "Average Fund Age" reports the average age of funds. "Annual Expense Ratio (%)" is the percentage of the total investment that shareholders pay for the operating expenses over the calendar year, reported in CRSP. "Annual Turnover" is the minimum of aggregate purchases of securities or aggregate sales of securities over the calendar year, divided by the average TNA of the fund, reported in CRSP. "Average Total Loads (%)" is the sum of maximum front and rear loads reported in CRSP. "Annual Return (%)" is the equally weighted average annual returns of mutual funds reported in CRSP. "Average Quarterly Fund Flow (% of TNA)" is the average quarterly fund flows as a percentage of TNA for each year.

Year	Number of Matched Funds	Number of Fund Families	Mean Fund TNA ($mn)	Combined TNA ($mn)	Average Stock Holding (%)	Average Cash Holding (%)	Average Fund Age	Annual Expense Ratio (%)	Annual Turnover	Average Total Loads (%)	Annual Return (%)
1980	101	74	237.9	24,027	86.3	7.4	24.6	0.87	0.722	4.77	31.02
1985	185	97	367.3	67,947	74.7	7.6	22.3	0.92	0.774	3.71	25.88
1990	293	134	413.8	121,247	69.7	8.6	19.7	1.12	0.758	1.98	-8.65
1995	566	237	885.6	501,271	90.3	6.2	12.6	1.18	0.819	1.99	30.35
2000	1115	395	1267.4	1,413,174	94.1	5.9	10.3	1.16	0.958	4.53	-2.36
2005	1266	377	1425.6	1,804,821	95.7	3.1	11.8	1.20	0.851	4.29	6.63
2008	1208	367	872.2	1,053,557	95.5	3.2	14.7	1.11	0.863	4.00	-42.51

Table 1.2: Mutual Funds by Flow Deciles

This table reports how quarterly mutual fund holdings change conditional on actual fund flows. Mutual fund flows are measured as a percentage of beginning-of-period total net assets (TNA). Mutual fund flows are estimated as the percentage change in TNA over the quarter controlling for capital gains and losses of the initial holdings, refer to equation (1.1) and (1.2). Each quarter, fund-quarter observations with available flow data are sorted into flow deciles. Within each flow decile, Panel A reports fund flow, change of holdings, quarterly return, average fund TNA, stock holdings and cash holdings averaged across all funds in the decile. Panels B report for the average fund the number of holdings (Avg. # of Stocks) at the end of the quarter, and the fraction of positions that were expanded, reduced, maintained, initiated or eliminated. The positions expanded include those initiated, and the positions reduced include those eliminated. The sum of the fractions expanded, reduced and maintained equals 1. All average values reported are equally weighted.

Panel A: Fund Characteristics by Flow Deciles

Decile	Flow (%)	Average Flows ($mn)	Changes of Stock Holding (%)	Average Quarterly Return (%)	Average TNA ($mn)	Average Stock Holding /TNA (%)	Average Cash /TNA (%)	# of obs
1 (outflow)	-13.7	-61	-3.8	0.7	433	94.1	4.7	7239
2	-5.9	-46	0.7	0.8	729	94.2	4.6	7295
3	-3.9	-40	1.6	1.0	968	94.1	4.7	7306
4	-2.5	-30	2.7	1.1	1186	93.8	4.9	7302
5	-1.3	-22	4.0	1.3	1620	93.5	5.0	7287
6	0.0	0	5.3	1.4	1933	93.4	5.3	7316
7	1.7	27	7.5	1.6	1697	93.1	5.4	7316
8	4.2	53	9.4	1.8	1386	92.8	5.8	7292
9	9.2	67	15.4	2.2	832	92.5	6.0	7309
10 (inflow)	34.8	85	34.9	3.0	425	92.1	6.5	7255

Panel B: Fund Trading Behavior by Flow Deciles

Decile	Flow (%)	Avg. # of Stocks	Fraction of Positions				
			Expanded	Reduced	Maintained	Initiated	Eliminated
1 (outflow)	-13.7	120	0.28	0.51	0.21	0.15	0.11
2	-5.9	120	0.28	0.41	0.30	0.14	0.10
3	-3.9	122	0.29	0.38	0.33	0.13	0.10
4	-2.5	127	0.30	0.35	0.35	0.13	0.09
5	-1.3	142	0.32	0.30	0.38	0.12	0.08
6	0.0	157	0.35	0.25	0.40	0.11	0.07
7	1.7	165	0.40	0.22	0.38	0.11	0.07
8	4.2	184	0.47	0.18	0.34	0.11	0.07
9	9.2	174	0.53	0.16	0.31	0.12	0.07
10 (inflow)	34.8	142	0.62	0.16	0.22	0.16	0.08

Table 1.3: The Average Stock Liquidity of Flow-Driven Trades across Flow Deciles

This table reports the average lnILLIQ values of stocks held, sold and bought by mutual funds for all flow deciles. Decile 1 for fund-quarter observations with extremely large fund outflows and decile 10 for those with extremely large fund inflows; column 2 reports the value-weighted average fund flows as a percentage of fund TNA; column 3, (1) reports the value-weighted average lnILLIQ of all stocks held by mutual funds in their portfolios; column 4, (2) reports the value-weighted average lnILLIQ of all stocks sold by mutual funds; column 5, (3) reports the value-weighted average lnILLIQ of all stocks bought by mutual funds; column 6, (2)-(1) reports the difference between average lnILLIQ of all stocks sold by mutual funds and that of all stocks held in their portfolios; and the last column, (3)-(1) reports the difference between average lnILLIQ of all stocks bought by mutual funds and that of all stocks held in their portfolios.

Decile	Flow (%)	average lnILLIQ of			(2)-(1)	(3)-(1)
		(1) stocks held	(2) stocks sold	(3) stocks bought		
1 (outflow)	-12.2	-7.59	-7.52	-7.15	**0.07**	**0.44**
2	-6.2	-7.83	-7.71	-7.42	**0.12**	**0.41**
3	-4.3	-7.98	-7.82	-7.58	**0.16**	**0.40**
4	-2.4	-8.03	-7.88	-7.70	**0.15**	**0.33**
5	-1.1	-8.16	-7.97	-7.78	**0.19**	**0.38**
6	-0.2	-8.17	-7.90	-7.89	**0.27**	**0.28**
7	2.0	-7.96	-7.68	-7.63	**0.28**	**0.33**
8	3.6	-7.81	-7.32	-7.53	**0.49**	**0.28**
9	8.9	-7.48	-7.06	-7.24	**0.42**	**0.24**
10 (inflow)	24.9	-7.20	-6.65	-7.01	**0.55**	**0.19**

Table 1.4: The Stock Liquidity of Flow-driven Trades (Fund level)

This table reports the regression results of average liquidity of stocks sold/bought on fund outflows/inflows. I do the regressions for outflow samples and inflow samples separately. For the regression of outflow samples, the dependent variable is the dollar-weighted-average lnILLIQ of all stocks sold by fund i in quarter t, and the independent variable is the dollar amount of the fund outflow as a percentage of the fund TNA at the beginning of quarter t; for the regression of inflow samples, the dependent variable is the dollar-weighted-average lnILLIQ of all stocks bought, and the independent variable is the dollar amount of the fund inflow as a percentage of the fund TNA. lnILLIQ is the natural logarithm of Amihud's annual ILLIQ measure in the past year (the average of stock's daily ILLIQ values in the past year). Dollar-weighted-average lnILLIQ of all stocks held in their portfolio is added as control variable. Both time and fund fixed effects are added and the standard errors are clustered at the fund level.

Dependent variable:	$lnILLIQ\_sold_{i,t}$ *(Outflow samples)*		$lnILLIQ\_bought_{i,t}$ *(Inflow samples)*	
	Coef.	t stat.	Coef.	t stat.
$flow_{i,t}$	**0.30**	**5.73**	**-0.16**	**-7.60**
$lnILLIQ\_held_{i,t}$	0.98	85.95	0.70	32.50
Constant	0.70	4.09	-0.23	-0.99
Quarter fixed effects	Yes		Yes	
Fund fixed effects	Yes		Yes	
Observations	40060		31861	
Adj R^2	0.900		0.851	

Table 1.5: The Stock Liquidity of Flow-driven Trades (Fund Stock Level)

This table reports the regression results of trading amount of each stock on fund flows and stock liquidity. The dependent variable is the change in shares held by fund i in stock j in quarter t as a percentage of shares held at the beginning of quarter t, $trade_{i,j,t}$, and the independent variables include the fund flows as a percentage of the fund TNA at the beginning of quarter t $flow_{i,t}$; the measure of stock liquidity $lnILLIQ_{j,t-1}$ for each stock j; stock ownership as a percentage of total shares outstanding $own_{i,j,t-1}$ for fund i's holding of stock j; the portfolio-weighted average lnILLIQ and ownership share ($lnILLIQ\_held_{i,t}$ and $own_{i,t-1}$); and all their interaction terms with fund flows. $lnILLIQ$ is the natural logarithm of Amihud's annual ILLIQ measure as show in equation (1.3), which is the average of stock's daily ILLIQ values in the past year. Both quarter and fund fixed effects are added and the standard errors are clustered at the fund level. Only the fund-stock observations with initial holdings, $holding_{i,j,t-1}$, larger than 0.2% of the fund TNA are included into the regression.

Dependent variable: $trade_{i,j,t}$ ($holding_{i,j,t-1} > 0.2\%$)								
	Outflow (1)		Outflow (2)		Inflow (1)		Inflow (2)	
	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.
$flow_{i,t}$ (β_1)	0.52	9.22	0.56	6.17	0.41	9.22	0.42	6.55
$lnILLIQ_{j,t-1}$	-0.01	-14.54	-0.01	-13.86	-0.01	-11.22	-0.01	-12.51
$flow_{i,t} \times lnILLIQ_{j,t-1}$	**-0.02**	**-3.36**	**-0.02**	**-2.91**	**-0.02**	**-3.30**	**-0.02**	**-4.25**
$own_{i,j,t-1}$	0.15	3.65	0.14	3.65	0.09	1.08	0.06	0.75
$flow_{i,t} \times own_{i,j,t-1}$	0.0001	1.39	**-0.0002**	**-2.60**	-1.08	-1.36	-0.98	-1.36
$lnILLIQ\_held_{i,t}$	-	-	-0.01	-4.08	-	-	-0.03	-7.11
$flow_{i,t} \times lnILLIQ\_held_{i,t}$	-	-	0.0048	0.33	-	-	0	0.03
$own_{i,t-1}$	-	-	-0.15	-1.96	-	-	0	0.21
$flow_{i,t} \times own_{i,t-1}$	-	-	**-5.38**	**-1.96**	-	-	0.18	0.41
$lnHolding_{i,j,t-1}$	-0.02	-16.44	-0.02	-16.73	-0.04	-19.48	-0.04	-20.21
Constant	0.18	8.89	0.14	6.32	0.37	11.24	0.28	8.08
Quarter fixed effects	Yes		Yes		Yes		Yes	
Fund fixed effects	Yes		Yes		Yes		Yes	
Observations	3082883		3082883		2498243		2498243	
Adj R2	0.0443		0.0447		0.0404		0.0391	

Table 1.6: Mutual Fund Trading Behavior by Flow Deciles

This table reports the total trading amount, average trading amount for each stocks traded and number of stock traded by fund flow deciles for sales and purchases separately. Column 1 is the flow decile; Column 2 reports the average fund flows as a percentage of fund TNA. Columns 3 to 5 are for stock sales, and columns 6 to 8 are for stock purchases. Specifically, Column 3 reports the average total dollar amount of stocks sold as a percentage of initial total stock holdings (equation 1.7); Column 4 reports average number of shares sold per stock sold as a percentage of initial number of shares held (equation 1.8); Column 5 reports average number of stocks sold as a percentage of total number of stocks (equation 1.9); Column 6 reports the average total dollar amount of stocks bought as a percentage of initial total stock holdings; Column 7 reports average number of shares bought per stock bought as a percentage of initial number of stocks held; Column 8 reports average number of stocks bought as a percentage of total number of stocks held. All averages are dollar weighted averages.

Flow deciles	Flow%	% of holdings sold $\overline{sold}_{i,t}$	% of holdings sold per stock sold $\overline{sold}_{i,j,t}$ $(sold_{i,j,t} < 0)$	% of number of stocks sold $\overline{\#sold}_{i,t}$	% of holdings bought $\overline{bought}_{i,t}$	% of holdings bought per stock bought $\overline{bought}_{i,j,t}$ $(bought_{i,j,t} < 0)$	% of number of stocks bought $\overline{\#bought}_{i,t}$
1	-12.2	**-20.6**	**-32.5**	**52.1**	14.6	90.1	27.1
2	-6.2	**-16.9**	**-32.1**	**42.3**	14.9	89.7	27.7
3	-4.3	**-14.6**	**-30.1**	**38.6**	13.6	74.0	28.7
4	-2.4	**-13.7**	**-30.5**	**35.7**	13.7	61.1	29.4
5	-1.1	**-11.7**	**-31.0**	**30.3**	12.7	54.6	31.5
6	-0.2	-9.4	-27.6	25.4	12.4	38.9	34.5
7	2.0	-8.6	-30.0	22.2	**12.6**	**33.1**	**39.2**
8	3.6	-9.9	-37.1	18.8	**14.9**	**32.4**	**46.1**
9	8.9	-10.4	-40.8	16.7	**21.4**	**41.7**	**52.9**
10	24.9	-11.1	-49.4	16.6	**35.1**	**61.9**	**62.1**

Table 1.7: The Spreading of Flow-driven Trades over Stocks

This table reports the regression results of funds' spreading of trades over stocks (regression 1.12 and 1.13). Panel A reports the spreading of sales for outflow samples. The dependent variable is the natural logarithm of the number of stocks sold by fund i in quarter t, $ln\#sold_{i,t}$. In columns 'Outflow (1) Flow-driven' and 'Outflow (2) Flow-driven', the main dependent variable is the proxy of the total dollar amount of outflow-driven sales $\widehat{lnSold}_{i,t}$, which is estimated by a first-step regression of total amount of sales on concurrent fund flows, regression 1.10. In column 'Outflow (2) Flow-driven' I also include the indicators for large funds, large-cap funds and large trades, $High\_TNA_{i,t-1}$, $Large\_Cap_{i,t-1}$, $Large\_Trade_{i,t}$ and their interactive terms with $\widehat{lnSold}_{i,t}$. Those indicators equal 1 if they are larger than the median, zero otherwise. Number of holding positions and fund TNA are added as control variables. In columns 'Outflow (1)' and 'Outflow (2)', I substitute the main independent variable $\widehat{lnSold}_{i,t}$ by the total dollar amount sold by fund i in quarter t, $lnSold_{i,t}$. Panel B reports the spreading of purchases for inflow samples. Both fund and quarter fixed effects are added, and the standard errors are clustered at the fund level.

Panel A: The spreading of sales for outflow sample

Dependent variable: $ln\#sold_{i,t}$ (Outflow sample only)

	Outflow (1)		Outflow (1) Flow-driven		Outflow (2)		Outflow (2) Flow-driven	
	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.
$\widehat{lnSold}_{i,t}$ ($lnSold_{i,t}$)	**0.53**	**54.85**	**0.97**	**49.88**	**0.52**	**38.07**	**1.26**	**28.49**
$\widehat{lnSold}_{i,t} \times High\_TNA_{i,t-1}$	-	-	-	-	0.03	1.29	0.08	0.97
$\widehat{lnSold}_{i,t} \times Large\_Cap_{i,t-1}$	-	-	-	-	**-0.02**	**-2.04**	**-0.05**	**-5.56**
$\widehat{lnSoldi}, t \times Large\_Trade_{i,t}$	-	-	-	-	-0.02	-0.86	-0.21	-1.78
Controls	...	...	...	...	...	...	...	...
Observations	40086		40086		40079		40079	
Adj R^2	0.74		0.61		0.75		0.56	

Panel B: The spreading of purchases for inflow sample

Dependent variable: $ln\#bought_{i,t}$ (Inflow sample only)

	Inflow (1)		Inflow (1) Flow-driven		Inflow (2)		Inflow (2) Flow-driven	
	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.
$\widehat{lnBought}_{i,t}$ ($lnBought_{i,t}$)	**0.54**	**72.54**	**0.63**	**80.09**	**0.57**	**45.76**	**0.74**	**52.63**
$\widehat{lnBought}_{i,t} \times High\_TNA_{i,t-1}$	-	-	-	-	**0.11**	**6.85**	**0.19**	**7.75**
$\widehat{lnBought}_{i,t} \times Large\_Cap_{i,t-1}$	-	-	-	-	0.00	0.49	0.00	-0.06
$\widehat{lnBoughti}, t \times Large\_Trade_{i,t}$	-	-	-	-	**-0.20**	**-9.53**	**-0.29**	**-8.73**
Controls	...	...	...	...	...	...	...	...
Observations	32004		32004		31870		31870	
Adj R^2	0.80		0.77		0.80		0.77	

Table 1.8: The Spreading of Flow-driven Trades over Stocks (lagged flows)

This table reports the regression results of funds' spreading of trades over stocks (regression 1.12 and 1.13) using **one-quarter-lagged fund flows** in the first-step regression. Panel A reports the spreading of sales for outflow samples. The dependent variable is the natural logarithm of the number of stocks sold by fund i in quarter t, $ln\#sold_{i,t}$. In columns 'Outflow (1) Flow-driven' and 'Outflow (2) Flow-driven', the main dependent variable is the proxy of the total dollar amount of outflow-driven sales $\widehat{lnSold}_{i,t}$, which is estimated by a first-step regression of total amount of sales on **one-quarter-lagged fund flows**. Panel B reports the spreading of purchases for inflow samples. Both fund and quarter fixed effects are added, and the standard errors are clustered at the fund level.

Panel A: The spreading of sales for outflow sample

Dependent variable: $ln\#sold_{i,t}$ (Outflow sample only)

	Outflow (1)		Outflow (1) Flow-driven		Outflow (2)		Outflow (2) Flow-driven	
	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.
$\widehat{lnSold}_{i,t}$ ($lnSold_{i,t}$)	**0.53**	**54.85**	**0.85**	**21.77**	**0.52**	**38.07**	**0.98**	**14.82**
$\widehat{lnSold}_{i,t} \times High\_TNA_{i,t-1}$	-	-	-	-	0.03	1.29	-0.08	-1.00
$\widehat{lnSold}_{i,t} \times Large\_Cap_{i,t-1}$	-	-	-	-	**-0.02**	**-2.04**	-0.01	-1.36
$\widehat{lnSold}_{i,t} \times Large\_Trade_{i,t}$	-	-	-	-	-0.02	-0.86	0.01	0.12
Controls	...	...	...	...	...	...	...	...
Observations	40086		24370		40079		24370	
Adj R^2	0.74		0.64		0.75		0.64	

Panel B: The spreading of purchases for inflow sample

Dependent variable: $ln\#bought_{i,t}$ (Inflow sample only)

	Inflow (1)		Inflow (1) Flow-driven		Inflow (2)		Inflow (2) Flow-driven	
	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.
$\widehat{lnBought}_{i,t}$ ($lnBought_{i,t}$)	**0.54**	**72.54**	**0.72**	**36.42**	**0.57**	**45.76**	**0.92**	**21.92**
$\widehat{lnBought}_{i,t} \times High\_TNA_{i,t-1}$	-	-	-	-	**0.11**	**6.85**	**0.16**	**2.35**
$\widehat{lnBought}_{i,t} \times Large\_Cap_{i,t-1}$	-	-	-	-	**-0.20**	**-9.53**	**-0.33**	**-3.30**
$\widehat{lnBought}_{i,t} \times Large\_Trade_{i,t}$	-	-	-	-	**-0.20**	**-9.53**	**-0.29**	**-8.73**
Controls	...	...	...	...	...	...	...	...
Observations	32004		16416		31870		16416	
Adj R^2	0.80		0.71		0.80		0.69	

Table 1.9: The Average Dollar Amount Sold for Each Stock Sold during Fund Outflows

This table reports the regression results of the dollar amount sold per stock sold on the fund outflows. The dependent variable is the natural logarithm of the dollar amount of stock j sold by fund i in quarter t, $lnSold_{i,j,t}$, and the independent variables include the natural logarithm of the total dollar amount of fund outflow for fund i in quarter t, $lnOutflow_{i,t}$, the indicators for large funds, large-cap funds and large trades, $High\_TNA_{i,t-1}$, $Large\_Cap_{i,t-1}$, $Large\_Trade_{i,t}$ and their interactive terms with $lnOutflow_{i,t}$. Those indicators equal 1 if they are larger than the median, zero otherwise. The initial holding of fund i in stock j, $lnHolding_{i,j,t-1}$, is added as control variable. Settings (1) and (3) include both quarter and fund fixed effects; Setting (2) and (4) include quarter fixed effects only. The standard errors are clustered at the fund level in all settings.

Dependent variable: $lnSold_{i,j,t}$ (for positions sold only)								
	(1)		(2)		(3)		(4)	
	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.
$lnOutflow_{i,t}$	**0.15**	**8.04**	**-0.08**	**-3.46**	**0.05**	**2.01**	**-0.23**	**-7.61**
$lnOutflow_{i,t} \times High\_TNA_{i,t-1}$	-	-	-	-	-0.03	-1.24	0.08	2.30
$lnOutflow_{i,t} \times Large\_Cap_{i,t-1}$	-	-	-	-	0.08	3.50	-0.02	-0.47
$lnOutflow_{i,t} \times Large\_Trade_{i,t}$	-	-	-	-	0.03	0.94	0.13	4.33
$High\_TNA_{i,t-1}$	-	-	-	-	-0.14	-1.75	-0.95	-6.73
$Large\_Cap_{i,t-1}$	-	-	-	-	-0.39	-4.17	-0.27	-2.94
$Large\_Trade_{i,t}$	-	-	-	-	0.60	7.92	0.72	7.31
$lnHolding_{i,j,t-1}$	0.77	38.69	0.97	54.76	0.76	36.51	0.96	45.14
Constant	0.96	3.62	-1.13	-4.54	1.2	4.12	-0.76	-2.72
Quarterly fixed effects	Yes		Yes		Yes		Yes	
Fund fixed effects	Yes		No		Yes		No	
Observations	2172317		2172317		2172310		2172310	
Adj R^2	0.60		0.63		0.62		0.66	

Table 1.10: Spreading of Flow-Driven Trades over Time

This table reports the regression results of the quarterly changes of stock holdings (as % of TNA) on concurrent and lagged flows (as % of TNA), the regression (1.15). I include the interaction terms of fund flows and the indicators for large funds and large-cap funds on the right side. Indicators for large funds and large-cap funds, and concurrent and lagged fund returns are added as control variables. Both quarter and fund fixed effects are included. Standard errors are clustered at the fund level.

Dependent variable: $\%\Delta holding_{i,t}$						
	(1)		(2)		(3)	
	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.
$flow_{i,t}$	**0.679**	**31.28**	**0.688**	**25.40**	**0.654**	**23.66**
$flow_{i,t-1}$	**0.081**	**7.70**	**0.071**	**5.61**	**0.092**	**6.72**
$flow_{i,t-2}$	**0.013**	**1.98**	**0.015**	**1.81**	**0.027**	**3.10**
$flow_{i,t-3}$	**0.021**	**3.78**	**0.021**	**2.98**	**0.027**	**3.43**
$flow_{i,t-4}$	-0.003	-0.49	-0.003	-0.40	-0.006	-0.81
$flow_{i,t-5}$	0.002	0.38	0.003	0.39	0.003	0.41
$flow_{i,t-6}$	0.001	0.18	-0.003	-0.49	0.004	0.57
$flow_{i,t} \times High\_TNA_{i,t-1}$	-	-	**-0.037**	**-1.11**	-	-
$flow_{i,t-1} \times High\_TNA_{i,t-2}$	-	-	**0.036**	**1.93**	-	-
$flow_{i,t-2} \times High\_TNA_{i,t-3}$	-	-	-0.008	-0.63	-	-
$flow_{i,t-3} \times High\_TNA_{i,t-4}$	-	-	-0.001	-0.10	-	-
$flow_{i,t-4} \times High\_TNA_{i,t-5}$	-	-	-0.005	-0.48	-	-
$flow_{i,t-5} \times High\_TNA_{i,t-6}$	-	-	0.000	-0.01	-	-
$flow_{i,t-6} \times High\_TNA_{i,t-7}$	-	-	0.014	1.41	-	-
$flow_{i,t} \times Large\_cap_{i,t-1}$	-	-	-	-	**0.058**	**1.46**
$flow_{i,t-1} \times Large\_cap_{i,t-2}$	-	-	-	-	**-0.025**	**-1.22**
$flow_{i,t-2} \times Large\_cap_{i,t-3}$	-	-	-	-	**-0.034**	**-2.75**
$flow_{i,t-3} \times Large\_cap_{i,t-4}$	-	-	-	-	-0.013	-1.28
$flow_{i,t-4} \times Large\_cap_{i,t-5}$	-	-	-	-	0.008	0.67
$flow_{i,t-5} \times Large\_cap_{i,t-6}$	-	-	-	-	-0.002	-0.17
$flow_{i,t-6} \times Large\_cap_{i,t-7}$	-	-	-	-	-0.006	-0.55
Constant	-0.033	-2.35	-0.037	-2.66	-0.037	-2.66
Controls for Returns	Yes		Yes		Yes	
Other Controls	Yes		Yes		Yes	
Quarterly fixed effects	Yes		Yes		Yes	
Fund fixed effects	Yes		Yes		Yes	
Observations	25120		25098		25098	
Adj R^2	0.527		0.531		0.531	

Table 1.11: Changes of Cash Holdings and Fund Flows

This table reports the regression results of the quarterly change of cash holdings (as % of TNA) on concurrent and lagged flows (as % of TNA), the regression (1.16). Under setting (2), concurrent and lagged fund returns are added as control variables. Both quarter and fund fixed effects are controlled. Standard errors are clustered at the fund level.

Dependent variable: $\Delta cash_{i,t}$				
	(1)		(2)	
	Coef.	t stat.	Coef.	t stat.
$flow_{i,t}$	**0.0199**	**4.86**	**0.0185**	**4.56**
$flow_{i,t-1}$	**-0.0095**	**-2.38**	**-0.0098**	**-2.40**
$flow_{i,t-2}$	**-0.0062**	**-2.11**	**-0.0058**	**-2.02**
$flow_{i,t-3}$	**-0.0065**	**-1.69**	**-0.0059**	**-1.41**
$flow_{i,t-4}$	-0.0013	-0.49	-0.0008	-0.31
$flow_{i,t-5}$	0.0002	0.07	0.0005	0.16
$flow_{i,t-6}$	0.0003	0.11	0.0004	0.14
Constant	0.0029	0.22	0.0064	1.51
Control for Returns	No		Yes	
Quarterly fixed effects	Yes		Yes	
Fund fixed effects	Yes		Yes	
Observations	20480		20480	
Adj R^2	0.010		0.011	

Table 1.12: Changes of Portfolio Liquidity and Fund Flows

This table reports the regression results of the changes of portfolio liquidity on concurrent and lagged flows and lagged changes of portfolio liquidity. I measure of the changes of portfolio liquidity, $Trade\_lnILLIQ_{i,t}$, as the dollar weighted average difference between the lnILLIQ values of stocks bought and sold. A negative value of this measure, $Trade\_lnILLIQ_{i,t}$, indicates that mutual fund i bought more liquid stocks than sold in quarter t; and a positive values indicates the opposite. The expression of this measure please refers to equation (1.17). And the regression please refers to equation (1.18). Concurrent and lagged fund returns are added as control variables. Both quarter and fund fixed effects are controlled. Standard errors are clustered at the fund level.

Dependent variable: $Trade\_lnILLIQ_{i,t}$						
	(1)		(2)		(3)	
	Coef.	t stat.	Coef.	t stat.	Coef.	t stat.
$flow_{i,t}$	**-0.5556**	**-10.03**	-	-	**-0.5587**	**-9.63**
$flow_{i,t-1}$	**-0.0718**	**-2.95**	-	-	**-0.0903**	**-3.17**
$flow_{i,t-2}$	**-0.0567**	**-2.73**	-	-	**-0.0692**	**-1.89**
$flow_{i,t-3}$	0.0023	0.13	-	-	-0.0057	-0.22
$flow_{i,t-4}$	-0.0117	-0.63	-	-	-0.0264	-0.80
$flow_{i,t-5}$	-0.0290	-1.83	-	-	-0.0634	-1.69
$flow_{i,t-6}$	-0.0437	-2.95	-	-	-0.0173	-0.70
$Trade\_lnILLIQ_{i,t-1}$	-	-	**0.0170**	**4.07**	-0.0024	-0.54
$Trade\_lnILLIQ_{i,t-2}$	-	-	**0.0097**	**1.62**	-0.0027	-0.33
$Trade\_lnILLIQ_{i,t-3}$	-	-	0.0045	1.13	-0.0020	-0.34
$Trade\_lnILLIQ_{i,t-4}$	-	-	0.0032	0.75	-0.0028	-0.43
$Trade\_lnILLIQ_{i,t-5}$	-	-	-0.0039	-0.66	-0.0116	-1.32
$Trade\_lnILLIQ_{i,t-6}$	-	-	0.0158	2.45	0.0124	1.81
Constant	0.0426	0.50	0.5006	6.41	0.1841	2.07
Control for Returns	Yes		Yes		Yes	
Quarterly fixed effects	Yes		Yes		Yes	
Fund fixed effects	Yes		Yes		Yes	
Observations	25136		23406		23337	
Adj R^2	0.069		0.022		0.074	

Table 1.13: Time Trend of Trading Cost Management

This table reports the time trend of all three aspects of trading cost management from 1980 to 2009. I do a rolling-window analysis for each aspect of trading cost management separately. I choose a window size of 10 years and 1 year per step. For the trading of liquid v.s. illiquid stocks, I report the coefficients of $flow_{i,t}$ in equation (1.4) & (1.5) for outflow and inflow samples separately; for the spreading of trades over stocks, I report the second-step coefficients of $lnSold_{i,t}$ in equation (1.12) for outflow samples and the second-step coefficients of $lnBought_{i,t}$ in equation (1.13) for inflow samples separately; and for the spreading of trades over time, I report the coefficients of contemporary flows $flow_{i,t}$ and first lagged flows $flow_{i,t-1}$ in equation (1.15).

Start Date	End Date	Trading Liquid (Outflow)	Trading Liquid (Inflow)	Spread over Stocks (Outflow)	Spread over Stocks (Inflow)	Spread over Time (Current)	Spread over Time (First Lag)
1980	1990	0.49	-0.16	0.82	0.57	0.54	0.14
1981	1991	0.32	-0.15	0.88	0.56	0.52	0.14
1982	1992	0.45	-0.20	0.88	0.60	0.52	0.14
1983	1993	0.62	-0.22	0.83	0.60	0.52	0.13
1984	1994	0.43	-0.25	0.81	0.59	0.53	0.13
1985	1995	0.21	-0.19	0.77	0.61	0.51	0.15
1986	1996	0.06	-0.18	0.74	0.61	0.50	0.15
1987	1997	0.08	-0.19	0.74	0.61	0.51	0.14
1988	1998	0.11	-0.21	0.74	0.61	0.53	0.11
1989	1999	0.14	-0.17	0.78	0.61	0.55	0.11
1990	2000	0.08	-0.13	0.83	0.60	0.62	0.11
1991	2001	0.10	-0.12	0.84	0.60	0.68	0.09
1992	2002	0.17	-0.13	0.83	0.60	0.75	0.09
1993	2003	0.19	-0.12	0.86	0.60	0.80	0.07
1994	2004	0.25	-0.13	0.92	0.60	0.76	0.07
1995	2005	0.32	-0.14	0.96	0.59	0.77	0.06
1996	2006	0.34	-0.16	0.99	0.59	0.76	0.06
1997	2007	0.34	-0.15	1.03	0.60	0.75	0.07
1998	2008	0.34	-0.13	1.03	0.61	0.74	0.07
1999	2009	0.35	-0.12	1.04	0.61	0.70	0.07

Table 1.14: Regressions Explaining Fund Flows

This table reports results from regressions of mutual fund flows on lagged fund flows and lagged fund returns. Mutual fund flows are measured as a percentage of beginning-of-period total net assets (TNA) and estimated as the percentage change in TNA over the quarter controlling for capital gains and losses of the initial holdings. Quarterly observations on flows and returns are used. Fama-MacBeth regression coefficients are the time-series average of periodic cross-sectional regression coefficients, with t-statistics calculated using the time-series standard error of the mean. The reported R^2 is the average across all cross sectional regressions. The pooled regression results are based on OLS coefficients and the standard errors are clustered at the fund level. The number of observations is denoted by 'observations', and t-statistics are in parentheses.

Dependent variable: $flow_{i,t}$				
	Fama−MacBeth		Pooled	
	Coef.	t stat.	Coef.	t stat.
$flow_{i,t-1}$	**0.162**	**4.65**	**0.314**	**16.51**
$flow_{i,t-2}$	**0.145**	**4.31**	**0.127**	**10.29**
$flow_{i,t-3}$	**0.112**	**2.50**	**0.048**	**4.80**
$flow_{i,t-4}$	**0.088**	**2.35**	**0.031**	**3.15**
$flow_{i,t-5}$	**0.072**	**2.49**	**0.022**	**2.72**
$flow_{i,t-6}$	**0.068**	**1.94**	0.012	1.50
$flow_{i,t-7}$	-0.029	-1.37	0.010	1.07
$flow_{i,t-8}$	0.00	-0.07	**0.025**	**3.17**
$Ret_{i,t-1}$	**0.41**	**9.65**	**0.061**	**8.47**
$Ret_{i,t-2}$	**0.30**	**5.96**	0.000	0.02
$Ret_{i,t-3}$	**0.23**	**5.04**	0.011	1.38
$Ret_{i,t-4}$	**0.13**	**2.97**	0.013	1.70
$Ret_{i,t-5}$	0.03	0.69	**0.018**	**2.29**
$Ret_{i,t-6}$	**0.07**	**2.12**	0.004	0.39
$Ret_{i,t-7}$	0.03	0.60	**-0.021**	**-2.83**
$Ret_{i,t-8}$	**0.10**	**2.06**	0.012	1.52
Constant	-0.032	-4.41	-0.005	-5.90
Observations	111		19373	
$AdjR^2$	0.1078		0.2135	

Table 1.15: Trading Cost Management of Expected v.s. Unexpected Flow-Driven Trades

This table reports the trading-cost-management behavior for unexpected flow-driven trades and expected flow-driven trades separately. The expected fund flows are predicted using past flows and past returns in the previous two years. For each aspect of trading cost management, I do the regressions separately for fund outflows and inflows. The coefficients used as measures of trading cost management are reported. For the spreading of trades over time, the coefficient of the concurrent flow is reported.

	Liquid v.s. Illiquid		Spreading over Stocks		Spreading over Time	
	Outflow	Inflow	Outflow	Inflow	Outflow	Inflow
Coefficient of	$flow_{i,t}$		$lnSold_{i,t}$	$lnBought_{i,t}$	$flow_{i,t}$	
Unexpected	**0.271*****	**-0.255*****	**1.224*****	**0.665*****	0.389***	0.595***
	(3.37)	(-3.69)	(14.43)	(24.54)	(16.36)	(16.11)
Expected	-0.169	-0.248	1.053***	0.572***	**0.145*****	**0.288*****
	(-1.20)	(-1.25)	(6.84)	(9.67)	(3.64)	(4.28)

Chapter 2

The Liquidity Risk Premium Demanded by Large Investors: Dynamic Portfolio Choice with Stochastic Illiquidity[12]

2.1. Introduction

Over the last 30 years, a growing literature has empirically analyzed the effect of illiquidity on asset prices. Recently, empirical work has focused in particular on the liquidity risk premium, which is a compensation for exposure to systematic liquidity shocks. Several articles document substantial liquidity risk premiums in realized returns (for example Pastor and Stambaugh (2003)), while other work finds that is difficult to disentangle the liquidity risk premium from the direct effect of transaction costs on prices, sometimes called the liquidity level premium (Acharya and Pedersen (2005)). In addition, the liquidity risk factors are often correlated with other risk factors, such as market risk, volatility risk and the Fama-French (1993) size factor. This makes it nontrivial to empirically pin down the liquidity risk premium. Surprisingly, there is little theoretical work on the size of the liquidity risk premium. In this paper we therefore add to the debate on the liquidity risk premium by analyzing what size for the liquidity risk premium can be justified theoretically. We do this by calculating the liquidity risk premium demanded by large investors, in setting with dynamic portfolio choice, stochastic price impact of trading, CRRA utility and a time-varying investment opportunity set.

Our first key finding is that our setup generates very small liquidity risk premiums, which are well below most empirical estimates. This is even the case under quite extreme

[12]This chapter is coauthored with Joost Driessen.

assumptions on the degree of liquidity risk and trading frequency. This result provides a benchmark for existing and future empirical work on the liquidity risk premium. In addition, as our setting follows as much as possible the standard portfolio choice framework, our work implies that nonstandard assumptions are necessary in theoretical models in order to have a chance at generating larger liquidity risk premiums.

Our second key finding is that in our setup the liquidity risk premium is always small relative to the liquidity level premium, which is the direct compensation for trading costs of a given asset (Amihud and Mendelson (1986)). Depending on the parameter settings, our model can generate a liquidity level premium of 1% to 2% per year, while the liquidity risk premium is at most 20 basis points. This provides some support for the empirical work that finds evidence for the existence of a substantial liquidity level premium.

Even though there is little theoretical work on the liquidity *risk* premium, several articles have developed theoretical models to understand the size of the liquidity *level* premium, including Constantinides (1986), Liu (2004), Lo, Mamaysky and Wang (2004), Jang, Koo, Liu and Loewenstein (2007). These articles study dynamic portfolio choice problems with transaction costs or other forms of illiquidity, but the degree of illiquidity is always constant and hence they cannot analyze the compensation demanded for liquidity risk. A few articles incorporate liquidity risk in theoretical asset pricing or portfolio choice problems (Acharya and Pedersen (2005), Lynch and Tan (2011), and Beber, Driessen and Tuijp (2012)). We compare to this work in more detail in the literature section.

We now explain our setup in more detail. Our approach is "partial equilibrium". We model an investor solving a multi-period portfolio choice problem with stochastic illiquidity, and obtain liquidity level and risk premiums by calculating how much expected return the investor is willing to give up to remove illiquidity or illiquidity risk. In our setup, we aim to follow as much as possible the most common features of multi-period portfolio choice. We focus on a CRRA agent who solves a multi-period portfolio choice problem, maximizing expected utility of terminal wealth. There are two assets, a risk-free asset and a risky asset with lognormal returns, calibrated to match U.S. equity index data. We allow for predictability of asset returns by having a time-varying expected return that mean reverts over time, which we calibrate using the often-documented predictability of returns by the dividend-price ratio. As noted by Lynch and Tan (2011), incorporating predictability induces the agent to trade more, which in turn makes illiquidity more important.

There are various way to model illiquidity, such as fixed transaction costs, proportional transaction costs, and periods where trading is not possible (see the literature section). We follow Garleanu and Pedersen (2013) and use transaction costs that are a quadratic function of transaction size. This is consistent with the idea that trading has price impact (Kyle (1985)). We choose this type of illiquidity as we want to focus on large investors, who are likely most important for the price formation in asset markets, and thus for the empirically observed liquidity premiums. For these large investors the price impact of trading is a key aspect of illiquidity. To incorporate liquidity risk we allow the price impact of trading to change stochastically over time. This is consistent with empirical findings. For example, Amihud (2002) proposes the ILLIQ measure to estimate price impact and finds substantial time variation in this measure. In addition, this existing work has found that shocks to price impact are negatively correlated to market returns: price impact is higher in bad times. We incorporate such correlation in our setting as it likely amplifies liquidity risk premiums. Acharya and Pedersen (2005) focus on these liquidity covariances as the source of liquidity risk premiums.

We calibrate the parameters of the illiquidity process to match empirical estimates of price impact of large transactions (Bikker, Spierdijk and van der Sluis (2007)). We then solve the dynamic portfolio choice problem numerically by backward induction. We calculate the liquidity level premium as the expected return the investor is willing to give up to remove a constant level of price impact of trading, and the liquidity risk premium as the expected return the investor is willing to give up to remove the time-series variation of the price impact (but not the average level of the price impact). In our benchmark setting the agent has a 10-year horizon and trades annually. More frequent trading leads to lower liquidity premiums as transaction sizes per trading round are smaller and hence total price impact is smaller.

In our benchmark parameter calibration, we find a rather small liquidity level premium of 17 basis points. The main reason for this small liquidity level effect is that investors endogenously choose to trade less in response to the presence of trading costs (as in Constantinides (1986)). Without trading costs investors rebalance their portfolio and trade to profit from the time-varying expected return. With trading costs, investors carefully trade off the benefits and costs of trading. The utility benefits of rebalancing and profiting from time-varying expected returns are rather small according to our calibrations, and hence even small trading costs strongly reduce the amounts traded. To see this quantitatively, we decompose the total premium into a part that directly compensates for average trading costs, which equals 4 basis points, and a part that captures the utility loss of deviating from the optimal weight in the risky asset (13 basis points). Lynch and Tan (2011) also study the effect of predictability on the liquidity level premium and find a somewhat larger effect of 43 basis points, which is still below most empirical estimates of the liquidity level premium.

Our key result is on the liquidity risk premium. In the benchmark setting, the liquidity risk premium is below 1 basis point per year. This effect is due to the negative covariance of the asset return and shocks to the price impact of trading. This effect is small for several reasons. First, since the agent cares only very moderately about the level of trading costs, variation in these trading costs does not affect the expected utility much either. Second, even though the negative covariance between costs and returns implies that trading costs are higher in bad states of the world, the agent can endogenously choose to trade less when trading costs are currently higher than usual. This is a key difference between our approach and the model of Acharya and Pedersen (2005), where agents always trade their entire portfolio irrespective of the state of the world. By looking at a case with zero covariance between price impact and asset returns, we also find that independent variation in the price impact of trading has no meaningful effect on the agent's utility.

We perform various robustness checks to validate this result. We vary risk aversion, the covariance between costs and returns, and the level of price impact costs, and find that all these aspects have only a very small effect of the liquidity risk premium. We then add two nonstandard features to the setup in order to try to generate a larger liquidity risk premium. First, we force the investor to completely build up his risky asset position at time zero and fully sell off this position after some time. Even if we force the investor to perform this building up and selling off every year, the liquidity risk premium is below 3 basis points, while the liquidity level premium is much higher at around 2% due to the much higher trading amounts. The liquidity risk premium remains small in this case because the "forced" buying and selling is fully anticipated in this setting. We therefore consider a second case where we add "liquidity crisis" periods to the model. In each period, if the market return is below (minus) one standard deviation, the agent has to sell part of the risky asset. The size of the amount sold depends negatively on the market return. This generates priced liquidity risk, as the amount traded depends on the market return and thus on the state of the world. However, even in this rather extreme setting, the maximum liquidity risk premium we obtain is 20 basis points per year, while the liquidity level premium is higher at 55 basis points. In sum, our results show that it is difficult to generate a large liquidity risk premium using standard preferences and dynamic portfolio choice. Nonstandard assumptions are necessary in order to generate large liquidity risk premium.

The paper is organized as follows. Section 2 discusses related literature and contributions. Section 3 describes the dynamic portfolio choice problem with quadratic and time-varying trading costs. Section 4 solves the problem numerically. In Section 5, we calculate the implied liquidity level premiums and liquidity risk premiums under the benchmark setting, setting with fixed frequency of rebuilding the portfolio and setting with forced selling during market downturn separately. Section 6 compare the correlation between market returns and turnovers indicated by our model and that in market data, and followed by conclusions in Section 7.

2.2. Related Literature and Contributions

Several papers investigate the magnitudes of liquidity and liquidity risk premiums in financial markets, both theoretically and empirically.[13][14] One major thread of the theoretical literature is the analysis of portfolio choice with trading costs. Most papers in this

[13] In the previous research of asset illiquidity there are many different definitions. For example, the existence of non-trading interval in Diamond (1982), Ang, Papanikolaou and Westerfield (2014); the limitation on trading quantities (e.g. Longstaff (2001)); or trading at deterministic times (e.g. Kahl, Liu, and Longstaff (2003); Koren and Szeidl (2003); Schwartz and Tebaldi (2006); Longstaff (2009) etc.). The type of illiquidity we study in this paper is the trading costs, the most common one investigated in both liquidity pricing and portfolio choice literature (e.g. Constantinides (1986); Grossman and Laroque (1990); Vayanos (1998); Pastor and Stambaugh (2003); Lo, Mamaysky and Wang (2004); Acharya and Pedersen (2005) etc.).

[14] Liquidity risk is defined in many different ways in previous literature. For example, Huang (2003) defines it as the randomly arrived liquidity shocks; in Vayanos (2004), it refers to the time variation of needs to liquidate; Ang, Papanikolaou and Westerfield (2014) uses it for the uncertainty of the length of non-trading interval. In this paper, we follow Acharya and Pedersen (2005) and define liquidity risk as the time variation of trading costs which is more consistent with the reality in stock market.

thread assume time constant trading-cost rates, which might be true for explicit costs (e.g. brokerage commissions) but is often not true for implicit trading costs (e.g. bid-ask spreads and price impact costs). As a starting point of this thread, Constantinides (1986) shows that for realistic proportional costs, the per-annum liquidity premium that must be offered to induce a constant relative risk aversion (CRRA) investor to hold the illiquid asset instead of an otherwise identical liquid asset is an order of magnitude smaller than the trading-cost rate itself. In subsequent work, Liu (2004) and Lo, Mamaysky and Wang (2004) use fixed trading costs. Realistic fixed trading costs can still hardly explain the large magnitude of the liquidity level premium. Longstaff (2001) limits the maximum amount of each transaction; and Garleanu (2008) models the illiquidity as the delay of trades.

The influence of trading costs largely relies on the trading frequency and the trading amounts. More trading leads to a larger liquidity level premium. The most popular way to achieve more trading is to add a time-varying investment opportunity set (return predictability or time-varying volatility). With this setting, many papers, such as Jang, Koo, Liu and Loewenstein (2007) and Lynch and Tan (2011), derive more trades and relatively larger liquidity level premiums.

Another choice is to create more trading motives with background risk. For example, Lynch and Tan (2011) include shocks to labor income in their model. Lo, Mamaysky and Wang (2004) and Garleanu (2008) both assume time-varying endowments in each period. Huang (2003) assumes that all investors face liquidity shocks and have to release their positions at some time point.

We add to this literature by letting trading-cost rates vary over time to study the magnitude of the liquidity risk premium, and we include forced selling during market downturns to further explore how this interacts with the time varying trading-cost rates and how it affects the liquidity risk premium.

Few theoretical studies include liquidity risk. The liquidity-adjusted CAPM proposed by Acharya and Pedersen (2005) assumes time varying trading-cost rates. It provides a unified framework for understanding the various channels through which liquidity risk may affect asset prices. The primary limitation of liquidity-adjusted CAPM is that it is a one-period model. The trading frequency and trading amount are determined exogenously. In reality, both of them should be determined endogenously by investors, and these decisions should affect liquidity level and liquidity risk premiums in equilibrium. To make the trading frequency and trading volume endogenous, a multi-period model is required. Beber, Driessen and Tuijp (2012) provide a multi-period extension of Acharya and Pedersen (2005), but continue to assume that investors do not trade at intermediate dates. In contrast, in our model the investor is allowed to rebalance and trade at intermediate dates.

To our best knowledge, Lynch and Tan (2011) and Garleanu and Pedersen (2013) are the only two dynamic portfolio choice papers assuming time-varying trading-cost rates while also having endogenously determined trading amounts and frequencies.

Lynch and Tan (2011) shows that permanent shocks on labor income and return predictability produce an additional trading motive and thus a first-order liquidity level premium. Their numerical results also show that time-varying trading-cost rates further inflate the premium since under their setting the trading-cost rate is high when the agent trades the most. Different from Lynch and Tan (2011), we study the portfolio choice problem of large institutional investors instead of individual investors and allow for price impact of trading. Institutional investors are more likely to be the marginal investors in financial markets. We thus use time-varying quadratic trading costs, instead of the percentage trading costs as Lynch and Tan (2011) do. In addition, institutional investors care more about funding liquidity shocks than labor income, therefore we assume exogenous liquidity shocks rather than labor income shocks. Finally we show that the forced selling of institutional investors during market downturns actually interacts with the time variation of trading costs and enlarges the liquidity risk premium.

Garleanu and Pedersen (2013) define a multi-period mean-variance portfolio choice problem, using additional assumptions on the objective function and return dynamics. Specifically, they assume that price changes (and not returns) are homoskedastic. They focus on the implications for portfolio choice, and do not calculate liquidity level or liquidity risk premiums. Different from their paper, we use a standard multi-period CRRA utility framework, with standard dynamics of returns. In terms of portfolio choice, we do find similar implications as Garleanu and Pedersen (2013). Specifically, we confirm their conclusion that investors "aim in front of the target": when chasing time-varying expected returns, investors balance trading costs, the utility benefits of these time-varying returns, and the extent to which these return opportunities are expected to disappear quickly over time or not. More generally, our paper provides useful implications to the trading cost management of long-term investors, showing how to balance trading costs, rebalancing and investment opportunities.

Our paper provides a benchmark to empirical work on liquidity level and liquidity risk premiums. A number of empirical papers (e.g. Amihud and Mendelson (1986), Amihud (2002), Pastor and Stambaugh (2003) and Acharya and Pedersen (2005)) find substantial differences in expected returns across portfolios sorted on liquidity measures, with a magnitude ranges from 4% to 7% per annum. Some recognize it as the premium for the level of illiquidity (Amihud and Mendelson (1986) and Amihud (2002)), while others understand it as the premium for liquidity risk (Pastor and Stambaugh (2003)) or both (Acharya and Pedersen (2005)). In general, existing theories can hardly explain the large liquidity premiums found empirically.

2.3. Model

Our model follows the most common features of the dynamic portfolio choice problem in the existing literature. We solve a dynamic portfolio choice problem for a CRRA agent by maximizing his expected utility of terminal wealth. The model has two assets, a risk-free asset and a risky asset with lognormal returns. We incorporate return predictability by allowing the expected return to vary over time. Our model deviates from the common features of dynamic portfolio choice by including quadratic transaction costs (price impact costs) into the setting and allows the price impact of trading to change stochastically over time.

We assume the log risk free rate r_f is constant over time, and the log return of the risky asset is

$$r_{t+1} = \mu_t + \sigma_r u_{t+1} \tag{2.1}$$

where μ_t is the conditional mean of log return, and σ_r is the volatility parameter. The return shock u_{t+1} is normally distributed with mean zero and standard deviation of one. We assume that μ_t depends on a driving factor F_t which follows an AR(1) process,

$$F_{t+1} = \rho F_t + v_{t+1} \tag{2.2}$$

$$\mu_t = \mu_0 + aF_t \tag{2.3}$$

In our model, F_t is the only state variable which drives the time variations of both expected return μ_t and the trading cost parameter λ_t, which will be introduced later. v_{t+1} is the shock on F_{t+1}, and it follows a standard normal distribution. We assume the correlation between the shocks of returns and state variable F_t as $Corr(u_t, v_t) = Corr$, the time persistency parameter of F_t is ρ, and the long-run mean of F_t is zero. Parameter a decides the magnitude of the time variation of μ_t. μ_t is constant over time if $a = 0$. By substituting F_t into the expression of μ_t, we can easily find that μ_t is also an AR(1) processes, and μ_0 is the long-run mean of the expected return.

Trading is costly in our setting. We follow Garleanu and Pedersen (2013) and use quadratic transaction costs. The expression for the dollar costs of trading a dollar amount V_t is

$$TC_t = \frac{1}{2} V_t^2 \sigma_r^2 \lambda_t \tag{2.4}$$

The trading costs TC_t depend on V_t^2, rather than V_t which is what proportional transaction costs imply. Like Garleanu and Pedersen (2013), we assume the price impact scales with the variance of returns σ_r^2, and multiply this by a stochastic trading cost parameter λ_t. This expression of quadratic transaction costs is consistent with the idea that trading has price impact (Kyle 1985). Under this setting, trading V_t moves the price by

$$PI_t = V_t \sigma_r^2 \lambda_t \tag{2.5}$$

For a given trading amount V_t, the corresponding proportional trading cost c_t equals half the total price change, which can be written as

$$c_t = \frac{1}{2} PI_t = \frac{1}{2} V_t \sigma_r^2 \lambda_t \tag{2.6}$$

We assume the natural logarithm of the trading cost parameter λ_t also depends on state variable F_t and follows an AR(1) process,

$$\ln \lambda_t = \ln \lambda_0 + bF_t \tag{2.7}$$

where b is the sensitivity of $\ln \lambda_t$ to shocks on F_t, and $\ln \lambda_0$ is the long-run mean of $\ln \lambda_t$. λ_t is constant over time if $b = 0$.

The investor has a finite investment horizon T, and his initial wealth W_0 is strictly positive. We assume that the investor maximizes the expected CRRA utility of the terminal wealth, W_T,

$$E_0(\frac{W_T^{1-\gamma} - 1}{1-\gamma}) \tag{2.8}$$

The weight in risky asset at each time step, $\alpha_t, t = 1, 2, \ldots, T-1$, serves as the control variable. The investor's objective is to maximize the expected CRRA utility of the terminal wealth by choosing the dynamic investment strategy $(\alpha_0, \alpha_1, \ldots, \alpha_{T-1})$,

$$\max_{\alpha_0, \alpha_1, \ldots, \alpha_{T-1}} E_0(\frac{W_T^{1-\gamma} - 1}{1-\gamma}) \tag{2.9}$$

Then the total trading amount at each time step is

$$V_t = (\alpha_t - \alpha_{t-})W_t \tag{2.10}$$

where α_{t-} is the weight in risky asset before rebalancing. Substituting equation (2.10) into equation (2.4), we get

$$TC_t(W_t, \alpha_t, \alpha_{t-}, \lambda_t) = \frac{1}{2}((\alpha_t - \alpha_{t-})W_t)^2 \sigma_r^2 \lambda_t \tag{2.11}$$

We assume that all trading costs are paid from the risky asset[15]. Thus, the level of wealth in next time step is

$$W_{t+1} = (1-\alpha_t)W_t exp(r_f) + (\alpha_t W_t - \frac{1}{2}((\alpha_t - \alpha_{t-})W_t)^2 \sigma_r^2 \lambda_t) exp(r_{t+1}) \tag{2.12}$$

[15] Assuming that trading costs are paid out of the risk-free asset instead of risky asset does not make any difference on our result, since it is the weight in risky asset after trading costs are paid that matters in our model.

and the weight of the risky asset before rebalancing in next time step is

$$\alpha_{(t+1)-} = \frac{(\alpha_t W_t - \frac{1}{2}((\alpha_t - \alpha_{t-})W_t)^2 \sigma_r^2 \lambda_t) exp(r_{t+1})}{W_{t+1}} \quad (2.13)$$

The value function J at each time step t can be expressed as

$$J(W_t, \alpha_{t-}, F_t, t) = \max_{\alpha_t} E_t(\frac{W_T^{1-\gamma} - 1}{1-\gamma}) \quad (2.14)$$

and the Bellman equation for this dynamic portfolio choice problem is

$$J(W_t, \alpha_{t-}, F_t, t) = \max_{\alpha_t} E_t[J(W_{t+1}, \alpha_{(t+1)-}, F_{t+1}, t+1)] \quad (2.15)$$

The problem is solved using backward induction. We search numerically for the weight in risky asset α_t which maximizes the expected utility of the terminal wealth from the last period to the first[16].

2.4. Numerical Solution

In this section, we further discuss how we solve this dynamic portfolio choice problem numerically with realistic parameter values comparable with U.S. stock market data. We use the setting with time-varying expected returns as the benchmark setting. The shocks on expected returns provide the trading motives needed to generate liquidity level premium and liquidity risk premiums[17].

2.4.1. Parameter Values

We assume that the long-term mean of expected annual return is 4% ($\mu_0 = 0.04$) and the standard deviation of return shocks is 10% ($\sigma_r = 0.10$). Risk free rate is 2% ($r_f = 0.02$), and the risk aversion level of our representative investor is 2.5 ($\gamma = 2.5$). Then if there is no trading cost and time variation in expected returns ($\mu_t = \mu_0 = 0.04$), the analytical

[16] Details of the numerical procedure please refer to Appendix 2.8.3.

[17] If the time-constant expected return is used, the only trading motive is to rebalance the portfolio after price fluctuation. Such trading motive is usually very small (refer to the Appendix). It does not even exist under the market clearing condition in our setting, since both the initial weight and the optimal weight of our risky asset is fixed to 100% and does not change with the price.

solution of the optimal weight is

$$\alpha^{LongRun} = \frac{\mu_0 - r_f + \sigma_r^2/2}{\gamma\sigma_r^2} = 100\% \tag{2.16}$$

for all t. It means it is optimal for the representative investor to invest all his wealth in risky asset. To add the time variation of expected returns to our setting, we set the standard deviation of the shocks to expected returns at 1% ($a = 0.01$)[18].

Since we want to document an upper bound of the liquidity risk premium, we use a high trading-cost rate with substantial time variation for our analysis. For the level of trading costs parameter λ_c, we take the estimates in Bikker, Spierdijk and van der Sluis (2007) as a reference and assume that the price impact of a 1.5 million dollar trade is 40 basis points, $\lambda_c = 26.88$[19], which indicates a trading costs of 20 basis points (half the price impact). This assumption is also consistent with the numbers found in most papers of price impact (for example, Chan and Lakonishok 1997 find a price impact about 54 bps, and Keim and Madhavan 1997 find a price impact about 30 bps to 65 bps). In addition, we allow the trading-cost rate to be 3 times higher in a robustness check. We set the parameter for time variation of the trading-cost rates to 0.3149 ($b = 0.3149$), which is calibrated using the variation in the annual $ln(ILLIQ)$ measure proposed in Amihud (2002)[20]. ILLIQ, as λ in our model, is a measure of price impact calculated as the absolute value of the daily return divided by the daily dollar trading volume. Under this setting, the 95% confidence interval of λ_t is $[0.18 * \lambda_c, 5.64 * \lambda_c]$, which means a 2 standard deviation positive (negative) shock on λ_t makes it more than five times (less than one fifth) its long-term level.

We set the annual time persistence of the state variable F_t at 0.7 ($\rho = 0.7$), which is calibrated using the monthly data ILLIQ series, and we set the initial wealth at 100 million dollars, ($W_0 = 1$), which is about the median size of U.S. hedge funds. Since hedge funds are more likely to be the marginal traders in the financial market and more likely to experience liquidity shocks than large mutual funds and pension funds do, we choose to use the median size of hedge funds in our benchmark setting.

[18] Assuming dividend yield as the only predictor, we use the dividend yield data from 1952 to 2010 for the calibration of parameter a. The calibration using monthly data indicates an annual standard deviation of 0.92%, and using annual data, it increases to 1.86%.

[19] It is calibrated using equation (2.5).

[20] The annual ILLIQ values from 1952 to 2010 are used for the calibration.

Considering there is only 1 asset in our economy, 100 million dollars holdings of one single asset is large enough to generate a significant price impact of trades. To further make sure we will not underestimate the liquidity risk premium, we also solve the problem with higher level of wealth, which is equivalent to using a higher trading-cost rate λ_t in our setting. We solve the portfolio choice problem for 10 years, with an annual trading frequency. For the calculation of liquidity risk premium, we solve the problem for different values of the correlation between shocks on realized returns and trading-cost rates, $Corr(v_t, u_t) = 0, -0.2, -0.4, -0.6$.

To sum up, in our assumptions we try incorporate a substantial degree of illiquidity, in an attempt to try to generate substantial liquidity level and liquidity risk premiums. We assume high levels for the trading-cost rate, large time variation in it (from one fifth to five time the mean level), large trading motives (time-varying expected returns, and later a fixed frequency of rebuilding the portfolio and exogenous liquidity shocks), a single risky asset (no spreading of trades over stocks to reduce the price impact of trades), large institutional investors (high price impact of trades and high exposure to liquidity shocks), and an annual trading frequency (no spreading of trades within a year to reduce the price impact of trades).

2.4.2. Numerical Results

The dynamic portfolio choice problem is solved by backward recursion. Gaussian Quadrature is used to deliver the joint distribution of shocks on the state variable F_t and return shocks (v_t, u_t). Four points are used for each shock. Figure 2.1 shows the weights in risky asset both before and after rebalancing under the reference case with a time constant trading-cost rate. Here we assume zero correlation between the shocks of investment opportunity set and the returns shocks thus there is no hedging demand.

[Insert Figure 2.1 about here]

Figure 2.1 plots one simulation of the weights in the risky asset across 10 time steps, for both the weights before rebalancing, α_{t-}, with black circles, and the weights after rebalancing and trading costs, α_{t+}, with red stars. In each time step, the investor trades partially towards the myopic optimal weight, α_t^{Myopic}, the pink crosses. The expression of α_t^{Myopic} is

$$\alpha_t^{Myopic} = \frac{\mu_t - r_f + \sigma_r^2/2}{\gamma \sigma_r^2} \tag{2.17}$$

which varies over time with the conditional expected return μ_t. If the investor trades the entire way from α_{t-} to α_t^{Myopic}, he needs to pay a large amount of trading costs. On the other hand, if he does not trade at all and keeps the weight at α_{t-}, he loses too much utility by deviating from the α_t^{Myopic}. Therefore, it is optimal to trade partially towards the aim. The optimal amount to trade is decided by the trade-off between the marginal utility gain of getting closer to the aim and the marginal trading costs incurred. We will show later that both the loss of utility caused by deviation from α_t^{Myopic} and the actual trading costs incurred should be compensated in the form of a higher expected return (liquidity level premium). Besides, the investor resists to trade further away from $\alpha^{LongRun}$, the green dash line, since it will generate more trading costs in the future. These results are consistent with the main findings in Garleanu and Pedersen (2013), when trading is costly, the investor should trade partially towards the current aim, and also aim in front of the target (consider the long-run optimal weight, $\alpha^{LongRun}$).

2.5. Liquidity Level Premium and Liquidity Risk Premium

In the previous section, we have shown that trading costs make the investor deviate from the optimal solution in the frictionless market. In a competitive market, investors should require a premium (higher expected return) to compensate for the loss of utility caused by trading costs. Therefore, in this section, we compute both the liquidity *level* premium, the premium compensates for the level of trading costs, and the liquidity *risk* premium, the premium compensates for the time variation of trading costs.

In this paper, the liquidity level premium is defined to be the decrease in the long-term mean of the expected return, μ_0, on the risky asset that the investor requires to be indifferent between having access to the risky asset without rather than with trading costs. The liquidity risk premium is defined to be the decrease in the long-term mean of the expected return on the risky asset that the investor requires to be indifferent between having access to the risky asset without rather than with *time variation* in trading costs. This approach is a "partial equilibrium". A positive premium means that the investor should be compensated for the utility loss caused by trading costs or time variation of trading costs, and a negative premium indicates investor benefits from them.

First, we discuss intuitively the sources of liquidity level premium and liquidity risk premium. As we mentioned in previous section, investors should be compensated for both the actual trading costs and the loss of utility caused by the deviation from the optimal weight. Liquidity level premium measures such compensation in term of a higher expected return. It is worth noting that the part of the liquidity level premium that compensates for the actual trading costs depends on the total amount of trading costs, which is the product of cost rate and total trading amount, rather than the cost rate itself. The larger the trading amount, the higher the liquidity level premium.

The liquidity risk premium measures the compensation for the loss of utility caused by the time variation of trading-cost rates, also in terms of the increase in expected return. The time variation of trading-cost rates has three different effects on the utility of the investor, thus it also enters the liquidity risk premium through three different channels: the variance of the cost rates (*Variance Effect*), the covariance between trading costs and realized returns (*Covariance Effect*), and the additional freedom to choose the weight in risky asset introduced by the time variation of cost rates (*Choice Effect*).

1. *Variance Effect:* Since the representative investor is risk averse, the time variation of trading costs should be penalized. A positive premium should be required as a compensation.

2. *Covariance Effect:* The investor dislikes to pay large amounts of trading costs during market downturns, hence a negative covariance between the trading costs and realized returns $Cov(c_t, r_t)$ should be penalized, and a positive premium should be required as a compensation.

3. *Choice Effect:* In a dynamic setting, investors respond actively to the time variation of cost rates. Investors trade more when cost rates are low and trade less when it is high. In this case, investors can actually benefits from the time variation of cost rates, and if this effect dominates, a negative liquidity risk premium should be found. We show later that the liquidity risk premium is actually negative in some of our settings.

To sum up, the liquidity risk premium is always an aggregate premium for these three different effects instead of just a single one.

2.5.1. Benchmark Setting

Under the benchmark setting, the only trading motive is the time-varying myopic aim introduced by the time-varying expected returns. To calculate the liquidity level premium and liquidity risk premium, we solve four different cases of the portfolio choice problem:

Case 1: with constant expected return and *no* trading costs
$(a = 0, b = 0, \lambda_t = \lambda_c = 0)$
Case 2: with time-varying expected returns and *no* trading costs
$(a = 0.01, b = 0, \lambda_t = \lambda_c = 0)$
Case 3: with time-varying expected returns and *constant* trading-cost rate
$(a = 0.01, b = 0, \lambda_t = \lambda_c = 26.88)$
Case 4: with time-varying expected returns and *time-varying* trading-cost rates
$(a = 0.01, b = 0.315, \lambda_c = 26.88)$

We calculate the expected utility for each case. The initial position in risky asset is assumed to be at 100%, the long-term optimal weight in risky asset. *Case 1*, the case with constant expected return and no trading costs is used as the reference case for the calculation of both the liquidity level premium and liquidity risk premium. Specifically, for each of *Case 2,3,4*, we find the corresponding level of expected return in the benchmark case (*Case 1*) which makes the investor indifferent between holding the risky asset in this case and the one in the reference case (it means investor has the same expected utility when holding either one of these two risky assets). Then we compare the corresponding levels of expected returns across different cases. The difference of corresponding expected returns between *Case 2* and *Case 3* is recorded as the liquidity level premium, and the difference of the corresponding expected returns between *Case 3* and *Case 4* is recorded as the liquidity risk premium. The liquidity risk premium for $Cov(\lambda_t, r_t)$, the covariance between trading-cost rates and returns, is calculated as the difference of the corresponding expected returns with nonzero correlation between trading-cost rates and returns, $Cov(\lambda_t, r_t) \neq 0$, and the case with zero correlation, $Cov(\lambda_t, r_t) = 0$.

[Insert Table 2.1 about here]

Table 2.1 reports the liquidity level premium and liquidity risk premium under the benchmark setting, for different values of the correlation between the return shocks and shocks on trading-cost rate (shocks on state variable F_t), 0, -0.2, -0.4, -0.6. Firstly, we find that the magnitudes of the liquidity risk premium are extremely small, ranging from -0.623 to -0.104 bps, significantly smaller than the liquidity level premium, which ranges from 16.43 to 15.68 bps. The effect of time variation of cost rates on investor's utility is substantially smaller than the effect of the trading cost level. The premium for $Cov(\lambda_t, r_t)$ indeed increases as the correlation between returns and cost rates becomes more negative, but the effect is always smaller than 1 bps and accounts for 3.3% of the total liquidity premium at most. The small liquidity risk premiums found in our analysis conflict with the empirical literature on the liquidity risk premium (e.g. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005)), where the covariance between trading-cost rates and returns, $Cov(c_t, r_t)$, generates a large liquidity risk premium.

If we put our estimate of liquidity risk premium into the framework of Acharya and Pedersen (2005), our estimate is the difference of liquidity risk premium between a stock with no exposure to liquidity risk (with a liquidity beta, $Cov(c_t, r_t) = 0$) and a stock with market average exposure (market average beta). The liquidity risk premium calculated in Acharya and Pedersen (2005) is the difference of liquidity risk premium between the most liquidity portfolio and the most illiquid portfolio (1.1% per year). Since the difference of (total) liquidity betas in Acharya and Pedersen (2005) between the most liquid and most illiquid is 5.83, and the market average (total) liquidity beta is 2.59. Their estimate of the market liquidity risk premium is about 0.47% (47 bps), which is substantially larger than our estimate of 1 bp. Pastor and Stambaugh (2003) add a market liquidity factor to the Fama-French 3 factor model. Hence, the market average beta of their liquidity factor is 0. In addition, the liquidity beta of their most liquid decile is -5.75. If we use this number as the liquidity beta of a stock with no exposure to liquidity risk, their measure of market liquidity risk premium is as large as 5.23% per year (liquidity beta * price of risk = 5.75 * 0.91% = 5.32%).

We find negative liquidity risk premiums in all 4 settings. As we have explained at the beginning of this section, it means the *Choice Effect* dominates the *Variance Effect* and *Covariance Effect*, the investor actually prefers to have time variation in trading-cost rates since he/she can react according to the realized cost rate and thus variation in cost rates increases the expected utility. To better understand how the *Choice Effect* generates a negative liquidity risk premium, we plot the expected utility of the terminal wealth as a function of the trading-cost parameter λ_c under the optimal strategy in Figure 2.2 (the solid curve), for the reference case with time constant trading-cost rate and zero correlation between return shocks and shocks on F_t. Since trading costs limit investor's rebalancing of the portfolio, the expected utility decreases with the increase of trading-cost parameter λ_c. When λ_c becomes larger, investors choose to trade less. So the increase of λ_c will have a smaller effect on investor's expected utility. Therefore, the expected utility is strictly convex in λ_c, which means the linear combination of any two points on the curve is above the curve. Then if we assume λ_c is stochastic at time 0, instead of deterministic, the expect utility of the investor should always be higher than the expect utility indicated by the curve. The uncertainty in λ_c always increases the expected utility of investor. Because of this, when we introduce time variation into the trading-cost parameter λ, the *Choice Effect* makes the liquidity risk premium negative. Economically, this effect is rather small however.

Secondly, it is also worth noting that the liquidity level premium, ranging from 15.68 to 16.48 bps, is significantly smaller than the 65 bps [21] price impact costs of an average trade under the benchmark setting. This result is consistent with Constantinides (1986), who shows that the liquidity premium is an order of magnitude smaller than the trading-cost rate itself. The reason is that investors trade less if the trading-cost rate is high. Under the benchmark setting, the only trading motive is to trade towards the time-varying myopic aim introduced by the time-varying expected return μ_t. If there is no trading cost, the utility gain of chasing the myopic aim is equivalent to a 22 bps increase in expected return μ_0. It means the upper limit of the liquidity level premium is 22 bps, since if the trading-cost rate is too high, investors will choose to not trade at all and bear all the utility loss of not trading. As Table 2.1 shows, the total liquidity premium is about 15.27-16.12 bps, slightly smaller than the 22 bps. It indicates that it is optimal for investors to trade slightly towards the myopic aim to reduce the utility loss of investing sub-optimally. Table 2.2, we show that only a small faction of liquidity level premium compensates for actual trading costs, about 4.18 bps (out of 16.34 bps), and a large fraction compensates for the utility loss of deviating from the myopic optimal weight, about 12.65 bps (out of 16.34 bps). This result is in accordance with the conjecture in

[21] The average trading amount for the benchmark setting is 4.9 million dollars, which corresponds to price impact costs of 65.3 bps (1/2*4.9m*0.01*26.88) according to equation (2.5).

Garleanu and Pedersen (2013) that investors balance between the trading costs and the loss of utility caused by deviating of the myopic optimal weight to maximize the expected utility.

[Insert Table 2.2 about here]

To further investigate how the level of trading-cost rate affects the magnitudes of liquidity risk premium as well as the liquidity level premium, we solve the dynamic problem for different values of the trading-cost parameter. Table 2.2 reports the liquidity level premium, for the parts compensating for trading costs (TC)[22] and compensating for the deviation from optimal weight[23] separately, liquidity risk premium and average trading amounts across different trading-cost rates, from 3.36 (1/8*26.88) to 107.52 (4*26.88). The correlation between return shocks and shocks on F_t, $Corr(u_t, v_t)$ is set to -0.3 in all cases. We see that the liquidity risk premium changes only slightly from -0.494 bps to -0.297 bps when the cost rate becomes 4 times as large as before. Considering a cost rate 4 times large indicates a 1.6% price impact from a 1.5 million $ trade, the liquidity risk premium of -0.297 bps is negligible. The magnitude of the cost rate does not have a significant effect on the liquidity risk premium under our benchmark setting. It is worth noting that since the wealth level and the trading amount are the only two assumptions based on dollar value in our model, and the trading-cost parameter λ_c is calibrated based on the trading amount, an increase in trading-cost parameter λ_c is equivalent to an increase in wealth level in our model. It means the liquidity premiums calculated for the setting with initial level of wealth as 100 million dollars and λ_c=4*26.88 are the same as the setting with initial level of wealth as 400 million dollars and λ_c=26.88. Therefore, the results shown in Table 2.2 also indicate that the liquidity risk premium is small also for higher levels of wealth.

[Insert Figure 2.3 about here]

Consistent with the Constantinides (1986) and Garleanu and Pedersen (2013), we find that investors trade less when the trading-cost rate is higher. Table 2.2 and Figure

[22] We calculate the trading costs generated as a percentage of total wealth for each time step of each simulation, and use the average value across all 10,000 simulations and all 10 steps each as a measure of liquidity level premium compensating for the actual trading costs.

[23] The liquidity level premium compensating for the deviation from optimal weight is calculated by deducting the liquidity level premium compensating for TC from the total liquidity level premium.

2.3 both show that the average trading amount per year decreases from 4.9 million dollars to 2.0 million dollars when the cost rate becomes 4 time the benchmark level, and it increases to 14.8 million dollars when the cost rate becomes 1/8 of the benchmark level. In addition, Figure 2.3 shows that the optimal trading amount is decreasing and convex in the cost rate. Trading amount is more sensitive to the cost rate when it is low. The relative importance of liquidity level premium compensating for TC decreases monotonically with the increase of trading-cost rate (from 64% for $\lambda_c = 1/8 * 26.88$ to 14% for $\lambda_c = 4 * 26.88$); and the premium compensating for the deviation from optimal weight increases with the increase of cost rate (from 2.88 bps for $\lambda_c = 1/8*26.88$ to 18.05 bps for $\lambda_c = 4 * 26.88$). More interestingly, different from the implications of models in Amihud and Mendelson (1986) and Acharya and Pedersen (2005), Figure 2.4 shows that rather than being proportional to trading-cost rate, the equilibrium liquidity premium is increasing and concave in the trading-cost rate, and there is an upper limit on the liquidity premium, which is about 22 bps for our benchmark setting. In Amihud and Mendelson (1986) and Acharya and Pedersen (2005), both the trading amount and the trading frequency are exogenous, and hence total trading costs, as the product of cost rate and total trading amount, increases linearly with the cost rate. In our benchmark setting, the trading amount is decided endogenously by the tradeoff between trading costs and utility gain of trading more. Therefore, under our setting, the liquidity premium does not only depend on the trading-cost rate, trading amount and trading frequency, but also on the sensitivity of investor's expected utility on the trading behavior.

[Insert Figure 2.4 about here]

2.5.2. Setting with Fixed Frequency of Rebuilding and Releasing

Until now, we assumed that the only trading motive is the time-varying expected returns. In the real world, investors may choose to rebuild their portfolios at a fixed time frequency. One main thread of liquidity literature (e.g. Amihud and Mendelson 1986 and Acharya and Pedersen 2005) is based on this assumption. Following their spirits, we also solve a dynamic portfolio choice problem under the assumption that investors release and rebuild their portfolios at a fixed time frequency in this subsection, in order to see whether this assumption helps to generate a large liquidity risk premium comparable to those found empirically.

[Insert Figure 2.5 about here]

We solve the problems for different frequencies of rebuilding the portfolio: every year, every 2 years, 5 years and 10 years. And for each frequency, we solve the problem for 3 values of the correlation between return shocks and the shocks on F_t, 0, -0.3 and -0.6. As an example, Figure 2.5 plots the trajectory of the optimal weights invested in the risky asset for rebuilding and releasing the portfolio every 10 years. The case with zero correlation is plotted. It shows that it is optimal for investors to trade gradually during the rebuilding and releasing of the portfolio to reduce the price impact of trades, as predicted in Garleanu and Pedersen (2013).

Using the same partial equilibrium approach, we calculate the liquidity level premiums and liquidity risk premium for different frequencies of rebuilding the portfolio. Table 2.3 shows that liquidity risk premiums are still very small, from 0.847 bps to 2.659 bps out of a total liquidity premium from 94.98 bps to 212.15 bps. The assumption of fixed frequency of releasing and rebuilding the portfolio does not help to generate a large liquidity risk premium.

Besides, similar to the increase of the trading-cost rate, as forced releasing and rebuilding of the portfolio becomes more frequent, it is optimal for investor to invest less into the risky asset and thus trade less and pay less trading costs. As Table 2.3 shows, the liquidity level premium compensating for trading costs and average trading amount per year both decrease as the rebuilding of portfolio becomes more frequent, and the liquidity level premium compensating for the deviation from the optimal weight increases. In addition, the total liquidity premium ranges from 94.98 bps to 212.15 bps.

[Insert Table 2.3 about here]

2.5.3. Setting with Exogenous Liquidity Shocks (Forced Selling)

The results in section 5.1 and 5.2 show that the magnitude of the liquidity risk premium is negligible under the setting with time-varying expected returns or rebuilding of the portfolio at a fixed time frequency as a trading motive. Does that mean that the liquidity risk premium is always negligible in financial markets, and all the large liquidity risk premiums documented in the recent liquidity literature are wrong? Not necessarily. During periods of crisis (e.g., the 1987 market crash, the 1997 Asian crisis, the Russian debt crisis of 1998, the hedge-funds meltdown of 2007, and the 2008 financial crisis), market liquidity goes down, trading-cost rates go up substantially, and at the same time, institutional investors are forced to release a large amount of their positions. The large amount of trading costs paid for their forced selling hurts those already wounded investors even more. Because of this, investors are supposed to worry about the high trading costs during market downturn a lot and require large compensation for that.

Assumptions of Exogenous Liquidity Shocks (Forced Selling)

To investigate how large a liquidity risk premium can be generated by the large trading costs during the market downturn, we add exogenous liquidity shocks into our model[24]. To further identify the importance of the correlation between the trading motive and the market condition, we distinguish between two types of liquidity shocks: the liquidity shocks depending on market condition, and the liquidity shocks independent of the market condition. Since there is only one risky asset in our model, the changes of the market condition are equivalent to the changes in the price of the risky asset.

For the cases with exogenous liquidity shocks *depending* on realized returns, if the risky asset performs badly (with a realized return r_{t+1} more than one standard deviation, σ_r, lower than the conditional mean μ_t), the investors are forced to release a proportion (or all) of his positions in risky asset. The effect of liquidity shocks on the portfolio weight in the risky asset before rebalancing, $\Delta\alpha_{(t+1)-}$, is as follows:

- *if $\mu_t - 3\sigma_r \leq r_{t+1} \leq \mu_t - \sigma_r$, investors are forced to sell a proportion of their positions in the risky asset, the positions released in terms of the change of weight in risky asset is $\Delta\alpha_{(t+1)-} = \alpha_{(t+1)-} * \frac{r_{t+1}-(\mu_t-\sigma_r)}{2\sigma_r}$, $\Delta\alpha_{(t+1)-} = 0$, if $r_{t+1} = \mu_t - \sigma_r$; $\Delta\alpha_{(t+1)-} = -\alpha_{(t+1)-}$, if $r_{t+1} = \mu_t - 3\sigma_r$. If $r_{t+1} < \mu_t - 3\sigma_r$, investors release all their positions in the risky asset: $\Delta\alpha_{(t+1)-} = -\alpha_{(t+1)-}$.*

For the cases with exogenous liquidity shocks *independent* of realized returns, we substitute the realized return r_{t+1} by a random variable ε_{t+1} which follows a normal distribution with a mean of 0 and a standard deviation of 1, ε_{t+1} â¼N(0,1):

[24]In the real world, investors are usually forced to release part of their positions when market goes down. For example, the mutual fund literature has a long history of documenting the flow-performance sensitivity (e.g. Warther 1995, Sirri and Tufano 1998, Froot, O'connell and Seasholes 2001, Huang, Wei and Yan 2007 etc.), they all show there are more fund outflows during market downturn; and Brunnermeier and Pedersen (2009) claim that investors' capital and margin requirements are binding when market deteriorates, thus they are forced to reduce their holdings.

- *if* $-3 \leq \varepsilon_{t+1} \leq -1$*, investors are forced to sell a proportion of their positions in risky asset, the positions released in terms of the change of weight in the risky asset is* $\Delta\alpha_{(t+1)-} = \alpha_{(t+1)-} * \frac{\epsilon_{t+1}-(-1)}{2}$, $\Delta\alpha_{(t+1)-} = 0$, if $\epsilon_{t+1} = -1$; $\Delta\alpha_{(t+1)-} = -\alpha_{(t+1)-}$*, if* $\epsilon_{t+1} = -3$*. If* $\epsilon_{t+1} < -3$*, investor releases all his positions in risky asset* $\Delta\alpha_{(t+1)-} = -\alpha_{(t+1)-}$.

Calculation of the Liquidity Level Premium and Liquidity Risk Premium

Similar to the benchmark setting, we solve four different cases of the portfolio choice problem to calculate the liquidity level premium and liquidity risk premium.

Case 1: with constant expected return, exogenous liquidity shocks *independent* of realized returns, and *no* trading costs[25]

$(a = 0, b = 0, \lambda_t = \lambda_c = 0, Cov_t(V_{t+1}^2, r_{t+1}) = 0)$

Case 2: with *time-varying* expected returns, exogenous liquidity shocks *independent* of realized returns, and *no* trading costs

$(a = 0.01, b = 0, \lambda_t = \lambda_c = 0, Cov_t(V_{t+1}^2, r_{t+1}) = 0)$

Case 3: with time-varying expected returns, exogenous liquidity shocks *independent* of realized returns, and *constant* trading-cost rate

$(a = 0.01, b = 0, \lambda_t = \lambda_c = 26.88, Cov_t(V_{t+1}^2, r_{t+1}) = 0)$

Case 4: with time-varying expected returns, exogenous liquidity shocks *depending* on realized returns, and *time-varying* trading-cost rates

$(a = 0.01, b = 0.315, \lambda_c = 26.88, Cov_t(V_{t+1}^2, r_{t+1}) > 0)$

As before, the initial position in risky asset is assumed to be 100%. *Case 1*, the case with constant expected return, exogenous liquidity shocks independent of realized returns, and no trading costs is used as the reference case for the calculation of liquidity level premium and liquidity risk premium. For each of *Case 2,3,4*, we find the corresponding level of expected return in the reference case (*Case 1*) which makes the investor indifferent between holding the risky asset in this case and the one in the reference case. Then the difference of corresponding expected returns between *Case 2* and *Case 3* is documented as the liquidity level premium, and the difference of the corre-

[25] Since there is no trading cost, investor will instantly trade back to the optimal weight after liquidity shocks without any utility loss or additional costs. Therefore, *Case 1,2* with liquidity shocks are exactly the same as the *Case 1,2* in benchmark setting. In our setting, liquidity shocks affect investors only if there are trading costs.

sponding expected returns between *Case 3* and *Case 4* is documented as the liquidity risk premium.

It is worth noting that under the benchmark setting, the only difference between *Case 3* and *Case 4* is that *constant* trading-cost rate becomes *time-varying*. However, under this setting with liquidity shocks, in addition, exogenous liquidity shocks *independent of* realized returns become *dependent on* realized returns. The reason is that besides the covariance between trading-cost rates and realized returns $Cov_t(\lambda_{t+1}, r_{t+1})$, the negative covariance between the square of trading amount (forced selling) and realized returns $Cov_t(V_{t+1}^2, r_{t+1})$ also generates a liquidity risk premium. To calculate the total liquidity risk premium, we need to include both effects, and the interaction of these two effects as well.

Relation to Liquidity-Adjusted CAPM in Acharya and Pedersen (2005)

The liquidity-adjusted CAPM proposed by Acharya and Pedersen (2005) assumes that investors have a fixed investment horizon with end releasing and no rebalancing in between (the same as the assumption in section 5.2), and they use the ILLIQ, which is a measure of price impact of trading (λ in our setup), to measure the effective percentage trading costs (c_t in our setup). Under their assumptions, the liquidity risk premium can be measured by the covariance between the trading-cost rates and the realized returns, $Cov_t(\lambda_{t+1}, r_{t+1})$, since λ_t is proportional to the effective percentage trading costs c_t. In reality, trading motives usually depend on the market condition as our setting with liquidity shocks assumes. If we relax the assumption in Acharya and Pedersen (2005) by allowing the trading amount to be different from the holding amount, (assume the holdings of the investor at time t is H_t, and the trading amount is V_t which is smaller than H_t and varying over time), then we have the actual trading costs $\hat{c}_t$ as a percentage of previous holdings H_{t-1} as

$$\hat{c}_t = \frac{c_t V_t}{H_{t-1}} = \frac{1}{2}\frac{\sigma_r^2 \lambda_t V_t^2}{H_{t-1}} \neq \lambda_t, s.t. 0 \leq V_t \leq H_t \tag{2.18}$$

Then following the logic of the liquidity-adjusted CAPM in Acharya and Pedersen (2005), liquidity risk should be priced by $Cov_t(\hat{c}_{t+1}, r_{t+1})$, the covariance between the actual trading costs paid as a percentage of holdings and realized returns, instead of

$Cov_t(\lambda_{t+1}, r_{t+1})$, the covariance between cost rates and realized returns. Since trading costs $\hat{c}_{t+1}$ depends on both cost rate λ_t and trading amount V_t, if investors have to trade a lot when the realized return r_t is low, the liquidity risk $Cov_t(\hat{c}_{t+1}, r_{t+1})$ is high even if the cost rate λ_t does not change with realized return r_t. Therefore, the correlation between trading amount and realized return $Cov_t(V_{t+1}^2, r_{t+1})$[26] is also an important element of liquidity risk which is not covered by the liquidity-adjusted CAPM in Acharya and Pedersen (2005). In addition, the interaction between $Cov_t(\lambda_{t+1}, r_{t+1})$ and $Cov_t(V_{t+1}^2, r_{t+1})$ could lead to even higher liquidity risk than the simple sum of these two.

Decomposition of Liquidity Risk Premium

To separate the liquidity risk premium induced by $Cov_t(\lambda_{t+1}, r_{t+1})$, $Cov_t(V_{t+1}^2, r_{t+1})$ and the interaction effect included in $Cov_t(\lambda_{t+1} V_{t+1}^2, r_{t+1})$, we solve 2 additional cases for the portfolio choice problem with liquidity shocks.

Case 4-1: with time-varying expected returns, exogenous liquidity shocks *dependent on* realized returns, and *constant* trading-cost rate

$(a = 0.01, b = 0, \lambda_t = \lambda_c = 26.88, Cov_t(V_{t+1}^2, r_{t+1}) > 0)$

Case 4-2: with time-varying expected returns, exogenous liquidity shocks *independent of* realized returns, and *time-varying* trading-cost rates

$(a = 0.01, b = 0.315, \lambda_c = 26.88, Cov_t(V_{t+1}^2, r_{t+1}) = 0)$

Again, for *Case 4-1* and *Case 4-2*, we find the corresponding level of expected return in the reference case (*Case 1*) which makes the investor indifferent between holding the risky asset in this case and the one in the reference case. Since the only difference between *Case 4-1* and *Case 3* is that liquidity shocks depend on realized returns, the difference of corresponding expected returns between these 2 cases is recorded as a liquidity risk premium for $Cov_t(V_{t+1}^2, r_{t+1})$. Similarly, since the only difference between *Case 4-2* and *Case 3* is that trading-cost rate becomes time-varying, the difference of the corresponding expected returns between these 2 cases is recorded as the total liquidity risk premium induced by the time variation of trading-cost rates. As in the benchmark setting, the premium for $Cov_t(\lambda_{t+1}, r_{t+1})$ is calculated as the additional liquidity risk premium introduced by the correlation between return shocks and shocks on state variable F_t, the

[26] According to equation (2.18), we see trading costs as a percentage of holdings $\hat{c}_t$ actually depends on $Cov_t(V_{t+1}^2, r_{t+1})$, rather than $Cov_t(V_{t+1}, r_{t+1})$ since $\hat{c}_t$ increases with both trading amount V_t and the price impact $PI_t = V_t \sigma_r^2 \lambda_t$, which increases with the trading amount V_t as well.

case with zero correlation ($Corr(u_t, v_t) = 0$) is used as the reference case. The difference of the corresponding expected returns between *Case 4* and *Case 3* is the total liquidity risk premium introduced by the liquidity shocks depending on realized returns and the time variation of trading-cost rates together. The premium for $Cov_t(\lambda_{t+1} V_{t+1}^2, r_{t+1})$ is also calculated using the case with zero correlation between return shocks and shocks on state variable F_t as the reference case.

Liquidity Risk Premiums for the Setting with Forced Selling

We solve the dynamic portfolio choice problem with exogenous liquidity shocks for three values of the correlation between return shocks and shocks on trading-cost rates $Corr(u_t, v_t)$, 0, -0.3, -0.6. Table 2.4 shows liquidity level premiums and liquidity risk premiums in this setting. We find that the total liquidity risk premium under this setting is significantly larger than before, 11.53 bps for the case with $Corr(u_t, v_t) = -0.3$, and 20.83 bps for the case with $Corr(u_t, v_t) = -0.6$. It accounts for a substantial fraction of the total liquidity premium, 18% and 28% correspondingly. Although the liquidity risk premium generated here is still substantially smaller than the annual 0.47%-1% premiums documented empirically, in term of relative importance of liquidity risk to liquidity level, this result is comparable to that in Acharya and Pedersen (2005), who find that 1.1% out of a 4.6% liquidity premium compensates for liquidity risk. More interestingly, although the total liquidity risk premium can be as large as 20.83 bps, the liquidity risk premiums for $Cov_t(V_{t+1}^2, r_{t+1})$ and $Cov_t(\lambda_{t+1}, r_{t+1})$ individually are very small, only about 6.03 bps for $Cov_t(V_{t+1}^2, r_{t+1})$, and 2.13 bps for $Cov_t(\lambda_{t+1}, r_{t+1})$. The large total liquidity risk premium mainly comes from the interacted covariance, $Cov_t(\lambda_{t+1} V_{t+1}^2, r_{t+1})$, 18.61 bps out of 20.83. Therefore, it is the large trading amount and high trading-cost rate during the market downturn together that hurt the investor and make him require a large liquidity risk premium. None of these two effects itself is sufficient to generate a large liquidity risk premium. However, previous researches about liquidity risk premium, such as Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005) etc., attribute the liquidity risk premiums purely to the covariance between the trading-cost rates and market returns, $Cov_t(\lambda_{t+1}, r_{t+1})$, and neglect the important role of the covariance between the trading amounts and market returns, $Cov_t(V_{t+1}^2, r_{t+1})$ and their interacting effect, which is the main source of the liquidity risk premium according to our analysis.

[Insert Table 2.4 about here]

In addition, under the setting with exogenous liquidity shocks, the liquidity level premium mainly compensates for the actual trading costs, about 30 out of 50 bps, rather than the deviation from the optimal weight if there is no trading cost. It is because the forced selling caused by liquidity shocks is inelastic to the level of the trading-cost rate, investor can only reduce the amount of the forced sales by investing less in risky assets. That sacrifices too much of the expected returns when compared with the possible trading costs caused by the potential liquidity shocks.

Varying the Cost Rate and the Frequency of Liquidity Shocks

Now, we have shown that the liquidity risk premium can account for as large as 28% of the total liquidity premium when investors are forced to sell during a market downturn. Next, to check the robustness of this finding, we investigate how the relative importance of the liquidity risk premium changes with the level of the trading-cost rate and the frequency of the liquidity shocks.

First, we solve the same problem with exogenous liquidity shocks for different levels of trading-cost rates λ_c, from 3.36(1/8*26.88) to 107.52(4*26.88). The correlation between return shocks and shocks on trading-cost rate is set to -0.3 for all cases. We see from Table 2.5 that both the liquidity level premium and liquidity risk premium increase with the trading-cost rate. As the cost rate becomes 4 times as large as before, the liquidity risk premium increases from 11.53 bps to 21.54 bps, and the relative importance decreases from 18% of total liquidity premium to 12%. Though it decreases slightly, it still accounts for a significant fraction of the total liquidity premium. Moreover, as we predict, the average trading amount decreases as the trading-cost rate becomes higher, and the % of liquidity premium compensating for trading costs also decreases from 61% to 57%, since the investor chooses to invest less into risky assets to reduce the total trading amount, and thus he pays less trading costs and bears more utility loss caused by underinvestment.

[Insert Table 2.5 about here]

Secondly, we solve the same problem for lower frequencies of the liquidity threat. Instead of facing a probability of forced selling every year as in the previous setting, the investor faces it now every 2 years or every 5 years. As usual, we solve it for 3 values of correlation between returns and cost rates, 0, -0.3, -0.6. Table 2.6 shows that both liquidity level premium and liquidity risk premium increases as the liquidity shocks become more frequent. The relative importance of the liquidity risk premium is almost the same for the cases with annual liquidity threats and per 2 years, about 18% of total premium when the correlation is -0.3, and about 28% when the correlation is -0.6. It decreases slightly to 12% and 22% as the liquidity threat becomes more infrequent, every 5 years, and it is negligible for the case with no liquidity threat at all as we have shown in the benchmark setting. Besides, both average trading amounts and the liquidity level premium compensating for trading costs increase as liquidity threat becomes more frequent, and the relative importance of premium for trading costs increases as we expect.

[Insert Table 2.6 about here]

To sum up, in this section, using the setting with exogenous liquidity shocks, we find that the liquidity risk premium is economically significant if and only if investors are forced to trade during a market downturn, and the trading-cost rate goes up at the same time. The liquidity risk premium, instead of generated by the covariance between trading-cost rates and the return shocks, $Cov_t(\lambda_{t+1}, r_{t+1})$, as claimed in most papers of liquidity risk, is mainly generated by the covariance between the total trading costs (the product of trading amounts and trading-cost rates) and the return shocks, $Cov_t(\lambda_{t+1}V_{t+1}^2, r_{t+1})$. In addition, we show the importance of liquidity risk premium remains for different levels of trading-cost rates and different frequencies of liquidity threats.

2.6. The Relation between Market Turnovers and Market Returns

We have shown that our benchmark setup generates very small liquidity risk premiums even under quite extreme assumptions on liquidity levels and liquidity risk. One nonstandard assumption, which has a chance at generating larger liquidity risk premiums, is the forced selling during market downturn. The forced selling introduces a large correlation between the portfolio turnovers and the realized returns. In this section, we compare the correlation of turnovers and returns (liquidity risk) of the U.S. stock market with the correlation predicted by our model. We find that the correlation of turnover and returns in market data is comparable to that in our benchmark setting, but substantially smaller than the extremely negative correlation in our setting with exogenous liquidity shocks (forced selling). This shows that the setting with forced selling in market downturns is quite extreme.

2.6.1. Market Data

Since both market turnover and market liquidity of U.S. stock market are highly persistent over time, we first do an AR(1) regression for the log values of both turnover and ILLIQ to capture the innovations. We use the data from 1966 to 2010.

$$lnTrn_{t+1} = \alpha^{trn} + \rho^{trn} lnTrn_t + \varepsilon_{t+1}^{trn} \tag{2.19}$$

$$lnILLIQ_{t+1} = \alpha^{ILLIQ} + \rho^{ILLIQ} lnILLIQ_t + \varepsilon_{t+1}^{ILLIQ} \tag{2.20}$$

We find that both the market turnover and ILLIQ are quite persistent at annually frequency. The time persistence of market turnover, ρ^{trn} in equation (2.19), is 0.9987, and the R^2 of equation (2.19) is 0.9696. The time persistence of ILLIQ, ρ^{ILLIQ} in equation (2.20), is 0.9735, and the R^2 of equation (2.20) is 0.9135.

Table 2.7 reports the correlations between the annual[27] market excess returns, the innovations in market liquidity and the innovations in market turnover from 1966 to 2010, and the covariance between the annually market excess returns and the innovations in market turnover. In accordance with the forced selling during the market downturn, Panel C of Table 2.7 reports a negative correlation (-0.170) between market excess returns and market turnovers when market excess returns $R_M - r_f$ are negative, but it is not significant because of the small number of observations. The correlation between market excess returns and market turnovers is positive for the entire sample (0.203), which is probably because investors on average trade more during bull markets than bear markets. In addition, Panel B of Table 2.7 reports a significant negative correlation (-0.584) between market excess returns and the innovations in lnILLIQ, which is because the market is more liquid during bull markets than bear markets, and a negative correla-

[27] The correlations of monthly data please refer to the Appendix 2.8.2.

tion (-0.281) between the innovations in lnILLIQ and the innovations in market turnover indicating investors on average trade more when the market is relatively more liquid.

For the level of the market turnover, the market data reports an average annual market turnover about 66%, which is substantially larger than the 5% - 10% in the simulations of our model. Therefore our model is not able to capture the high turnover in stock market. Previous literature suggests it could be caused by noise trades of investors, high-frequency traders and the large variation of investment sentiment, and those are not included in our setting.

2.6.2. Comparison with Simulated Results

For each setting of our model, we simulate 10,000 trajectories of the stock returns and turnovers. Then for each trajectory of turnovers, we do the AR(1) regression, equation (2.19), to calculate the innovation in the natural logarithm of turnovers. The correlation and covariance between excess returns and innovations in turnover are calculated across all 10,000 simulations with 10 steps each.

Table 2.8 reports the correlation between the annual returns and turnover for the simulations of our model, and Table 2.9 reports the covariance.

Now we compare the simulated results with the market data. In general, the covariances between turnovers and returns of our simulated data in benchmark case are comparable with the market data. For the correlation between the excess returns and innovations in turnover, $Corr(R_m - r_f, \Delta lnTrn)$, Panel A in Table 2.8 reports that for the benchmark setting with $Corr(u_t, v_t)$ between -0.4 and -0.6, the $Corr(R_m - r_f, \Delta lnTrn)$ for the entire sample ranges from -0.010 to 0.023, which is smaller than the 0.203 in market data. This positive correlation is partially caused by the fact that investor trade more when the market is liquid, but the even higher correlation in market data might be caused by higher investment sentiment during the bull market than bear market. The $Corr(R_m - r_f, \Delta lnTrn)$ for the positive sample ranges from -0.014 to 0.049, slightly higher than the -0.056 in market data, and the $Corr(R_m - r_f, \Delta lnTrn)$ for the negative sample ranges from -0.087 to -0.110, slightly smaller than the -0.170 in market data in terms of magnitude, which is because the forced selling is not included in the benchmark setting. The magnitude of the covariance between the excess returns and innovations in turnover, $Cov(R_m - r_f, \Delta lnTrn)$, in our simulated data, Panel A in Table 2.9, is comparable to that in the market data, ranging from -51.6 to 16.2 (*10^{-4}).

Panel B in Table 2.8 reports that for the setting with exogenous liquidity shocks (forced selling) and a $Corr(u_t, v_t)$ as -0.6, the $Corr(R_m - r_f, \Delta lnTrn)$ shoots up to -0.220 for the entire sample, and -0.673 for the negative sample only. It means our assumption of forced selling is extremely strong. The fact that such a strong assumption of liquidity risk can only generate a 20 bps liquidity risk premium strengthens our claim that the actual liquidity risk premium in the market required by investors is very small. Consistently, the magnitude of the covariances reported in Panel B of Table 2.9 is substantially larger than that in the market data in term of magnitude.

To understand the correlations of turnovers and returns of our simulated data more, there are mainly 4 effects affecting these values of correlation and covariance.

1. Time-varying expected returns: Investor trades more when the conditional expected return is either higher or lower than the average level (high realized return usually comes with low expected return, vice versa). We see this from the column with $Corr(u_t, v_t) = -0.6$ in the Panel A of Table 2.8 and Table 2.9 for the benchmark setting where time-varying expected returns play the most crucial role. Both $Corr(R_m - r_f, Trn)$ and $Cov(R_m - r_f, Trn)$ are positive for the positive sample and negative for the negative sample as we expected. In addition, in the Panel B of Table 2.8 and Table 2.9 for the setting with exogenous liquidity shocks, both $Corr(R_m - r_f, Trn)$ and $Cov(R_m - r_f, Trn)$ are positive for the positive sample where there is no liquidity shock.

2. Time-varying price impact of trading: Investor trades more when the market is more liquid (high realized return comes with high market liquidity when $Corr(u_t, v_t)$ is negative in our model). See row 'Entire sample' in both Panel A and B of Table 2.8 and Table 2.9. Both $Corr(R_m - r_f, Trn)$ and $Cov(R_m - r_f, Trn)$ increases as $Corr(u_t, v_t)$ becomes more negative from 0 to -0.6.

3. Forced sales during crisis: The investor is forced to sell when the realized return is too low. See Panel B of Table 2.8 and Table 2.9 for the setting with exogenous liquidity shocks. Both $Corr(R_m - r_f, Trn)$ and $Cov(R_m - r_f, Trn)$ are negative for the entire sample and the negative sample. It is the most dominant effect in our setting.

4. Wealth effect: A higher wealth level means larger price impact for the same level of turnover (higher realized returns lead to higher wealth level). See column $Corr(u_t, v_t) = 0$ in the Panel A of Table 2.8 and Table 2.9 for the benchmark setting. Both $Corr(R_m -$

$r_f, Trn)$ and $Cov(R_m - r_f, Trn)$ are negative when $Corr(u_t, v_t) = 0$ for the entire sample under the benchmark setting.

2.7. Conclusions

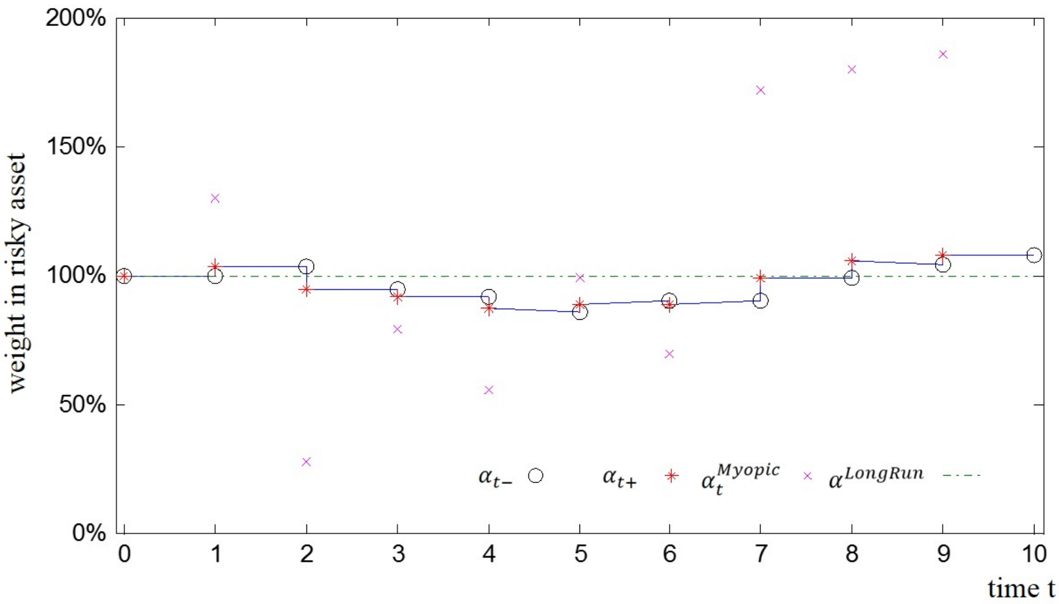
In this paper we solve a dynamic portfolio choice problem with stochastic illiquidity, CRRA utility and a time-varying expected return. Our goal is to generate theoretical predictions for the liquidity risk premium that large investors demand.

We find that the liquidity risk premium generated by the covariance between trading-cost rates and realized returns, $Cov_t(\lambda_{t+1}, r_{t+1})$, which is documented as the main source of liquidity risk (e.g. Pastor and Stambaugh 2003 and Acharya and Pedersen 2005), is negligible, less than 1 bp per year, under our benchmark setting with time-varying expected returns. Larger trading amounts and higher trading frequencies increase the premium for the level of trading costs (liquidity level premium) only but not the liquidity risk premium.

However, once we add exogenous liquidity shocks (forced selling) into the setting, the liquidity risk premium becomes economically significant and accounts for a large fraction of the total liquidity premium. Forced selling and high trading-cost rate during the market downturn together hurt the investor but the liquidity risk premium generated by any of these two itself is still negligible. It indicates that large liquidity risk premiums documented in previous empirical papers, such as Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), might largely compensate for the forced selling and high trading-cost rate during market downturn together, rather than simply the high trading-cost rate itself as they claim. Moreover, even with forced selling, the largest liquidity risk premium required by large investors in our setting, 20 bps, is still substantially smaller than those documented in empirical literature. More nonstandard assumptions are necessary in theoretical models in order to generate a large liquidity risk premium comparable to existing empirical estimates.

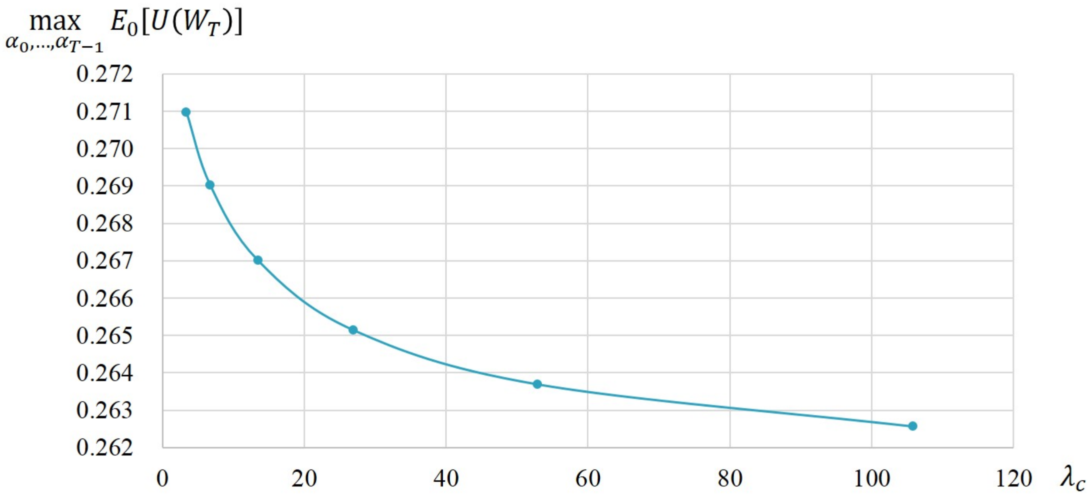
2.8. Appendix

Figure 2.1: Weights in risky asset under benchmark setting (1 simulation)



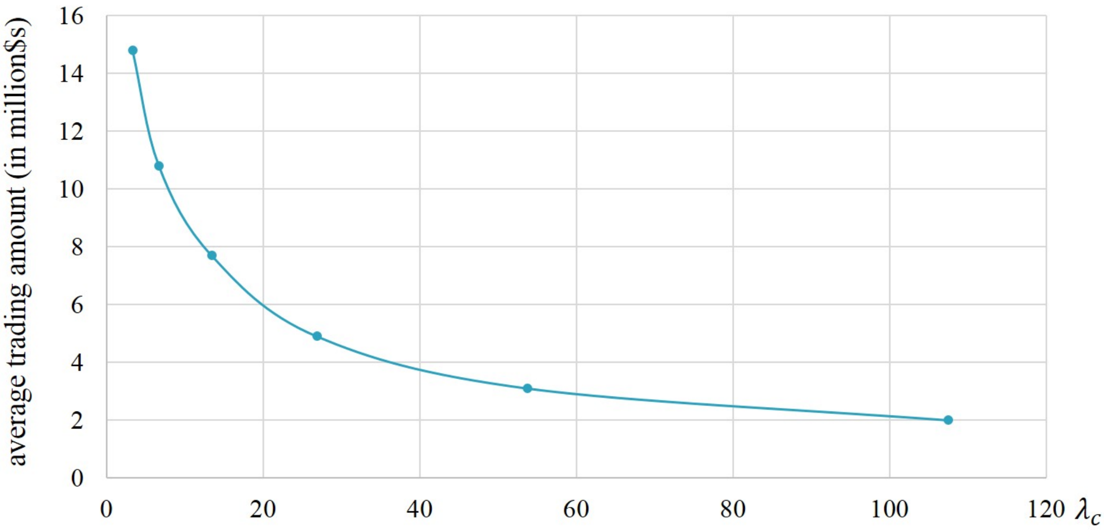
This figure plots one simulation of the weights in risky asset from time 0 to 10 (10 years), for the benchmark setting with time constant trading-cost rate and 0 correlation between returns and costs. The initial weight is set as $\alpha_{0-} = 100\%$. In each time step t, we plot both the weight before rebalancing α_{t-}, the black circle, and the weight after rebalancing and trading costs α_{t+}, the red star. The pink cross denotes the myopic optimal weight in each time step, α_t^{Myopic}, and the green dash line is the long-run optimal weight, $\alpha^{LongRun}$ which equals 100%.

Figure 2.2: Expected utility for different levels of time constant trading-cost rate λ_c



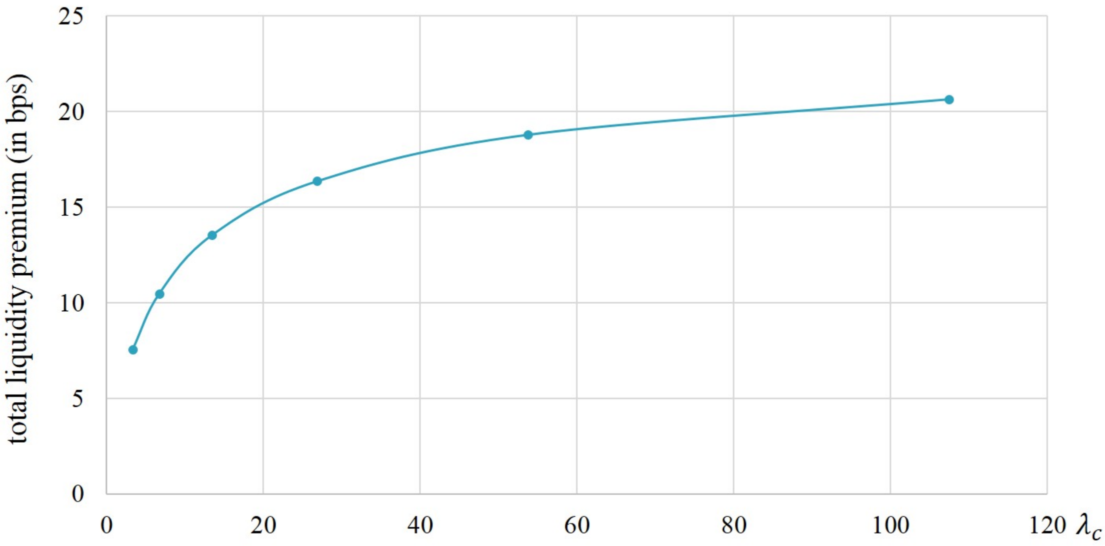
This figure plots the expected utility of the terminal wealth as a function of the trading-cost parameter λ_c under the optimal strategy, $\max E_0 U(W_T)$, for the benchmark setting with time constant trading-cost rate. The fact that expected utility is convex in trading-cost rate indicates that the uncertainty in trading-cost parameter λ_c always increases the expected utility under the benchmark setting when there is no correlation between returns and costs, $Corr(u_t, v_t) = 0$.

Figure 2.3: Average trading amount as a function of the trading-cost rate



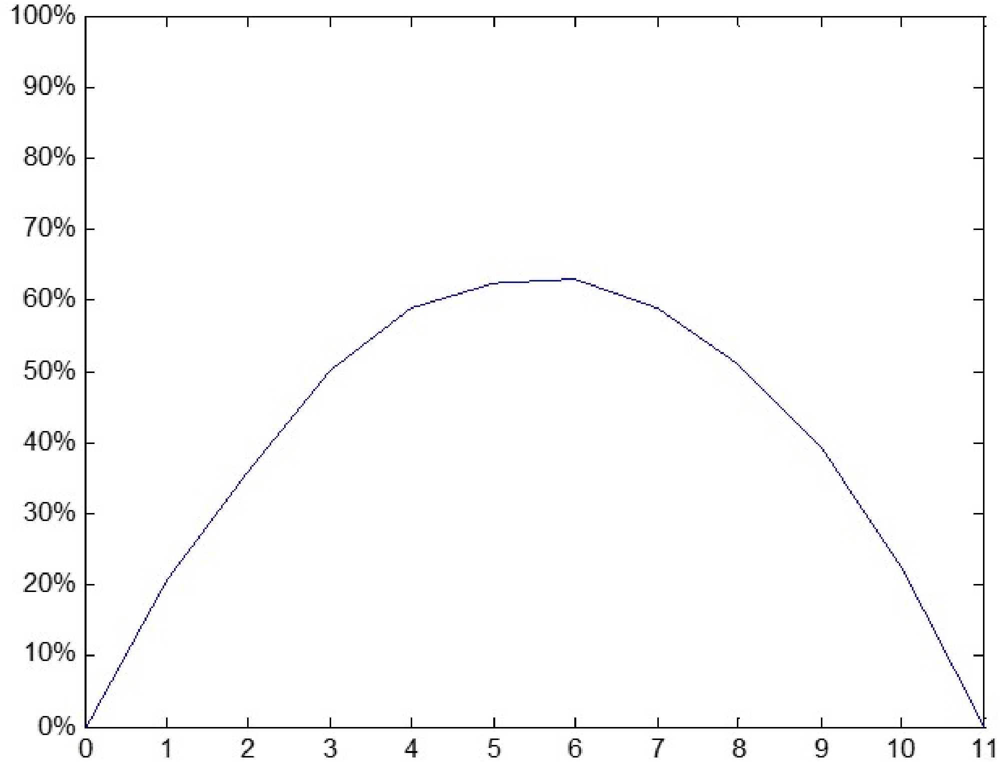
This figure plots the average trading amount as a function of the trading-cost parameter λ_c under the optimal strategy, for the benchmark setting with time constant trading-cost rate. The correlation between returns and costs, $Corr(u_t, v_t) = -0.3$.

Figure 2.4: Total liquidity premium as a function of trading-cost rate



This figure plots the total liquidity premium as a function of the trading-costs parameter λ_c under the optimal strategy, for the benchmark setting with time constant trading-cost rate. The correlation between returns and costs, $Corr(u_t, v_t) = -0.3$.

Figure 2.5: Optimal weights for building and releasing the portfolio every 10 years



This figure plots the average trajectory of the optimal weights for building the portfolio from the beginning and releasing all the positions before the end of time period 10. The correlation between returns and costs, $Corr(u_t, v_t) = 0$. The weight is averaged across 10,000 simulations.

Table 2.1: Liquidity risk premium for the benchmark setting

This table reports the liquidity level premium and liquidity risk premium under the benchmark setting, for different values of the correlation between the returns and trading costs, $Corr(u_t, v_t)$, 0, -0.2, -0.4, -0.6. The liquidity level premium is defined as the decrease in the long-term mean of the expected return, μ_0, on the trading-cost-free risky asset that the investor requires to be indifferent between having access to the risky asset without rather than with trading costs. The liquidity risk premium is the decrease in μ_0 on the trading-cost-free risky asset that the investor requires to be indifferent between having access to the risky asset without rather than with *time variation* in trading costs. The premium for $Cov(\lambda_t, r_t)$ is calculated as the liquidity risk premium additional to the liquidity risk premium for the case with zero correlation between returns and trading costs, $Corr(u_t, v_t) = 0$. All premiums are reported in basis points (bps).

in bps	$Corr(u_t, v_t)$			
	0	***-0.2***	***-0.4***	***-0.6***
Liquidity Level Premium (Total)	16.43	15.86	16.48	15.68
Liquidity Risk Premium (Total)	-0.623	-0.582	-0.353	-0.104
Total Liquidity Premium	15.80	15.27	16.12	15.58
liquidity risk premium for $Cov(\lambda_t, r_t)$	*0.000*	*0.042*	*0.270*	*0.519*
premium for $Cov(\lambda_t, r_t)$ *as % of total premium*	*0.0%*	*0.3%*	*1.7%*	*3.3%*

Table 2.2: Liquidity level premium for difference levels of trading-cost rate

This table reports liquidity level premium (for the parts compensating for TC and compensating for the deviation from optimal weight separately), liquidity risk premium and average trading amount across different trading-cost rates λ_c, from 3.36(1/8*26.88) to 107.52(4*26.88). Liquidity level premium for TC is the premium compensating for actual trading costs paid, and liquidity level premium compensating for the deviation from optimal weight is the premium compensating for the utility loss caused by deviating from the none-trading-cost optimal weight. Both liquidity level premium compensating for TC and average trading amount per year are calculated through 10,000 simulations with 10 steps each. Liquidity level premium for TC as % of total liquidity premium is also reported. All premiums are reported in basis points (bps), and the correlation between the returns and trading costs, $Corr(u_t, v_t) = -0.3$ for all cases.

in bps, $Corr(u_t, v_t) = -0.3$	Average value of trading-cost parameter λ_c					
	3.36	***6.72***	***13.44***	***26.88***	***53.76***	***107.52***
Liquidity Level Premium (compensating for TC)	4.83	5.30	5.35	4.18	3.45	2.88
Liquidity Level Premium (compensating for the deviation from the optimal weight)	2.88	5.45	8.56	12.65	15.69	18.05
Liquidity Risk Premium (Total)	-0.167	-0.316	-0.393	-0.494	-0.370	-0.297
Total Liquidity Premium	7.54	10.44	13.51	16.34	18.77	20.63
liquidity level premium for TC as % of total liquidity premium	*64%*	*51%*	*40%*	*26%*	*18%*	*14%*
avg. trading amount (million$s)	*14.8*	*10.8*	*7.7*	*4.9*	*3.1*	*2.0*

Table 2.3: Liquidity risk premium with fixed releasing and rebuilding of the portfolio

This table reports the liquidity level premium (compensating for TC and for the deviation from the none-trading-cost optimal weight separately), liquidity risk premium and average trading amount per year for different frequencies of rebuilding the portfolio (per 1, 2, 5 and 10 years), and for 3 values of the correlation between returns and trading costs ($Corr(u_t, v_t) = 0$, -0.3, -0.6) for each frequency. Both liquidity level premium compensating for TC and average trading amount per year are calculated through 10,000 simulations with 10 steps each. Liquidity level premium for TC as % of total liquidity premium is also reported. All premiums are reported in basis points (bps).

$\hat{A}$ *in bps*	$Corr(u_t, v_t)$	Frequency of rebuilding (per X years)			
		1	***2***	***5***	***10***
Liquidity Level Premium (compensating for TC)	0	8.37	11.00	24.97	33.63
	-0.3	7.98	11.26	25.22	36.90
	-0.6	7.85	11.27	25.85	38.14
Liquidity Level Premium (compensating for the deviation from the optimal weight)	0	184.35	171.56	121.10	60.49
	-0.3	195.38	181.77	128.46	64.38
	-0.6	202.44	188.73	134.99	68.28
Liquidity Risk Premium (Total)	0	1.509	0.907	0.847	0.861
	-0.3	1.645	1.163	1.925	1.439
	-0.6	1.859	1.447	2.659	1.846
Total Liquidity Premium	0	194.23	183.47	146.92	94.98
	-0.3	205.01	194.19	155.61	102.72
	-0.6	212.15	201.45	163.50	108.27
liquidity level premium for TC as % of total liquidity premium	*0*	*4%*	*6%*	*17%*	*35%*
	-0.3	*4%*	*6%*	*16%*	*36%*
	-0.6	*4%*	*6%*	*16%*	*36%*
avg. trading amount (million $s)	*0*	*9.49*	*8.75*	*11.39*	*12.43*
	-0.3	*9.26*	*8.83*	*11.46*	*13.06*
	-0.6	*9.18*	*8.87*	*11.68*	*13.39*

Table 2.4: Liquidity risk premium with exogenous liquidity shocks (forced selling)

This table reports liquidity level premiums and liquidity risk premiums for the setting with exogenous liquidity shocks (forced selling). We report it for 3 values of the correlation between returns and trading costs ($Corr(u_t, v_t) = 0$, -0.3, -0.6) separately. Liquidity level premiums and liquidity risk premiums are reported based on their sources. We report the liquidity level premiums compensating for TC and the deviation from the none-trading-cost optimal weight separately, the total liquidity risk premium, and the liquidity risk premiums for the covariance between trading amounts and realized returns, $Cov_t(V_{t+1}^2, r_{t+1})$, the covariance between trading-cost rates and realized returns, $Cov_t(\lambda_{t+1}, r_{t+1})$, and total covariance including the interaction of these two, $Cov_t(\lambda_{t+1}V_{t+1}^2, r_{t+1})$, separately. Liquidity risk premium as % of total liquidity premium is also reported. All premiums are reported in basis points (bps).

in bps	$Corr(u_t, v_t)$		
	0	***-0.3***	***-0.6***
Liquidity Level Premium (compensating for TC)	29.92	31.94	33.19
Liquidity Level Premium (compensating for the deviation from the optimal weight)	19.47	20.72	21.41
Liquidity Risk Premium (Total)	2.22	11.53	20.83
Total Liquidity Premium	51.61	64.19	75.44
liquidity risk premium as % of total liquidity premium	*4%*	*18%*	*28%*
liquidity risk premium for $Cov_t(V_{t+1}^2, r_{t+1})$	*1.17*	*3.80*	*6.03*
liquidity risk premium for $Cov_t(\lambda_{t+1}, r_{t+1})$	*0.00*	*0.75*	*0.93*
liquidity risk premium for $Cov_t(\lambda_{t+1}V_{t+1}^2, r_{t+1})$	*0.00*	*9.31*	*18.61*

Table 2.5: Liquidity risk premium with exogenous liquidity shocks for different levels of trading-cost rate

This table reports liquidity level premiums, liquidity risk premiums and average trading amount per year under the setting with exogenous liquidity shocks for different levels of trading-cost rate λ_c, from 3.36 (1/8*26.88) to 107.52 (4*26.88). We assume the correlation between returns and trading costs, $Corr(u_t, v_t) = -0.3$. We report the liquidity level premiums (compensating for TC and the deviation from the none-trading-cost optimal weight separately) and the total liquidity risk premiums. Both liquidity level premium compensating for TC and average trading amount per year are calculated through 10,000 simulations with 10 steps each. Liquidity risk premium as % of total liquidity premium, and liquidity level premium for TC as % of total liquidity premium are also reported. All premiums are reported in basis points (bps).

in bps, $Corr(u_t, v_t) = -0.3$	Average value of trading-cost parameter λ_c					
	3.36	***6.72***	***13.44***	***26.88***	***53.76***	***107.52***
Liquidity Level Premium (compensating for TC)	10.93	15.48	21.79	31.94	49.51	86.53
Liquidity Level Premium (compensating for the deviation from the optimal weight)	2.17	5.91	11.96	20.72	34.58	66.56
Liquidity Risk Premium (Total)	4.88	7.52	9.92	11.53	13.71	21.54
Total Liquidity Premium	17.98	28.91	43.67	64.19	97.81	174.62
liquidity risk premium as % of total premium	*27%*	*26%*	*23%*	*18%*	*14%*	*12%*
liquidity level premium for TC as % of total liquidity premium	*83%*	*72%*	*65%*	*61%*	*59%*	*57%*
avg. trading amount (million $s)	*20.69*	*16.04*	*12.22*	*9.58*	*8.03*	*7.68*

Table 2.6: Liquidity risk premium for different frequencies of liquidity threats

This table reports liquidity level premiums, liquidity risk premiums and average trading amount per year for different frequencies of liquidity threats (per 1, 2 and 5 years), and for 3 values of the correlation between returns and trading costs ($Corr(u_t, v_t) = 0, -0.3, -0.6$) for each frequency. We report the liquidity level premiums compensating for TC and the deviation from the none-trading-cost optimal weight separately, the total liquidity risk premium. Both liquidity level premium compensating for TC and average trading amount per year are calculated through 10,000 simulations with 10 steps each. Liquidity risk premium as % of total liquidity premium, and liquidity level premium for TC as % of total liquidity premium are also reported. All premiums are reported in basis points (bps).

in bps	$Corr(u_t, v_t)$	Frequency of liquidity threats (per X years)			
		1	***2***	***5***	***Never***
Liquidity Level Premium (compensating for TC)	0	29.92	20.50	12.28	3.57
	-0.3	31.94	22.13	13.55	4.17
	-0.6	33.19	22.76	13.91	3.93
Liquidity Level Premium (compensating for the deviation from the optimal weight)	0	19.47	13.84	11.47	12.85
	-0.3	20.72	14.14	11.41	12.67
	-0.6	21.41	14.17	10.71	11.75
Liquidity Risk Premium (Total)	0	2.22	1.64	0.47	-0.62
	-0.3	11.53	7.87	3.47	-0.49
	-0.6	20.83	14.49	7.06	-0.10
Total Liquidity Premium	0	51.61	35.97	24.21	15.80
	-0.3	64.19	44.13	28.43	16.34
	-0.6	75.44	51.43	31.68	15.58
liquidity risk premium as % of total premium	*0*	*4%*	*5%*	*2%*	*-4%*
	-0.3	*18%*	*18%*	*12%*	*-3%*
	-0.6	*28%*	*28%*	*22%*	*-1%*
liquidity level premium for TC as % of total liquidity premium	*0*	*58%*	*57%*	*51%*	*23%*
	-0.3	*50%*	*50%*	*48%*	*26%*
	-0.6	*44%*	*44%*	*44%*	*25%*
avg. trading amount (million $s)	*0*	*9.25*	*7.70*	*6.13*	*4.43*
	-0.3	*9.58*	*7.57*	*6.40*	*4.89*
	-0.6	*9.65*	*7.60*	*6.53*	*4.81*

Table 2.7: Correlation and Covariance between Market Returns, Innovations in ILLIQ and Turnover (annually)

This table reports summary statistics, the correlations between the annually market excess returns, the innovations in market liquidity ($\Delta lnILLIQ$) and the innovations in market turnover ($\Delta lnTrn$) from 1966 to 2010, and the covariance between the annually market excess returns and the innovations in market turnover. Panel A for the summary statistics, Panel B for the correlations, and Panel C for the correlations and covariance of the annually market excess returns and the innovations in market turnover for the entire sample, sample with positive returns only ($R_m - r_f > 0$), and sample with negative returns only ($R_m - r_f < 0$) separately.

Panel A: Summary Statistics

	Mean	Std.Dev	# obs	Min	Max
Rm-rf	0.056	0.185	45	-0.399	0.321
$\Delta lnTrn$	0.000	0.139	44	-0.318	0.252
$\Delta lnILLIQ$	0.000	0.244	44	-0.431	0.760

Panel B: Correlations for Entire Sample

	Rm-rf	$\Delta lnILLIQ$	$\Delta lnTrn$
Rm-rf	1	-.584***	.203
$\Delta lnILLIQ$		1	-.281*
$\Delta lnTrn$			1

Panel C: Correlation and Covariance of Returns and Turnovers

	$Corr(R_m - r_f, \Delta lnTrn)$	$Cov(R_m - r_f, \Delta lnTrn)$ (*10^{-4})	# obs
Entire sample	.203	51.9	44
$R_m - r_f > 0$	-.056	-6.6	30
$R_m - r_f < 0$	-.170	-25.9	14

Table 2.8: Correlation of the Returns and Innovations in Turnovers (simulation results)

This table reports the correlation between the annual returns and the innovations in turnovers ($\Delta lnTrn$) for different settings of our model. Panel A for the benchmark setting with time-varying trading-cost rates, Panel B for the setting with exogenous liquidity shocks (forced selling) and time-varying trading-cost rate. For each setting, we report the correlation values for cases with different values of the correlation between returns and trading costs, $Corr(u_t, v_t)$ separately. We also report them for the entire sample, sample with positive returns only ($R_m - r_f > 0$), and sample with negative returns only ($R_m - r_f < 0$) separately. We do 10,000 simulations for each case within each setting.

Panel A: Benchmark setting with time-varying trading-cost rates

$Corr(R_m - r_f, \Delta lnTrn)$	$Corr(u_t, v_t)$			
	0	***-0.2***	***-0.4***	***-0.6***
Entire sample	-0.100***	-0.058***	-0.010***	0.023***
$R_m - r_f > 0$	-0.074***	-0.031***	-0.014***	0.049***
$R_m - r_f < 0$	-0.075***	-0.039***	-0.087***	-0.110***

Panel B: Setting with liquidity shocks and time-varying trading-cost rates

$Corr(R_m - r_f, \Delta lnTrn)$	$Corr(u_t, v_t)$		
	0	***-0.3***	***-0.6***
Entire sample	-0.328***	-0.303***	-0.220***
$R_m - r_f > 0$	-0.087***	-0.047***	0.091***
$R_m - r_f < 0$	-0.683***	-0.662***	-0.673***

Table 2.9: Covariance of the Returns and Innovations in Turnover (simulation results)

This table reports the covariance between the annual returns and the innovations in turnovers ($\Delta lnTrn$) for different settings of our model. Panel A for the benchmark setting with time-varying trading-cost rates, Panel B for the setting with exogenous liquidity shocks (forced selling) and time-varying trading-cost rate. For each setting, we report the covariance values for cases with different values of the correlation between returns and trading costs, $Corr(u_t, v_t)$ separately. We also report them for the entire sample, sample with positive returns only ($R_m - r_f > 0$), and sample with negative returns only ($R_m - r_f < 0$) separately. We do 10,000 simulations for each case within each setting.

Panel A: Benchmark setting with time-varying trading-cost rates

Cov($R_m - r_f, \Delta lnTrn$) ($*10^{-4}$)	$Corr(u_t, v_t)$			
	0	***-0.2***	***-0.4***	***-0.6***
Entire sample	-93.5	-61.0	-10.9	16.2
$R_m - r_f > 0$	-33.2	-15.9	-7.7	25.7
$R_m - r_f < 0$	-32.1	-18.5	-44.1	-51.6

Panel B: Setting with liquidity shocks and time-varying trading-cost rates

Cov($R_m - r_f, \Delta lnTrn$) ($*10^{-4}$)	$Corr(u_t, v_t)$		
	0	***-0.3***	***-0.6***
Entire sample	-351.6	-327.3	-235.9
$R_m - r_f > 0$	-36.4	-19.9	38.4
$R_m - r_f < 0$	-393.2	-384.3	-391.9

2.8.1. Robustness Check for the Effect of Rebalancing on Liquidity Risk Premium (Varying the Risk Aversion Level)

Table 2.10 and 2.11 show that the liquidity risk premium are still negligible even if the long-run optimal weight is 50% ($\gamma = 5$) and 150% ($\gamma = 5/3$). The need to rebalance does not affect our conclusion.

Table 2.10: Liquidity risk premium for the benchmark setting with optimal weight as 50%

This table reports the liquidity level premium and liquidity risk premium under the benchmark setting with optimal weight of 50% on risky asset ($\gamma = 5$), for different values of the correlation between returns and trading costs, $Corr(u_t, v_t)$, 0, -0.2, -0.4, -0.6. The liquidity level premium is defined as the decrease in the long-term level of the expected return, μ_0, on the trading-cost-free risky asset that the investor requires to be indifferent between having access to the risky asset without rather than with trading costs. The liquidity risk premium is the decrease in μ_0 on the trading-cost-free risky asset that the investor requires to be indifferent between having access to the risky asset without rather than with *time variation* in trading costs. The premium for $Cov(\lambda_t, r_t)$ is calculated as the liquidity risk premium additional to the liquidity risk premium for the case with zero correlation between returns and trading costs, $Corr(u_t, v_t) = 0$. All premiums are reported in basis points (bps).

in bps	$Corr(u_t, v_t)$			
	0	***-0.2***	***-0.4***	***-0.6***
Liquidity Level Premium (Total)	17.14	17.76	19.26	18.75
Liquidity Risk Premium (Total)	-0.682	-0.635	-0.398	0.069
Total Liquidity Premium	16.46	17.12	18.86	18.82
liquidity risk premium for $Cov(\lambda_t, r_t)$	*0.000*	*0.047*	*0.283*	*0.750*
premium for $Cov(\lambda_t, r_t)$ as % of total premium	*0.0%*	*0.3%*	*1.5%*	*4.0%*

Table 2.11: Liquidity risk premium for the benchmark setting with optimal weight as 150%

This table reports the liquidity level premium and liquidity risk premium under the benchmark setting with optimal weight of 150% on risky asset ($\gamma = 5/3$), for different values of the correlation between returns and trading costs, $Corr(u_t, v_t)$, 0, -0.2, -0.4, -0.6. The liquidity level premium is defined as the decrease in the long-term level of the expected return, μ_0, on the trading-cost-free risky asset that the investor requires to be indifferent between having access to the risky asset without rather than with trading costs. The liquidity risk premium is the decrease in μ_0 on the trading-cost-free risky asset that the investor requires to be indifferent between having access to the risky asset without rather than with *time variation* in trading costs. The premium for $Cov(\lambda_t, r_t)$ is calculated as the liquidity risk premium additional to the liquidity risk premium for the case with zero correlation between returns and trading costs, $Corr(u_t, v_t) = 0$. All premiums are reported in basis points (bps).

in bps	$Corr(u_t, v_t)$			
	0	***-0.2***	***-0.4***	***-0.6***
Liquidity Level Premium (Total)	15.12	13.70	12.98	11.31
Liquidity Risk Premium (Total)	-0.569	-0.473	-0.354	-0.077
Total Liquidity Premium	14.55	13.22	12.62	11.24
liquidity risk premium for $Cov(\lambda_t, r_t)$	*0.000*	*0.096*	*0.215*	*0.492*
premium for $Cov(\lambda_t, r_t)$ as % of total premium	*0.0%*	*0.7%*	*1.7%*	*4.4%*

2.8.2. Relation between Monthly Market Turnovers and Monthly Market Returns

Since small and active investors usually react to the price changes within a month, the correlation between market returns and innovations in market turnover can be higher in monthly frequency than in annual frequency. In this section, we also document the correlation between monthly market returns and monthly innovations in market turnover for comparison.

Similarly, we do an AR(1) regression for the ln values of both turnover and ILLIQ to capture the monthly innovations in market turnover and liquidity. Both the market turnover and ILLIQ are quite persistent at monthly frequency. The time persistency of monthly market turnover, ρ^{trn} in equation (2.19), is 0.980, and the R square of equation (2.19) is 0.959. The time persistency of monthly ILLIQ, ρ^{MILLIQ} in equation (2.20), is 0.993, and the R square of equation (2.20) is 0.980.

Figure 2.6 plots the innovations in monthly market turnover and their corresponding market excess returns for each month from 1966 January to 2010 December, and Figure 2.7 plots the innovations in monthly market turnover and their corresponding innovations in market ILLIQ. The red dots are the observations in 2008 financial crisis (2008 September to 2009 June). In Figure 2.6, we could see that on average innovation in market turnover becomes larger when the market excess return becomes either more positive or more negative, and Figure 2.7 shows there is a weak negative correlation between the innovations in market turnover and market ILLIQ.

Consistent with the figures, Table 2.12 reports a correlation of 0.106 between the monthly market returns and the innovations in market turnover, a correlation of -0.255 for negative returns, and a correlation of 0.309 for positive returns. Consistent with our expectation, the magnitudes of correlations are larger for monthly frequency, and the correlation for positive returns is more positive since there are more active trades at the monthly frequency.

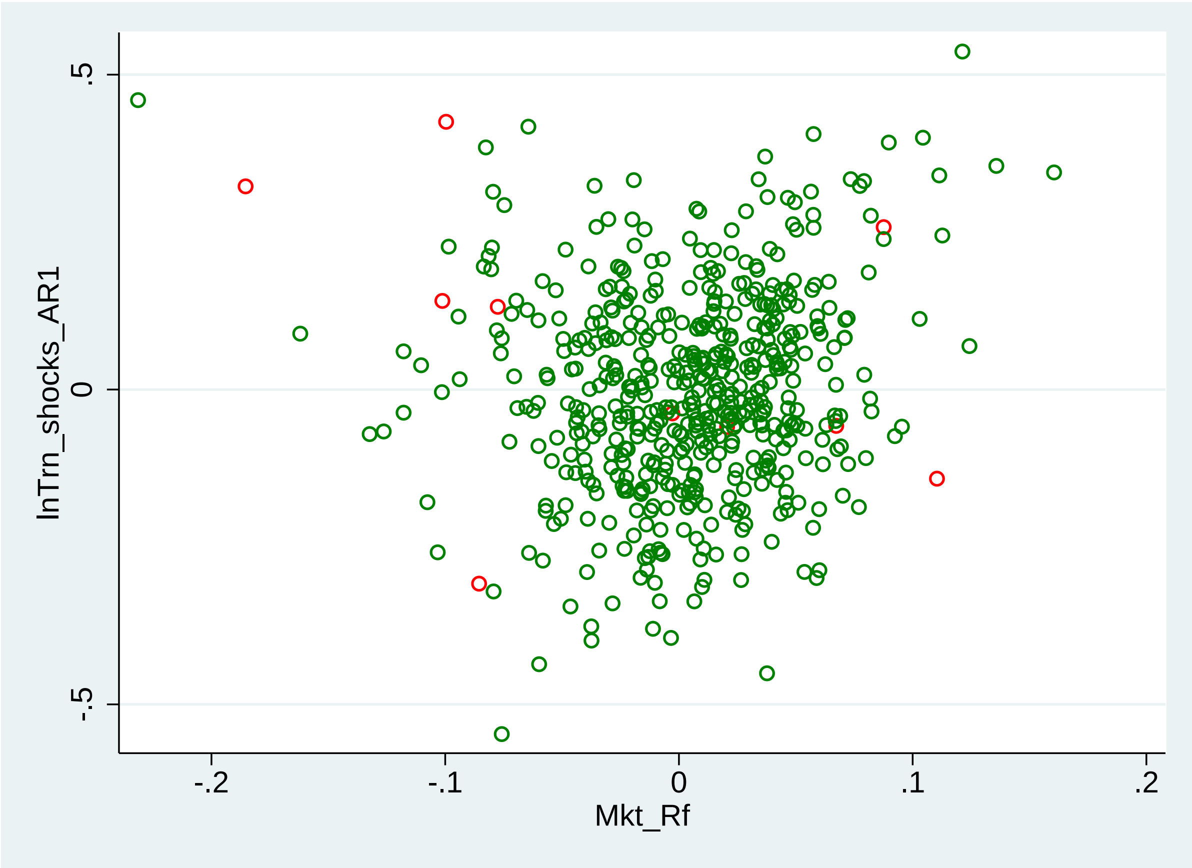


Figure 2.6: Relation between Innovations of Turnover and Market Returns

This figure plots the innovations in monthly market turnover and their corresponding market excess returns for each month from 1966 January to 2010 December. The red dots are the observations in 2008 financial crisis (2008 September to 2009 June).

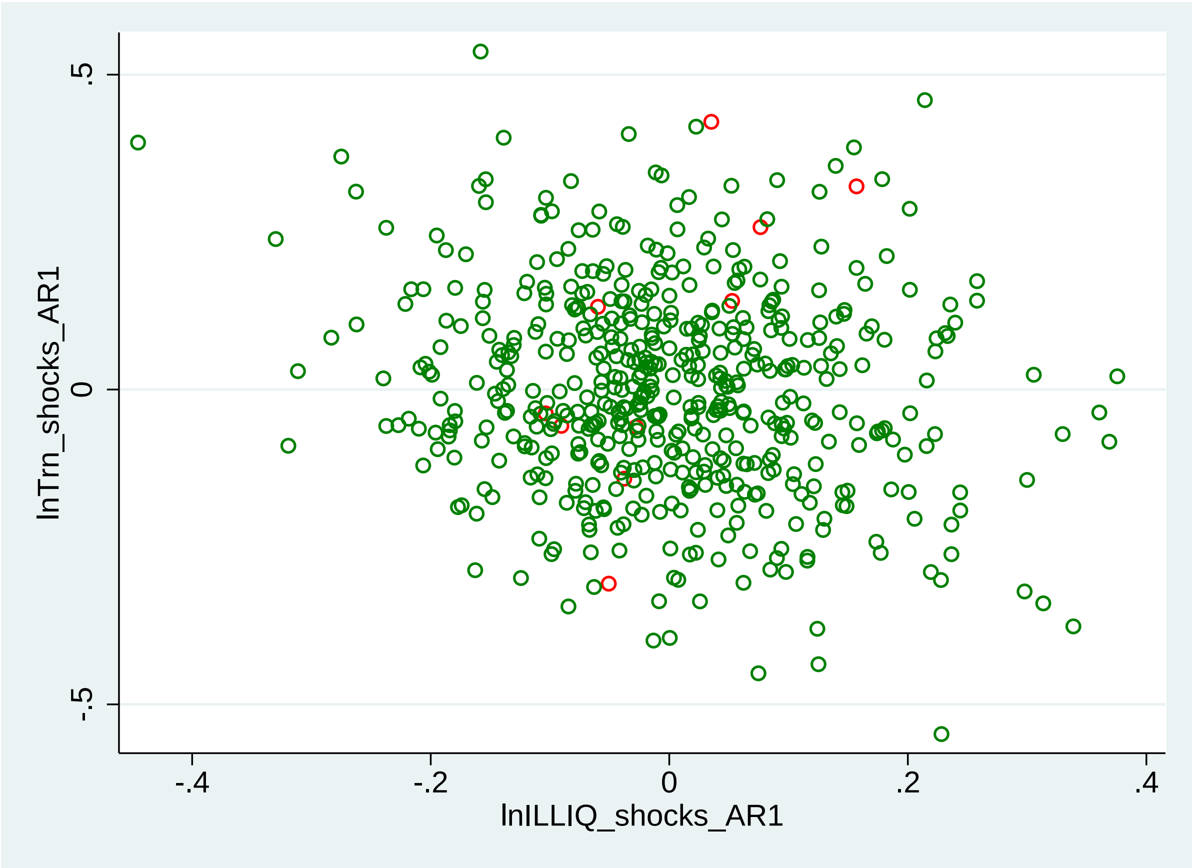


Figure 2.7: Relation between Innovations of Turnover and Market Returns

This figure plots the innovations in monthly market turnover and their corresponding innovations in monthly ILLIQ for each month from 1966 January to 2010 December. The red dots are the observations in 2008 financial crisis (2008 September to 2009 June).

Table 2.12: Correlation between Market Return, Innovations in ILLIQ and Turnover (monthly)

This table reports the correlation between the monthly market excess returns, innovations in monthly ILLIQ and innovations in market turnover from 1966 January to 2010 December. Panel A for the entire sample, Panel B for the observations with negative market excess returns, and Panel C for the observations with positive market excess returns.

Panel A: Entire sample

	Rm-rf	$\Delta lnILLIQ$	$\Delta lnTrn$
Rm-rf	1	$-.411^{***}$	$.106^{**}$
$\Delta lnILLIQ$		1	$-.156^{***}$
$\Delta lnTrn$			1

Panel B: $Rm - Rf < 0$

	Rm-rf	$\Delta lnILLIQ$	$\Delta lnTrn$
Rm-rf	1	$-.278^{***}$	$-.255^{***}$
$\Delta lnILLIQ$		1	$-.054$
$\Delta lnTrn$			1

Panel C: $Rm - Rf > 0$

	Rm-rf	$\Delta lnILLIQ$	$\Delta lnTrn$
Rm-rf	1	$-.139^{**}$	$.309^{***}$
$\Delta lnILLIQ$		1	$-.172^{***}$
$\Delta lnTrn$			1

2.8.3. Numerical Procedure in Detail

The model is solved using backward induction. In the last period, the value function corresponds to the CRRA utility of the final wealth. We can use this value function to compute the decision variable, optimal weights in risky asset α_{T-1}, for the previous period, and given these, obtain the corresponding value function. This procedure is then iterated backwards.

We optimize over the space of the decision variable α_t using standard grid search. We use 50 grids for α_t in the benchmark case with a lower bound of 50% and an upper bound of 150%. The upper and lower bounds for the decision variable is chosen to be nonbinding in all periods. To increase the accuracy of the grid search, we first obtain the distribution of α_t across all time periods under equally spaced grids. Then we choose the grid points optimally using the inverse density of this distribution, making the density the same across all grids.

The state-space is also discretized. To reduce the overall computational burden, we search for each state variable a relatively small number of grids that still guarantees the accuracy of our solution, by solving the model with different number of grids for each variable. In the paper, we approximate the density function for returns in the risky asset and innovations in driving factor F_t using gaussian quadrature methods, with 4 nodes each. We use 20 grids for the weight in risky asset before rebalancing α_{t-}, 10 grids for the driving factor F_t, and 16 grids for wealth level W_t. All grid points are chosen optimally using the inverse density of the distributions of their corresponding state variables, which are firstly estimated under equally spaced grids. In order to evaluate the value function corresponding to wealth level that do not lie in the chosen grid, we used a cubic spline interpolation in the log wealth level. This interpolation has the advantage of being continuously differentiable and having a nonzero third derivative, thus preserving the prudence feature of the utility function. Since the lower bound on wealth level is strictly positive, the value function at each grid point is also bounded below. This fact makes the spline interpolation work quite well given a sufficiently fine discretization of the state-space.

Chapter 3

Liquidity Management of Hedge Funds around the 2008 Financial Crisis

3.1. Introduction

In the previous decade, the theoretical literature of dynamic portfolio choice with trading costs[28] has developed rapidly. After experiencing the financial crises in 1998 and 2008, more and more scholars started to notice the important role of liquidity management in portfolio choice, especially during times of liquidity crisis. For example, Scholes (2000) suggests that financial institutions should sell liquid assets first for urgent liquidity needs to reduce the transaction costs, and he emphasizes the need to build "a dynamic liquidity cushion" for future liquidity needs. Duffie and Ziegler (2003) investigate numerically the trade-off between selling off an illiquid asset to keep a "cushion of liquid assets", and selling a liquid asset to maximize short-term portfolio value. Brown, Carlin, and Lobo (2010) solve the optimal liquidation problem in a dynamic framework and show that it is optimal for myopic investors to first trade liquid assets, but long-run investors may decide to postpone selling their most liquid securities if they expect their liquidity needs are going to be larger in later periods.

Among all types of investors, hedge funds might be the group of investors that care most about their liquidity management. It is because clients of hedge funds are mainly sophisticated institutional investors which react quickly to market changes. Moreover, the use of leverage and short positions makes hedge funds more sensitive to fund outflows than other investors. Yet there is no empirical work on how hedge funds manage the

[28]The groundbreaking paper in this thread of literature is Constantinides (1986), and other well-known papers include Liu (2004), Lo, Mamaysky and Wang (2004), Jang, Koo, Liu and Loewenstein (2007), Lynch and Tan (2011), Gârleanu and Pederson (2012) etc..

liquidity of their portfolios dynamically around crisis periods.

In this paper, I analyze the quarterly stock holdings of 60 largest hedge funds in U.S. before, during and after the 2008 financial crisis, and document the liquidity composition of their portfolios. For comparison, I do a similar analysis for pension funds.

First, I study the changes of hedge funds' aggregate equity holdings from 2007 to 2010. Figure 3.1 presents both the total equity holdings of hedge funds and the S&P 500 index. It shows that the equity holdings of hedge funds dropped severely in the second half of 2008 and reversed strongly in 2009 and 2010 Q1. The reversal of hedge funds' equity holdings started even one quarter before the reversal of the S&P 500 index. Different from hedge funds, pension funds reduced their equity holdings gradually from 2007 to 2010. There was no sudden drop or reversal in their equity holdings. It might be because, unlike hedge funds, pension funds did not face large urgent liquidity needs at that time, and attempt to time the market.

[Insert Figure 3.1 about here]

Second, to investigate whether hedge funds trade liquid and illiquid stocks differently around the crisis, I sort stocks into deciles based on their ILLIQ values, a liquidity measure proposed in Amihud (2002). Interestingly, I find that hedge funds sold more liquid than illiquid stocks at the peak of the crisis, and they repurchased a large amount of liquid stocks during the upturn but continued to sell illiquid stocks. In accordance, the portfolio composition of hedge funds shows a delayed "flight to liquidity". The fraction of relatively liquid stocks held by hedge funds decreased slightly at the peak of the crisis (the second half of 2008), from 40% to 38%, and increased substantially to 48% in 2009. Rather than providing liquidity to the market, hedge funds consume liquidity through the entire financial crisis. These results are consistent with the predictions in Scholes (2000), Duffie and Ziegler (2003) and Brown, Carlin, and Lobo (2010) for both myopic and long-term liquidity management. Different from hedge funds, pension funds did not trade liquid and illiquid stocks differently around the crisis.

Finally, I do a stock-level regression to control for other effects. For each stock, I regress the change of hedge funds' ownership on stock liquidity, where I control for a set of variables and other stock characteristics, including volatility, size, book-to-market, past 6-month return variables, and previous hedge fund holdings. I do the analysis for the crisis period (2008 Q3 and Q4) and the reversal period (2009 and 2010 Q1) separately. My findings of hedge funds' dynamic liquidity management survive and become even more substantial.

This paper contributes to at least three threads of literature.

First, as mentioned at the beginning of this paper, it provides direct empirical evidence to theoretical predictions in the literature of dynamic portfolio choice with trading costs. It confirms the predictions in Scholes (2000), Duffie and Ziegler (2003) and Brown, Carlin, and Lobo (2010) that investors should sell liquid assets first during a crisis and build a liquidity cushion later. To my best knowledge, it is the first piece of empirical evidence that hedge funds manage their liquidity dynamically as theories predict.

Second, it contributes to the literature documenting institutional investors' dynamic behavior. Because of the availability of data, this thread mainly focuses on mutual funds. There are only few papers about hedge funds. Brunnermeier and Nagel (2004) show that hedge funds successfully ride the technology bubble in 2000; Ben-David, Franzoni and Moussawi (2012) present that hedge funds faced large fund outflows in 2008 financial crisis and reduced their equity holdings significantly; and Ang, Gorovyy, and van Inwegen (2011) report that hedge fund deleverage substantially at the same period. In this paper, I document hedge funds' dynamic behavior from the perspective of their liquidity management across individual stocks, which provides evidence for both their inclinations of trading liquid stocks first and precautionary holdings of liquid stocks.

Third, this paper contributes to the theoretical literature on the limits of arbitrage which emphasizes the role of financial institutions. This thread of literature investigates how costs and financial constraints faced by arbitrageurs can prevent them from eliminating mispricing and providing liquidity to other investors. Simultaneously, financial institutions are the source of many non-fundamental demand shocks (Gromb and Vayanos 2002, 2009, Brunnermeier and Pedersen 2009). In this sense, financial institutions do not necessarily correct anomalies but can also cause them. Brunnermeier and Nagel (2004) find that because of predictable investor sentiment and limits to arbitrage, hedge funds ride bubbles instead of correcting them. For crisis periods, this paper confirms the finding in Ben-David, Franzoni and Moussawi (2012) that there are even more fire sales in hedge funds than other investors. My paper compliments their findings by showing that, to keep a liquidity buffer for future crisis, hedge funds continued to sell their illiquid stocks during the market reversal. It, in theory, would further enlarge the underpricing of illiquid stocks and delay the price reversal.

This paper proceeds as follows. Section 2 summarizes the data sources and provides the summary statistics for both hedge funds and pension funds. Section 3 analyzes the dynamics of liquid stock holdings v.s. illiquid stock holdings around the crisis for both hedge funds and pension funds. Section 4 offers concluding remarks and possible directions for extensions.

3.2. Data and Sample Characteristics

3.2.1. Data Source

Holding Data of Hedge Funds and Pension Funds

I use the Thomson-Reuters Institutional Holdings (13F) Database for the equity holdings of hedge funds (HFs), and for pension funds (PSs) as well. It provides institutional common stock holdings, as reported on form 13F filed with the SEC. This database is formerly known as CDA/Spectrum database, and contains ownership information by institutional managers with $100 million or more in assets under management. This data allows us to track positions in individual stocks at a quarterly frequency.

Since 1978, all institutions with more than $100 million under discretionary management are required to disclose their holdings in U.S. stocks and a few other securities to the SEC each quarter on form 13F. This concerns all long positions greater than 10,000 shares or $200,000 over which the manager exercises sole or shared investment discretion. The 13F filings do not contain information on short positions or derivatives, which is a limitation of our analysis. The 13F reporting requirements apply regardless of whether an institution is regulated by the SEC or not, and it also applies to foreign institutions if they “use any means or instrumentality of United States interstate commerce in the course of their business.” Hence, it also applies to HFs, provided that their holdings of U.S. stocks exceed the specified thresholds.

In this paper, I investigate the HF managing firms included in “Hedge Fund Top 100” in 2010 from the website “www.institutionalinvestor.com”. This rank is based on the size of the assets under management, which serves my research interest. Since large trades have larger price impacts than small trades, large funds are more sensitive to stock liquidity than small funds do. Following the procedure in Brunnermeier and Nagel (2004), I discard some managing firms because HF assets only make up a small part of their aggregated institutional portfolio. For each manager, I check whether the firm is registered as an investment adviser with the SEC. Registration is a prerequisite to conduct non-hedge-fund business such as advising mutual funds and pension plans. I search whether it is registered investment adviser. If the firm is not registered, I include it in our sample. If the firm is registered, I obtain registration documents (Form ADV). For a registered firm to be eligible for our sample, I require (1) that at least 50% of its clients are "Other pooled investment vehicles (e.g., hedge funds)" or "High net worth individuals", and (2) that it charges performance-based fees, according to Form ADV. This process leaves us with 70 HF managers. Commonly, each firm manages multiple funds, so our sample comprises stock holdings of probably several hundreds different HFs. Second, I look up each candidate HF managing firm by name in the Thomson-Reuters 13F database. I find records for 68 managing firms. Only 60 managing firms have complete holding data around the crisis, from 2007 Q1 to 2010 Q4.[29] The total holding of these 60 HF managing firms is $240 billion in 2008 Q1, and $250 billion in 2010 Q4. BarclayHedge shows that the total assets under management in the HF industry is $1457.9 billion in 2008 and $1795.8 billion in 2011 Q1. It suggests that our data capture a significant part of total HF stock holdings.

For PFs, I follow the classification of institutional investors on Brian Bushee's website[30], where corporate (private) PFs and public PFs are identified from "other institutional investors" with type code 5 in Thomson-Reuters Institutional Holdings (13F) Database. Similarly, I only keep the PFs which have complete holding data from 2007 Q1 to 2010 Q4. It leaves us with 56 PFs in total.

Wilshire consulting estimates that the cash and securities holdings of the 126 largest public-employee pensions were $2.217 trillion in 2010. State pension portfolios have, on

[29]Since I only include HF managing firms which have complete holding data from 2007 to 2010, my sample is exposed to survivorship bias. Luckily, the survivorship bias here serves, rather than hurts, my research question. Since the survivors are more likely to be those HFs who managed their liquidity properly during the 2008 crisis. Even if my sample bias toward those HFs who survive for reasons other than liquidity management (such as, stock picking skill, market timing skill or purely luck), it does not affect the main finding of this paper that âa significant subset of HFs manage their liquidity dynamically around the 2008 financial crisis.â Those alternative stories are not consistent with the fact that they continue to sell the illiquid stocks after the crisis.

[30]"http://acct3.wharton.upenn.edu/faculty/bushee/"

average, a 65.6% allocation to equities, including real estate and private equity. Among them, the allocation to U.S. equity is 31.1%, which is about $689.49 billion. The total equity holdings of our sample are $446.5 billion. Among them, $348.5 billion are held by public PFs. Our sample thus captures about half of PFs' total equity holdings in the market.

Stock Returns and Firm Accounting Data

I use the data of stock returns and accounting information from CRSP and Compustat. The stock data from different databases are linked by "Ticker" on 2008 June 30. The criteria used to filter the stocks are as below:

(1) I include the stocks that are ordinary common shares (CRSP sharecodes 10 and 11), excluding ADRs, SBIs, certificates, units, REITs, closed-end funds, companies incorporated outside the U.S., and Americus Trust Components.

(2) I include the stocks that have return data for more than 18 months in 2008 & 2009 and complete return data from 2008 Q3 to 2009 Q2.

3636 stocks, from NYSE, AMEX and Nasdaq and fulfilling these three criteria, are included into our scope of analysis.

3.2.2. Summary Statistics

Next I summarize equity holdings of HFs and PFs at the aggregate level and the characteristics of stocks held by them.

Summary of Hedge Funds and Pension Funds' equity holdings

[Insert Table 3.1 about here]

Table 3.1 provides the summary of HFs' total equity holdings in my sample. They held about three quarters of the stocks in the market (2727 to 3032, out of 3636 stocks in my sample), and 0.3%-0.6% of total market capitalization. The smaller than 1 percent total market ownership is not surprising, as aggregate stock holdings of HFs in my sample (about $115 billion to $325 billion) are dwarfed by holdings of other institutional investors such as mutual funds and PFs. Consistent with Figure 3.1, HFs released their equity holdings substantially in 2008 q3 and q4, from 0.52% of the total market capitalization to 0.34%, and they repurchased those equity holdings strongly in 2009 and 2010 Q1, to 0.50% of the total market capitalization. Similarly, the last column shows that HFs' aggregate dollar equity holdings decreased substantially in 2008 q3 and q4, from $250 billion to $115 billion, and reversed in 2009 and 2010 Q1 to $235 billion. These changes are caused by both the trades of HFs and the changes of the stock prices. In section 3.1, I fixed the stock price to estimate the trades made by HFs.

[Insert Table 3.2 about here]

Table 3.2 shows that the PFs in my sample held about five-sixth of the stocks in the market (3027 to 3398, out of 3636 stocks in my), and about 0.91%-1.18% of total market capitalization. Note that different from HFs, PFs constantly reduced their equity holdings since the second quarter of 2007, from 1.18% to 0.91% in 2010 q4. The last row shows that the total dollar amount of PFs' equity holdings decreased in 2008 Q3 & Q4 and 2009 Q1, from $519 billion to $300 billion, and reversed slightly in the last three quarters of 2009 and 2010 Q1, from $300 billion to $446 billion. Since PFs' equity holdings as a fraction of the market size decreased continuously instead, the reversal of the total dollar holdings is caused by the reversal of the market stock price rather than their trades.

Summary of Stock Characteristics

The definitions and calculations of stock characteristics are listed in Table 3.3. Because I want to study the trades of HFs rather than the changes of characteristics for each stock, I do not allow those measures of stock characteristics to change over time[31]. I use the data just before the crisis to construct those measures. Since Lehman's bankruptcy happened in the third quarter of 2008, I use the data on 2008 June 30 (for "*Hedge Fund Ownerships*", "*Market Cap*" and "*Book-to-Market*"), and the daily data in the first half of 2008 (for "*Share turnover*", "*Bid-Ask Spread*", "*ILLIQ*", "*Past Return*" and "*Return Variability*"). Only the "*Market Beta*" is calculated using the return data from 2001 January 1 to 2011 June 30.

[31] We use time-varying measures of stocks liquidity, ILLIQ values, for robustness check. The results are quite similar.

[Insert Table 3.3 about here]

In Table 3.4, I summarize the characteristics of the whole sample of stocks, the stocks held by HFs and the stocks held by PFs separately. The average percentage of shares held by HFs (Hedge Funds Ownership) for the whole samples is 2.7%, and that for the stocks held by HFs is 3.3%, which are obviously larger than 0.5% to 0.8%, the fraction of total market capitalization held by HFs reported in Table 3.1. The main reason is that the numbers in Table 3.4 are calculated as equally weighted, while those in Table 3.1 are value weighted. For the same reason, the average percentage of shares held by PFs (Pension Funds Ownership) reported in the second row, 1.7% for the whole sample and 1.9% for those held by PFs, are also larger than the 0.9% to 1.2% reported in Table 3.1. Because PFs put more shares in large stocks than HFs do, the average stock ownership of PFs reported in Table 3.4 is smaller than that of HFs. The other average stock characteristics of HFs' and PFs' holdings are quite similar.

[Insert Table 3.4 about here]

3.3. Hedge Funds' Liquidity Management around 2008 Financial Crisis

3.3.1. Hedge Funds' aggregate equity holdings around 2008 Crisis

First, I aggregate all equity holdings of HFs in my sample and present its time variation from 2007 Q1 to 2010 Q4. As we know, both the changes of shares held by HFs and the changes of the stock prices can lead to the variation of HFs' equity holdings over time. To estimate the trades (changes of shares) of HFs, I need a measure of HFs' equity holdings that is insensitive to the price changes. Figure 3.1 measures HFs' aggregate equity holdings as the fraction of the total market capitalization, which is insensitive to the fluctuations of market price. However, the price changes of stocks held by HFs relative to the price changes of other stocks in the market can still affect this measure. To eliminate the effect of price changes on HFs' equity holdings, I fix all stock prices to their levels at the end of 2008 q2. For each stock in each quarter, I calculate the fixed-price dollar amount of HFs' equity holding as the number of shares held by HFs at the end of that quarter times the stock price per share at the end of 2008 q2. This fixed-price dollar amount changes with the number of shares held by HFs and does not change with stock prices. For brevity, I will call the equity holdings based on the stock prices at the end of 2008 q2 "fixed-price equity holdings" in the rest of the paper.

Figure 3.2 plots HFs' total fixed-price equity holdings in billion $s over time. Similar to Figure 3.1, Figure 3.2 shows significant decline in HFs' holdings around Lehman Brothers' bankruptcy (2008 Q3 & Q4), about 66.7 billion $s, and a quick and large reversal in 2009 and 2010 Q1, about 54.7 billion $s. The magnitude of the reversal is about 81.9% of the drop in 2008 Q3 and Q4.

[Insert Figure 3.2 about here]

The large drop of HFs' fixed-price equity holdings in 2008 Q3 and Q4 is consistent with the forced deleveraging proposed by Vayanos (2004) and Brunnermeier and Pedersen (2009). Ben-David, Franzoni and Moussawi (2012) document that redemption and margin calls were the primary drivers of those selloffs.

Surprisingly, HFs' fixed-price equity holdings reversed substantially in 2009, still the darkest hours of the crisis. Ben-David, Franzoni and Moussawi (2012) show that HFs still had significant funds outflows in this period, and Ang, Gorovyy, and van Inwegen (2011) show that after the deleveraging in the second half of 2008, the average leverage ratios of HFs, including equity funds, were still low in 2009. In this case, why did HFs increase their equity holding in this period?

One possible explanation is that HFs increased their holdings of liquid stocks to prepare for their potential liquidity needs in the near future (dynamic liquidity management hypothesis). This hypothesis is strongly supported by my empirical findings in next subsection. And there are also other explanations. For example, HFs might be good at timing the market reversal, so they buy stocks just before and during the market reversal to benefit from the stock market upturn; or, HFs managers might decide to gamble the market upturn because of their concave payoff function, which means they benefit more from superior fund performances. Figure 3.1 has shown that the reversal of HFs' fixed-price equity holdings started one quarter before the reversal of the S&P 500 index. Thus they captured much of the upturn.

In fact, the dynamic liquidity management hypothesis is not exclusive to those other explanations. It is true that if HFs want to reduce the transaction costs of building up the portfolio in a short time, they would trade liquid stocks rather than illiquid stocks. But the fact that HFs continued to sell illiquid stocks during the market reversal (will be shown in next subsection) supports the dynamic liquidity management hypothesis only, and conflicts with the other explanations.

To compare with HFs, I also plot PFs' aggregate equity holdings from 2007 q1 to 2010 q4 in Figure 3.3. Panel A of Figure 3.3 plots it as a percentage of total U.S. stock market capitalization; and Panel B plots their fixed-price equity holding based on the stock prices at the end of 2008 q2. Thus the fluctuations in Figure 3.3 stand for the trades of PFs instead of the changes of stock prices. Both Panel A and B in Figure 3.3 show that PFs reduced their equity holdings gradually before, during and even long time after the crisis, from 2007q2 to 2010q4. It seems that PFs neither reduced their equity holdings at the peak of the crisis nor increased their holdings to capture the reversal. Instead, they strategically reduced their equity holdings gradually over time. It might because PFs have less urgent liquidity needs than HFs and mutual funds do, and they seldom time the market.

[Insert Figure 3.3 about here]

3.3.2. Hedge funds' holdings of liquid stocks vs. illiquid stocks

In this section, I study HFs' equity holdings of liquid stocks vs. illiquid stocks around the 2008 financial crisis, where I find that HFs sold more liquid than illiquid stocks at the peak of the crisis, and they repurchased a large amount of liquid stocks during the upturn but continued to sell illiquid stocks.

Following Amihud (2002), I use ILLIQ to measure stock liquidity. An individual stock's ILLIQ value is calculated as the ratio of the absolute value of daily returns to daily dollar trading volume, which measures the average price impact of trades. Though currently there is no sole measure of liquidity capturing all aspects of stock illiquidity, Korajczyk and Sadka (2008) show that ILLIQ is highly correlated with most mainstream liquidity measures, such as bid-ask spread, Kyle's lambda, etc., both in cross section and in time series. For each individual stock, I calculate its average ILLIQ value using the daily return data from 2008 January 1 to 2008 June 30. Then I sort all 3636 stocks within our sample into deciles based on their average ILLIQ values. It gives us approximately

364 stocks in each ILLIQ decile[32]. ILLIQ decile 1 is for the most liquid stocks and ILLIQ decile 10 for the most illiquid stocks.

Table 3.5 reports the summary of the stock characteristics for all ILLIQ deciles. The first row shows that HFs' total equity holdings differs a lot across ILLIQ deciles, from \$149 billion to \$0.2 billion. Consistent with our sorting criteria, the mean of "ILLIQ" increases across ILLIQ deciles, "Bid-Ask Spread" increases across ILLIQ deciles, and "Share Turnover" decreases across ILLIQ deciles. "Market Cap" also decreases from ILLIQ decile 1 to decile 10 since the size and the stock liquidity are highly correlated in cross section.

[Insert Table 3.5 about here]

To show how HFs trade liquid stocks and illiquid stocks differently around the crisis, Figure 3.4 plots the cumulative percentage changes of HFs' fixed-price equity holdings for each ILLIQ decile, using the holdings at the end of 2008 Q2 as a benchmark. It ranges from 2007 Q1 to 2010 Q4. We can see from Figure 3.4 that HFs sold both liquid and illiquid stocks substantially in 2008 Q3 & Q4. This result is consistent with the forced deleveraging documented in Ben-David, Franzoni and Moussawi (2012). Surprisingly, in 2009 and 2010 Q1, they bought large amount of extremely liquid stocks, stocks in ILLIQ decile 1, but continued to sell relatively illiquid stocks, stocks in ILLIQ decile 6 to 10. The large purchases of liquid stocks and the continuous selling of illiquid stocks strongly support our dynamic liquidity management hypothesis that HFs built liquidity cushion for future liquidity shocks. The continuous selling of illiquid stocks indicates that HFs not only purchased more liquid stocks, they also shifted some of their holdings from illiquid stocks to liquid stocks. In 2009 and 2010 Q1, HFs' total fixed-price equity holdings of the stocks in ILLIQ decile 1 increased 46.59 billion dollars (31.3% of HFs' equity holdings at the end of 2008 Q2). I have shown in previous subsection (Figure 3.2) that the reversal of HFs' total fixed-price equity holding (for both liquid and illiquid stocks) is 54.65 billion dollars. It means 85.3% (46.59/54.65) of such reversal can be attributed to the purchases of extremely liquid stocks, stocks in ILLIQ decile 1. They continued to sell both liquid and illiquid stocks only since 2010 Q2.

[32] I also do the same analysis with time-varying ILLIQ deciles constructed every quarter. More than 50% of stocks stay at the same ILLIQ deciles within my sample period, and the results of my analysis are similar.

[Insert Figure 3.4 about here]

[Insert Table 3.8 about here]

To have a direct comparison between the changes of equity holdings across ILLIQ deciles, I document the percentage changes of HFs' fixed-price equity holdings for each ILLIQ decile in two periods, 2008 Q3 & Q4 and 2009 Q1 to 2010 Q1, separately. Table 3.8 reports that HFs reduced a larger proportion of their holdings of liquid stocks (around 30% for ILLIQ decile 1 to 6) than that of illiquid stocks (around 15% for ILLIQ decile 7 to 10) in 2008 Q3 & Q4, which is in accordance with my previous finding. And in 2009 and 2010 Q1, they purchased liquid stocks (positive numbers in the second row for ILLIQ decile 1 to 5), but continued to sell illiquid stocks (negative numbers in the second row for ILLIQ decile 6 to 10). Moreover, the reversal of HFs' fixed-price equity holdings of extremely liquid stocks (ILLIQ decile 1) is substantial, 41.1% of their holdings at the end of 2008, and 131.3% the drop of their holdings in 2008 Q3 & Q4. HFs held even more liquid stocks than just before the crisis. To make these findings more visualized, Figure 3.5 plots the changes of HFs' fixed-price equity holdings across ILLIQ Deciles for drop and reversal separately. Consistently, Panel A of Figure 3.5 presents a rough increasing trend; and Panel B of Figure 3.5 presents a rough decreasing trend.

[Insert Figure 3.5 about here]

Since I assigned equal number of stocks in each decile, the ILLIQ decile 1 accounts for about two-thirds of their total equity holdings in dollar amounts, and the other 9 ILLIQ deciles all together account for the rest one-third only. Such imbalance makes current ILLIQ deciles inappropriate for the analysis of HF's portfolio composition of liquid holdings versus illiquid holdings over time. Therefore, I construct ILLIQ dollar-quintiles where HFs' equity holdings are the same at the end of 2008 Q2 for each quintile. Table 3.7 summarizes the stock characteristics for ILLIQ dollar-quintiles. The first row of Table 3.7 reports the number of stocks in each ILLIQ dollar-quintile, it varies largely from 70 stocks for ILLIQ dollar-quintile 1 to 2351 stocks for ILLIQ dollar-quintile 5. HFs holdings actually concentrate in a small number of liquid stocks. The second row reports similar HFs' total dollar equity holdings at the end of 2008 Q2 for each ILLIQ dollar-quintile, approximately $50 billion, and the third row report that the average value of ILLIQ increases monotonically from 0.000226 for ILLIQ dollar-quintile 1 to 0.385 for ILLIQ dollar-quintile 5, which are both consistent with my sorting criteria. And the Market Cap decreases monotonically from ILLIQ dollar-quintile to ILLIQ dollar-quintile 5.

[Insert Table 3.7 about here]

Figure 3.6 plots HFs' fixed-price equity holdings for each ILLIQ dollar-quintile as a percentage of HFs' total fixed-price equity holdings. It shows a clear delayed "flight to liquidity": the percentage of HFs' fixed-price equity holdings in relatively liquid stocks, ILLIQ dollar-quintile 1 & 2, decreased slightly in 2008 Q3 (from 40% to 38%) and increased substantially in the period from 2008 Q4 to 2010 Q1 (to 47%), and it decreased gradually since 2010 Q2. This result further confirms the dynamic liquidity management hypothesis.

[Insert Figure 3.6 about here]

3.3.3. Pension funds' holdings of liquid stocks vs. illiquid stocks

In this section, I do the analysis for PFs' holdings of liquid stocks versus illiquid stocks using the same methodology as for HFs. I find only slight changes of PFs' equity holdings when compared with those of HFs. First, I study PFs' fixed-price equity holdings across ILLIQ deciles. Table 3.8 shows that PFs reduced their holdings of both liquid stocks and illiquid stocks in both periods. At the peak of the crisis (08 Q3 & Q4), PFs' fixed-price equity holdings decreased for 8 out of 10 deciles, and the magnitudes of the only two increases are quite small. During the market upturn (2009 and 2010 Q1), PFs' fixed-price equity holdings decreased for 10 out of 10 deciles. Besides, the changes of PF's fixed-price equity holdings did not show a clear increasing or decreasing trend across ILLIQ deciles. It indicates that PFs did not trade liquid stocks and illiquid stocks differently. In general, there is no evidence that PFs managed the liquidity of their equity portfolios actively around the 2008 financial crisis.

[Insert Table 3.8 about here]

[Insert Figure 3.7 about here]

To have a closer look at PFs' average portfolio composition of liquid stocks versus illiquid stocks, I also sort stocks into ILLIQ dollar-quintiles, where PFs' equity holdings for all ILLIQ dollar-quintiles are the same at the end of 2008 Q2. PFs' total equity holdings is roughly 83 billion $ at the end of 2008 Q2 for each ILLIQ dollar-quintile. Figure 3.7 plots PFs' fixed-price equity holdings for each ILLIQ dollar-quintile as a percentage of PFs' total fixed-price equity holdings. I find that PFs' aggregate portfolio composition of liquid and illiquid stocks is almost constant from 2007 to 2010, which is fundamentally different from the aggregate portfolio composition of HFs as expected.

3.3.4. Regression Analysis

Besides trading more liquid stocks, HFs may tend to trade more volatile stocks and apply momentum strategies and value strategies as well around the crisis period. I did not control for those effects in previous section. In this section, I do a stock-level cross-sectional regression to analyze HFs' trading of liquid stocks versus illiquid stocks during and after the crisis formally, where I control for other effects. Specifically, I regress the changes of HF ownership on variables of stock characteristics and previous HF ownership. I do the analysis for the drop (2008 Q3 & Q4) and the reversal (2009 and 2010 Q1) periods separately. The change of HF ownership is computed as the changes of number of shares held by HFs in that period scaled by the total number of shares outstanding. For stock characteristics, I calculate stocks' ILLIQ values, "ILLIQ", standard deviations of daily returns, "SD" and the past 6-month returns, "past 6-month return", using the half year data just before the period of my analysis. Market capitalization, "size", book-to-market ratios, "book-to-market ratio", and previous HF ownerships, "Previous HF holdings(%)" are based on the data just before the analysis period. I take the natural logarithmic values of ILLIQ, size and book-to-market ratio, and I normalize the mean values of all the stock characteristics to 0 and standard deviations to 1. As the changes of holdings, the "Previous HF holdings(%)" is measured as a percentage of shares outstanding for each stock.

[Insert Table 3.9 about here]

As shown in Table 3.9 Column (1), the coefficient of "ln(ILLIQ)" is 0.174 and significant at 1% significance level when other variables are included as controls. HFs actually sold more liquid than illiquid stock at the peak of the crisis (in 2008 Q3 and Q4). The drops of HF ownerships (holdings as a percentage of the total shares outstanding) are 0.174% larger on average for stocks with a liquidity level 1 standard deviation higher. Considering the average HF ownership is only 2.7% at the end of 2008 Q2. This difference is economically significant. In addition, Column (3) reports an even larger difference between the holding changes of liquid stocks and illiquid stock in 2009 and 2010 Q1. HF increased 0.446% more on average for stocks with a liquidity level 1 standard deviation higher. In Column (2) and (4), I also include the market capitalization, "ln(size)" into the regression. It shows that coefficients of "ln(ILLIQ)" remain significant, and their signs do not change.

Similar to our findings on HF sales in 2008 Q3 & Q4, Ben-David, Franzoni and Moussawi (2012) also find that HFs sold more liquid stocks than illiquid stocks in the same period. Jotikasthira, Lundblad, and Ramadorai (2009) document that during fire sales, mutual funds and HFs tend to reduce price impact, and Manconi, Massa, and Yasuda (2010) show that in the 2007 crisis, mutual funds sold liquid bonds first. Complementing their results, I document HFs created a liquidity cushion just after their large selloffs.

Besides, some theoretical papers, such as Vayanos (2004) and Brunnermeier and Pedersen (2009), indicate that volatile stocks should be sold first since they require high margins and may increase overall portfolio volatility. Consistently, Ben-David, Franzoni and Moussawi (2012) find that HFs sold more volatile stocks than stable ones during the crisis. Different from Ben-David, Franzoni and Moussawi (2012), I find only weak evidence that HFs sold more volatile stocks than stable stocks at the peak of the crisis (2008 Q3 & Q4). The coefficient of "SD", standard deviation of returns, is only significantly negative when "ln(size)" is added. Since small stocks are in general more volatile, there might be some multi-collinearity problem. No significant evidence were found even when I use the same measure of stock volatility (past 24-month volatility of monthly returns) as they do. However, I find that in 2009 and 2010 Q1, HF holdings as a percentage of the total shares outstanding increased 0.166% more on average for stocks with "ln(SD)" (standard deviations of returns in 2008 Q3 & Q4) 1 standard deviation higher. It might because given the large losses during the crisis, some HFs increased their risk exposures by holding stocks which were more volatile during the crisis. They bet the stocks which were most volatile during the crisis should reverse more during market upturn. Besides, there is also evidence that HFs purchased more value stocks than growth stocks during the market reversal.

Column (2) and (4) include the size indicator into the explanatory variables. Stock market capitalization "ln(size)" measures both the liquidity and risk of stock, and it is highly negatively correlated with the liquidity measure "ln(ILLIQ)" across individual stocks. The correlation between "ln(size)" and "ln(ILLIQ)" is as large as -0.88. Thus our regressions in Column (2) and (4) have multi-collinearity problems for the coefficients of "ln(ILLIQ)" and "ln(size)". Consistently, the adjusted R squares are almost the same for the regressions with and without size variable "ln(size)". However, including size variable into the regression makes the coefficients of liquidity variable "ln(ILLIQ)" even larger for both HF sales in 2008 Q3 and Q4 and HF purchases in 2009 and 2010 Q1. The evidence of HFs' liquidity management survives both during and after the crisis.

To sum up, the result of regression analysis (where other stock characteristics are controlled) provides even stronger supports to the dynamic liquidity management hypothesis.

3.4. Conclusions

Since Constantinides published the groundbreaking paper of dynamic portfolio choice with trading costs in 1986, the theoretical literature in this thread has developed rapidly, (e.g. Liu 2004, Lo, Mamaysky and Wang 2004, Jang, Koo, Liu and Loewenstein 2007, Lynch and Tan 2011, Gârleanu and Pederson 2013 etc..) After the financial crises in 1998 and 2008, a lot more scholars started to notice the important role of liquidity management in portfolio choice. However, the size of empirical literature in this thread is nowhere nearly comparable to the size of theoretical literature, and there is no empirical work on how hedge fund managers manage the liquidity of their portfolios dynamically around crisis periods. This paper studies the liquidity management of hedge funds before, during and after the 2008 financial crisis. The liquidity management of pension funds is also analyzed for comparison.

Specifically, I sort stocks into deciles based on the their liquidity levels and find that hedge funds sold more liquid stocks than illiquid stocks at the peak of the crisis. Moreover, they repurchased a large amount of liquid stocks since the market started to recover in 2009, but they continued to sell illiquid stocks in the same period. Consistently, the proportion of relatively liquid (versus illiquid) stocks in hedge funds' portfolio decreased slightly at the peak of the crisis, from 40% to 38%, and increased substantially to 48% in 2009 and 2010 Q1. It shows a delayed "flight to liquidity". Overall, these empirical results of hedge funds are consistent with existing theories about investors' liquidity management. Scholes (2000) and Brown, Carlin, and Lobo (2010) both predict that to reduce the trading costs, hedge funds should sell more liquid assets than illiquid ones during the crisis. And to make their portfolios easy to unwind in future crises, the liquid assets should be repurchased as a "liquidity cushion".

Those findings are confirmed by the results of my stock-level regression analysis, where other stock characteristics, such as stock size, book-to-market ratio, past returns, return volatility etc., are controlled for. In addition, different from hedge funds, pension funds held a constant proportion of liquid stocks versus illiquid stocks from 2007 to 2010. They sold both liquid and illiquid stocks gradually since 2007.

The analysis of hedge funds' liquidity management in this paper is largely limited by the availability of hedge funds' holding data. Thomson Reuters (13F) database provides only hedge funds' stock holding data. It is on the level of hedge fund managing firms, and quarterly based. It would be interesting to include hedge funds' holdings of other types of assets, such as bonds and cash equivalents, into the analysis, to see whether they shifted from relatively illiquid types of assets to liquid ones during the crisis period, and it is also interesting to do more studies using fund level data or data with higher frequency.

3.5. Appendix

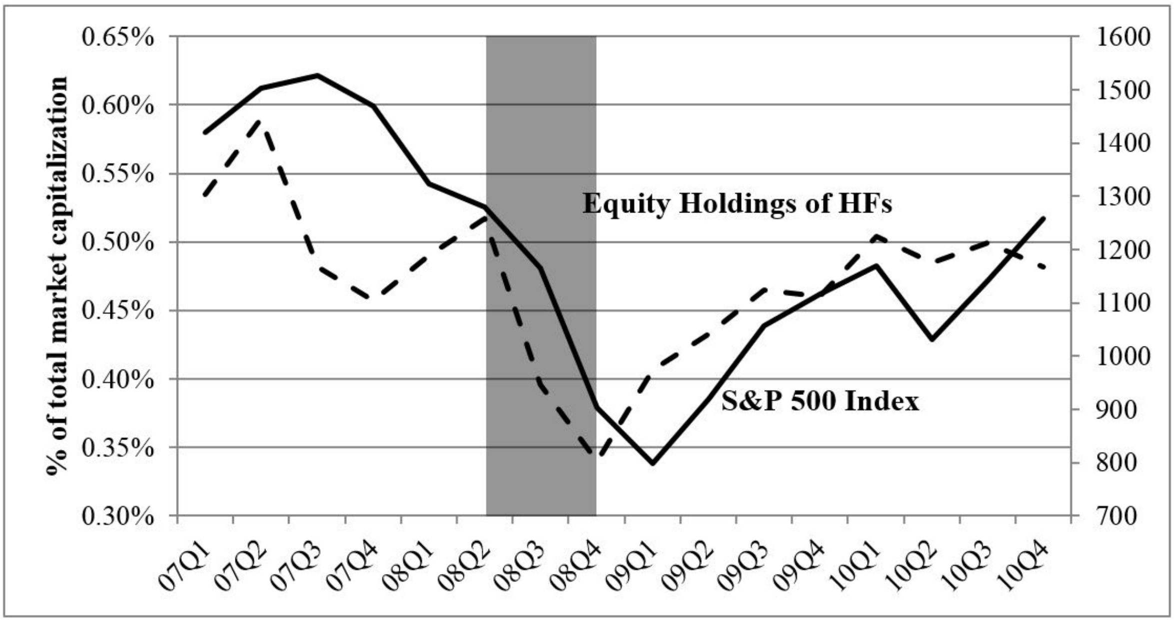


Figure 3.1: Hedge Funds' Equity Holdings and S&P 500 Index

This figure plots the total equity holdings of hedge funds in my sample (as a percentage of total U.S. stock market capitalization) and the S&P 500 index. The vertical axis on the left side is for equity holdings of hedge funds (dashed line), and the one on the right side is for the S&P 500 index (solid line). The data ranges from 2007 Q1 to 2010 Q4. Only equity holdings of "the largest 100 hedge fund managers in 2010" (from website: "www.institutionalinvestor.com") are included. "Wilshire 5000 Total Market Index" is used as the measure of total market capitalization. The shaded area marks the quarters around Lehman Brothers' bankruptcy (2008 Q3 & Q4).

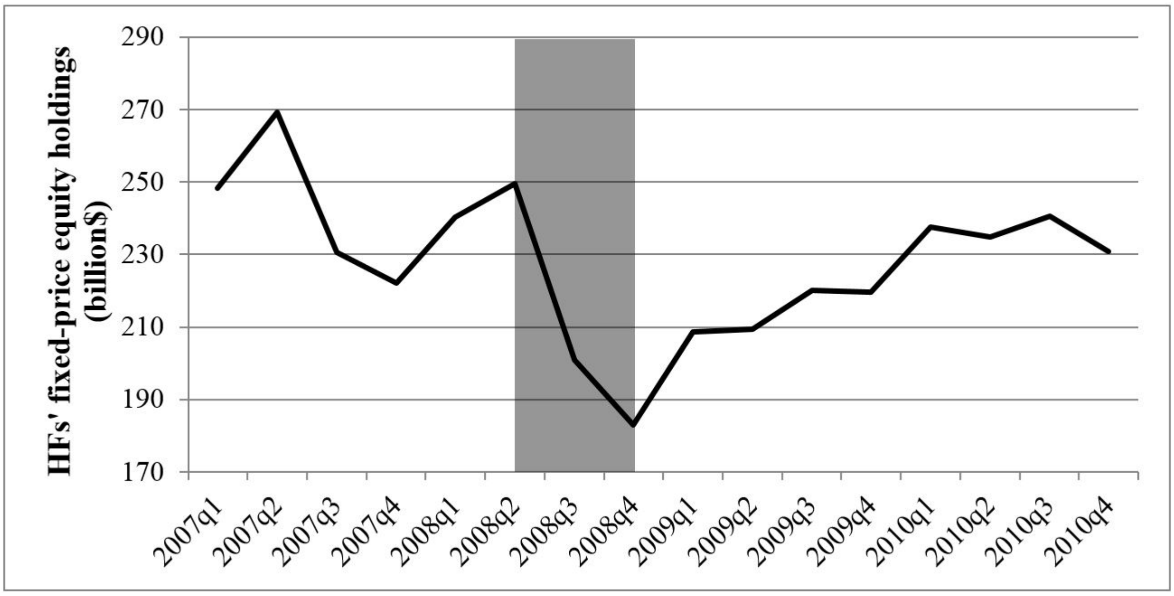
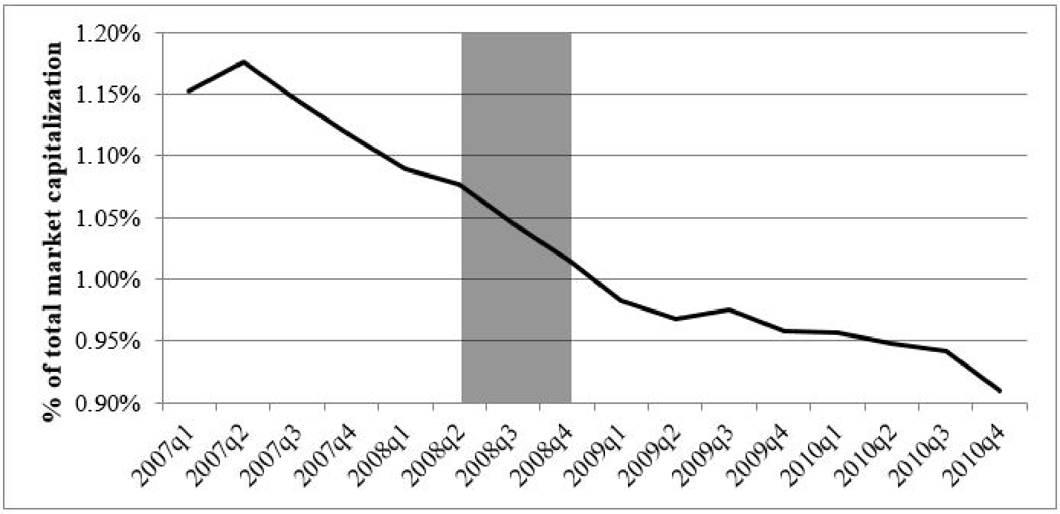


Figure 3.2: Hedge Funds' Total Fixed-Price Equity Holdings

The figure plots the total fixed-price dollar amount of equities held by hedge funds in my sample. I calculate the fixed-price equity holding as the total number of shares held by hedge funds at the end of each quarter times the price per share at the end of 2008 Q2. Therefore, the time variation of this curve represents the changes of shares held (proxy for trades) but not the changes of stock prices. The data ranges from 2007 Q1 to 2010 Q4. The shaded area marks the quarters around Lehman Brothers' bankruptcy (2008 Q3 & Q4).

Panel A:



Panel B:

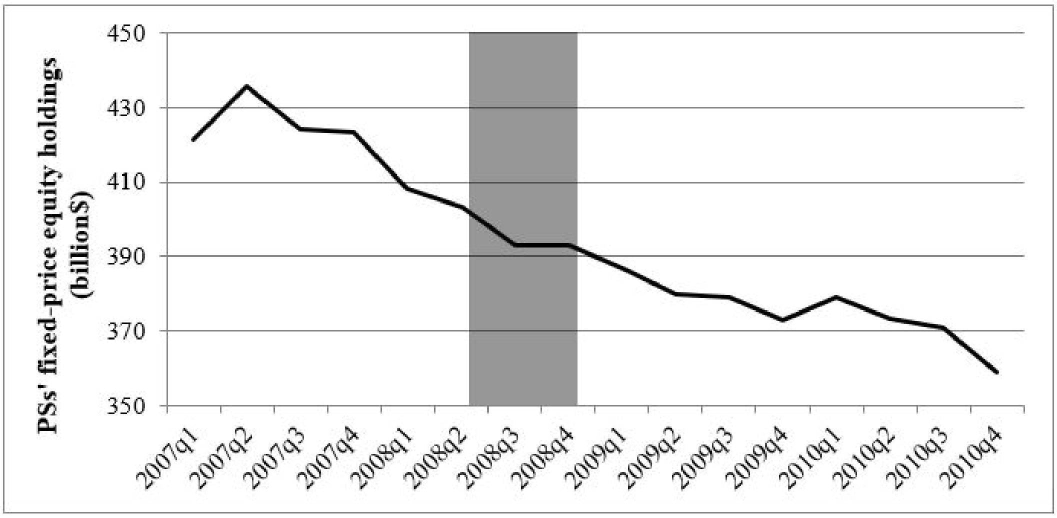


Figure 3.3: Pension Funds' Aggregate Equity Holdings

This figure plots pension funds' aggregate equity holdings in my sample. Panel A plots it as a percentage of total U.S. stock market capitalization. "Wilshire 5000 Total Market Index" is used as the measure of total market capitalization. Panel B plots pension funds' total fixed-price equity holdings. I calculate the fixed-price equity holding as the total number of shares held by pension funds at the end of each quarter times the price per share at the end of 2008 Q2. Therefore, the time variation of this curve represents the changes of shares held (proxy for trades) but not the changes of stock prices. The data ranges from 2007 Q1 to 2010 Q4. The shaded area denotes the quarters around Lehman Brothers' bankruptcy (2008 Q3 & Q4).

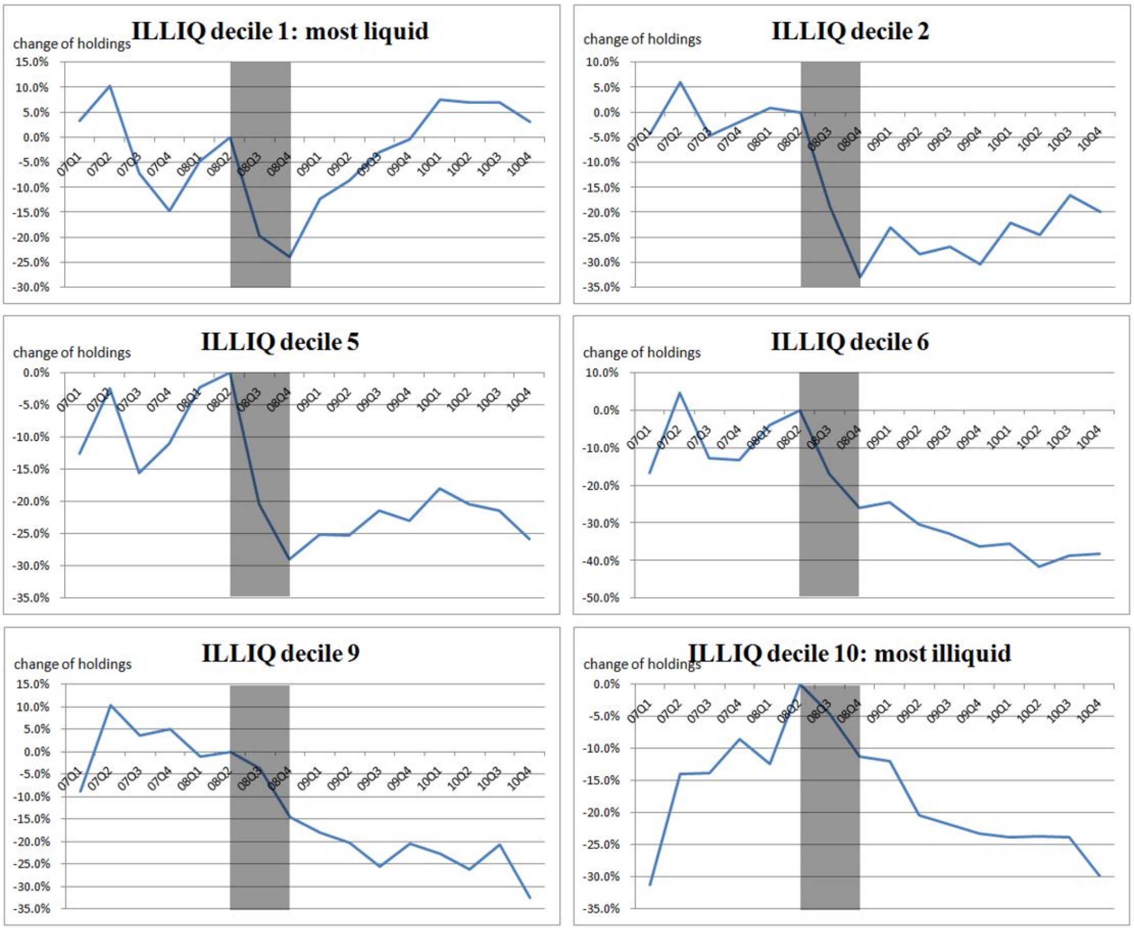


Figure 3.4: Cumulative Percentage Changes of Hedge Funds' Fixed-Price Equity Holdings for each ILLIQ Decile

The figure plots the cumulative percentage changes of HFs' fixed-price equity holdings for each ILLIQ decile separately, using the holdings at the end of 2008 q2 as a benchmark. I calculate the fixed-price equity holding as the total number of shares held by hedge funds at the end of each quarter times the price per share at the end of 2008 Q2. The data ranges from 2007 Q1 to 2010 Q4. The shaded areas mark the quarters around Lehman Brothers' bankruptcy (2008 Q3 & Q4).

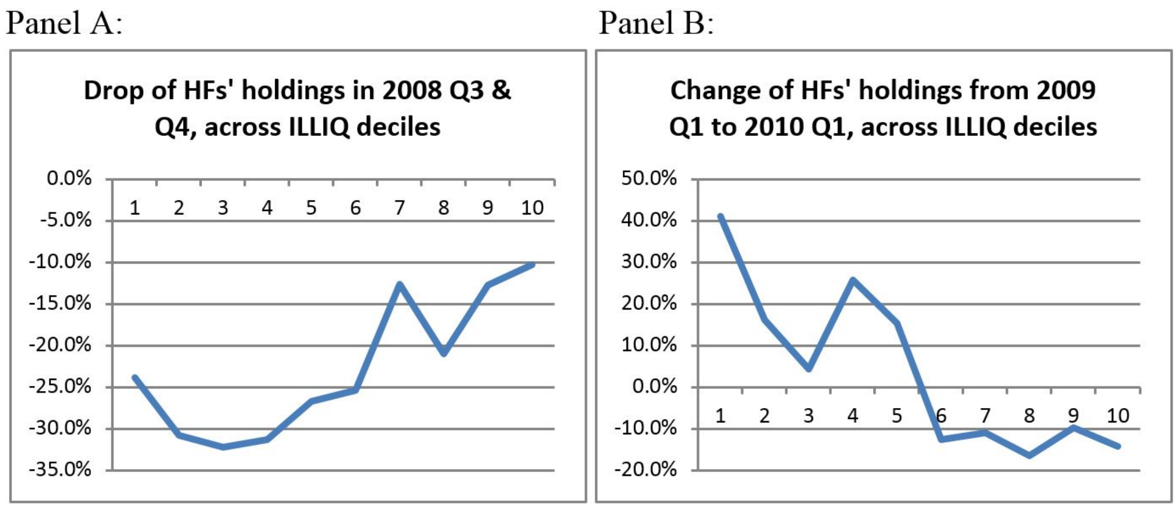


Figure 3.5: Changes of Hedge Funds' Equity Holdings across ILLIQ Deciles

Panel A plots the percent drops of hedge funds' holdings in 2008 Q3 Q4 across ILLIQ deciles (The first row of Table 3.8). Panel B plots the percent changes of hedge funds' holdings from 2009 Q1 to 2010 Q1 across ILLIQ deciles (The second row in Table 3.8).

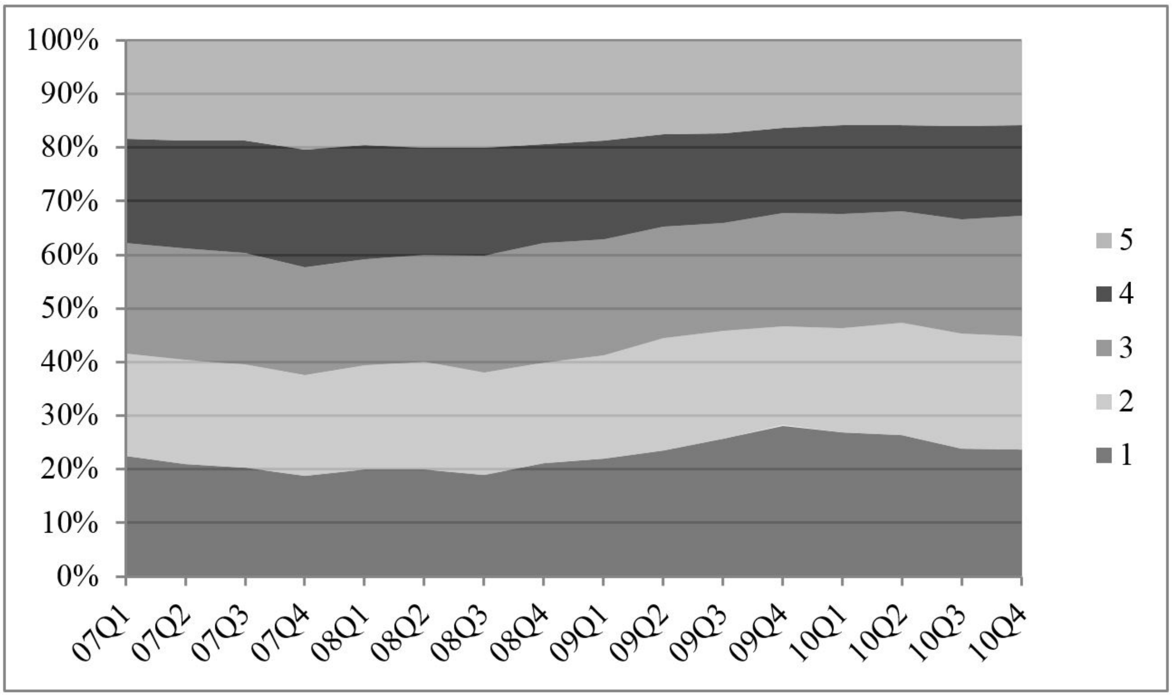


Figure 3.6: Hedge Funds' Portfolios Composition of Liquid Stocks versus Illiquid Stocks (by ILLIQ dollar-quintiles)

This figure plots hedge funds' fixed-price equity holdings for each ILLIQ dollar-quintile as a percentage of hedge funds' total fixed-price equity holdings. I sort stocks into 5 ILLIQ dollar-quintiles based on their values of ILLIQ, where hedge funds' equity holdings in each ILLIQ dollar-quintile is the same at the end of 2008 Q2. I calculate the fixed-price equity holding as the total number of shares held by hedge funds at the end of each quarter times the price per share at the end of 2008 Q2. Therefore it represents the changes of shares (trades) but not the changes of prices. The data ranges from 2007 Q1 to 2011 Q4.

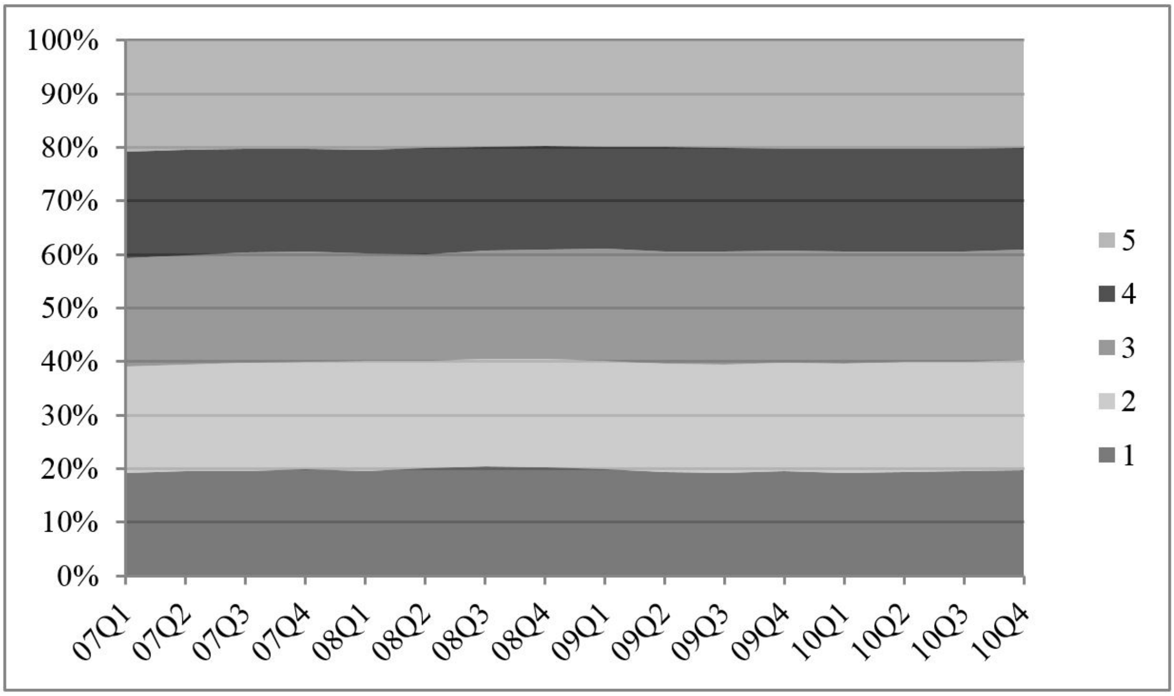


Figure 3.7: Pension Funds' Portfolios Composition of Liquid Stocks versus Illiquid Stocks (by ILLIQ dollar-quintiles)

This figure plots pension funds' fixed-price equity holdings for each ILLIQ dollar-quintile as a percentage of pension funds' total fixed-price equity holdings. I sort stocks into 5 ILLIQ dollar-quintiles based on their values of ILLIQ, where pension funds' equity holdings in each ILLIQ dollar-quintile is the same at the end of 2008 Q2. I calculate the fixed-price equity holding as the total number of shares held by pension funds at the end of each quarter times the price per share at the end of 2008 Q2. Therefore it represents the changes of shares (trades) but not the changes of prices. The data ranges from 2007Q1 to 2010Q4.

Table 3.1: Summary of Hedge Funds' Equity Holdings

This table sample comprises 60 hedge fund (HF) managing firms for which I have holding data in Thomson Reuters Institutional Holdings (13F) Database. The period is from 2007 Q1 to 2010 Q4. The "Number of stocks held" in the third column refers to the total number of stocks held by those HF managing firms in each quarter, out of 3636 stocks within the scope of my analysis. The "Fraction of total MC (%)" is the total dollar amount of the shares held by those HF managing firms as a fraction of the entire equity market measured by "Wilshire 5000 Total Market Index". "$ amount (bill$)" is the total dollar amount of equities held by those HF managing firms.

Total equity holdings of hedge funds (HFs)				
Year	Quarter	Number of stocks held	Fraction of total MC (%)	$ amount (bill$)
2007	1	2727	0.53%	278
	2	2850	0.59%	325
	3	2909	0.48%	269
	4	3010	0.46%	247
2008	1	3015	0.49%	240
	2	3032	0.52%	250
	3	3004	0.40%	174
	4	2956	0.34%	115
2009	1	2966	0.41%	124
	2	2921	0.43%	154
	3	2933	0.46%	193
	4	2932	0.46%	202
2010	1	2898	0.50%	235
	2	2932	0.49%	201
	3	2906	0.50%	232
	4	2829	0.48%	250

Table 3.2: Summary of Pension Funds' Equity Holdings

This table sample comprises 56 pension funds for which I have holding data in Thomson-Reuters Institutional Holdings (13F) Database. The period is from 2007 Q1 to 2010 Q4. "Number of stocks held" in the third column refers to the total number of stocks held by pension funds in each quarter, out of 3636 stocks within the scope of our analysis. "Fraction of total MC (%)" is the total dollar amount of shares held by pension funds as a fraction of the entire equity market measured by "Wilshire 5000 Total Market Index". "$ amount (bill$)" is the total dollar amount of equities held by pension funds.

Total equity holdings of pension funds (PFs)				
Year	Quarter	Number of stocks held	Fraction of total MC (%)	$ amount (bill$)
2007	1	3027	1.15%	599
	2	3093	1.18%	648
	3	3130	1.15%	640
	4	3235	1.12%	605
2008	1	3320	1.09%	533
	2	3374	1.08%	519
	3	3301	1.05%	460
	4	3195	1.02%	345
2009	1	3398	0.98%	300
	2	3363	0.97%	345
	3	3325	0.98%	404
	4	3308	0.96%	421
2010	1	3303	0.96%	446
	2	3277	0.95%	394
	3	3282	0.94%	437
	4	3197	0.91%	471

Table 3.3: Description of Stock Characteristics

Characteristics	**Description**
Hedge Fund (HF) Ownership	Percentage of shares outstanding held by hedge funds. Period: 2008 June 30; Source: 13F filling data
Pension Fund (PF) Ownership	Percentage of shares outstanding held by pension funds. Period: 2008 June 30; Source: 13F filling data
Market Cap	Company's shares outstanding multiplies current market price (in millions of dollars). Period: 2008 June 30; Source: CRSP
Book-to-Market	Book value of common equity divided by the market value of equity. Period: Quarterly report from 2008 April to June; Source: Compustat, merged by Ticker.
Share Turnover	Average value of daily volume of shares transacted divided by the number of shares outstanding. Period: Average from 2008 January 1 to 2008 June 30; Source: CRSP
Bid-Ask Spread	Average difference between bid and ask quotes divided by the daily price. Period: Average from 2008 January 1 to 2008 June 30; Source: CRSP
Market Beta	CAPM beta. Period: From 2001 January 1 to 2011 June 30; Source: CRSP
Past Returns	Annualized average daily stock returns. Period: From 2008 January 1 to 2008 June 30; Source: CRSP
Return Variability	Standard deviation of daily stock returns. Period: From 2008 January 1 to 2008 June 30; Source: CRSP
ILLIQ	ILLIQ is calculated as the average ratio of the absolute value of daily returns to daily dollar trading volume (Amihud 2002). Period: From 2008 January 1 to 2008 June 30; Source: CRSP

Table 3.4: Summary of Stock Characteristics

This table presents descriptive statistics of the stock returns and characteristics for all stocks in my sample, stocks held by hedge funds, and stocks held by pension funds separately. I obtain ownership data from Thomson Reuters, stock information from CRSP and accounting information from COMPUSTAT. The Ownerships and the stock Market Cap are based on the data at the end of 2008 Q2. The descriptions of other stock characteristics are in Table 3.3. All mean values of stocks characteristics are calculated as equally weighted.

	Entire Sample			Held by Hedge Funds			Held by Pension Funds		
Stock Characteristics	N	Mean	SD	N	Mean	SD	N	Mean	SD
Hedge Funds Ownership	3636	2.7%	4.4%	3032	3.3%	4.7%	-	-	-
Pension Funds Ownership	3636	1.7%	2.5%	-	-	-	3374	1.9%	2.5%
Market Cap	3636	3661	16292	3032	4252	17556	3374	3834	16689
Book-to-Market	3371	0.69	0.75	2857	0.66	0.78	3166	0.68	0.76
Share Turnover	3636	0.9%	1.0%	3032	1.1%	1.0%	3374	1.0%	1.0%
Bid-Ask Spread	3636	1.1%	2.0%	3032	0.6%	1.1%	3374	0.9%	1.7%
Market Beta	3636	1.15	0.68	3032	1.23	0.66	3374	1.17	0.66
Past Return	3636	-28.7%	109.4%	3032	-31.3%	109.9%	3374	-29.2%	107.8%
Return Variability	3636	3.5%	1.6%	3032	3.4%	1.4%	3374	3.4%	1.4%
ILLIQ	3636	0.31	1.22	3032	0.2	0.72	3374	0.24	0.75

Table 3.5: Summary of Stock Characteristics for ILLIQ Deciles

This table presents descriptive statistics of stock and firm characteristics by ILLIQ deciles, ILLIQ decile 1 for most liquid stocks and ILLIQ decile 10 for most illiquid ones. I sort all stocks in my sample (3636 stocks) into ILLIQ deciles based on their average ILLIQ values in the first half of 2008. ILLIQ value, the liquidity measure of individual stocks proposed in Amihud (2002), is calculated as the ratio of the absolute value of daily return to daily dollar trading volume. I obtain ownership data from Thomson Reuters, stock information from CRSP and accounting information from COMPUSTAT. “HFs’ total holding (bill$)” reports hedge funds’ total equity holdings at the end of 2008 Q2. The descriptions of stock and firm characteristics are in Table 3.3.

		ILLIQ Decile 1		ILLIQ Decile 2		ILLIQ Decile 3		ILLIQ Decile 4		ILLIQ Decile 5	
Stock Characteristics	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
HFs’ total holding (bill$)	364	149	-	53.6	-	25.5	-	9.1	-	5.4	-
HFs Ownership	364	2.3%	4.5%	4.5%	6.3%	4.0%	5.8%	3.2%	4.6%	3.2%	4.8%
Market Cap	364	27306	42215	3485	1789	1534	795	764	325	425	183
Book-to-Market	338	0.42	0.32	0.5	0.33	0.52	0.42	0.63	0.54	0.61	0.49
Share Turnover	364	1.1%	0.7%	1.4%	0.9%	1.5%	1.1%	1.4%	1.1%	1.1%	1.0%
Bid-Ask Spread	364	0.1%	0.1%	0.2%	0.1%	0.2%	0.2%	0.2%	0.4%	0.4%	0.5%
Market Beta	364	0.95	0.51	1.09	0.6	1.19	0.58	1.27	0.7	1.24	0.65
Past Return	364	-20.5%	64.5%	-8.8%	77.5%	-10.5%	90.9%	-29.7%	100.0%	-29.7%	100.4%
Return Variability	364	2.2%	0.8%	2.5%	0.8%	2.9%	0.9%	3.2%	1.0%	3.2%	0.9%
ILLIQ	364	0.001	0.001	0.006	0.002	0.015	0.003	0.03	0.006	0.055	0.009

		ILLIQ Decile 6		ILLIQ Decile 7		ILLIQ Decile 8		ILLIQ Decile 9		ILLIQ Decile 10	
Stock Characteristics	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
HFs’ total holding (bill$)	364	3.5	-	2	-	1.1	-	0.4	-	0.2	-
HFs Ownership	364	2.9%	5.2%	2.7%	5.1%	2.3%	4.3%	1.8%	4.6%	1.4%	2.6%
Market Cap	364	267	136	170	81	101	46	57	29	24	21
Book-to-Market	338	0.76	0.63	0.83	1.23	0.82	0.94	0.94	1	1.03	1.07
Share Turnover	364	0.9%	0.9%	0.7%	0.7%	0.5%	0.8%	0.3%	0.4%	0.4%	1.5%
Bid-Ask Spread	364	0.6%	0.8%	0.9%	1.0%	1.7%	1.6%	2.7%	2.2%	5.2%	3.8%
Market Beta	364	1.24	0.75	1.17	0.73	1.09	0.8	1.09	0.86	1.04	0.79
Past Return	364	-45.3%	121.0%	-47.2%	118.7%	-49.7%	114.4%	-56.9%	159.7%	-16.8%	171.3%
Return Variability	364	3.5%	1.3%	3.7%	1.5%	4.0%	1.4%	4.5%	1.8%	5.9%	2.4%
ILLIQ	364	0.091	0.013	0.15	0.022	0.258	0.047	0.513	0.118	2.756	3.836

Table 3.6: Change of Hedge Funds' Fixed-Price Equity Holdings across ILLIQ Deciles

This table presents the percent changes of hedge funds' fixed-price equity holdings for each ILLIQ decile in two periods, 2008 Q3 & Q4 and 2009 Q1 to 2010 Q1, separately. "Change of holding in 08 Q3 & Q4" is reported as a fraction of the hedge funds' equity holdings at the end of 2008 Q2, which is calculated as (holding in 2008 Q4 - holding in 2008 Q2)/(holding in 2008 Q2). "Change of holding from 09 Q1 to 10 Q1" is reported as a fraction of the hedge funds' equity holdings at the end of 2008 Q4, which is calculated as (holding in 2010 Q1 - holding in 2008 Q4)/(holding in 2008 Q4). The last row of reports the "Reversal as a percentage of the Drop", the dollar change of holding from 2009 Q1 to 2010 Q1 as a percentage of the dollar change of holding in 2008 Q3 & Q4, which is calculated as (holding in 2010 Q1 - holding in 2008 Q4)/(holding in 2008 Q2 - holding in 2008 Q4).

ãILLIQ Decile	1 liquid	2	3	4	5	6	7	8	9	10 illiquid
Change of holding in 08 Q3 & Q4	**-23.8%**	**-33.0%**	**-29.5%**	**-32.6%**	**-29.0%**	**-26.1%**	-14.7%	-18.9%	-14.5%	-11.2%
Change of holding from 09 Q1 to 10 Q1	**41.1%**	**16.2%**	**4.3%**	**25.8%**	**15.4%**	-12.6%	-11.0%	-16.6%	-9.7%	-14.2%
Reversal as a percentage of drop	**131.3%**	32.9%	10.3%	53.3%	37.7%	-35.7%	-64.2%	-71.2%	-57.3%	-112.8%

Table 3.7: Summary of Stock Characteristics for ILLIQ Dollar-Quintiles

This table presents descriptive statistics of stock and firm characteristics by ILLIQ dollar-quintiles. I sort all stocks in my sample (3636 stocks) into ILLIQ dollar-quintiles, making hedge funds' equity holdings in each ILLIQ dollar-quintile the same at the end of 2008 Q2. ILLIQ dollar-quintile 1 is for most liquid stocks and ILLIQ dollar-quintile 5 for most illiquid ones. I obtain ownership data from Thomson Reuters, stock information from CRSP and accounting information from COMPUSTAT. "HFs' total holding (bill$)" reports hedge funds' total equity holdings at the end of 2008 q2. The descriptions of stock and firm characteristics are in Table 3.3.

	Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
Stock Characteristics	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
# of Stocks	70	-	105	-	186	-	320	-	2351	-
HFs' total holding (bill$)	49.7	-	49.67	-	49.85	-	49.92	-	50.31	-
ILLIQ	0.0002	0.0001	0.0007	0.0002	0.0020	0.0006	0.0051	0.0015	0.3850	1.3440
Hedge Funds Ownership%	1.0%	0.9%	2.0%	2.0%	3.1%	5.7%	3.9%	5.0%	3.3%	4.7%
Market Cap	86312	72736	24051	9661	9334	4762	3959	1841	482	654
Book-to-Market	0.39	0.28	0.43	0.24	0.43	0.35	0.48	0.34	0.75	0.81
Share Turnover	0.9%	0.7%	1.0%	0.6%	1.2%	0.8%	1.4%	0.8%	0.9%	1.1%
Bid-Ask Spread	0.1%	0.2%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	1.3%	2.2%
Market Beta	0.87	0.47	0.87	0.44	1.02	0.54	1.13	0.58	1.18	0.7
Past Return	-30.3%	50.5%	-9.6%	61.6%	-23.2%	64.7%	-8.4%	77.2%	-32.0%	116.7%
Return Variability	1.9%	0.6%	2.1%	0.7%	2.3%	0.7%	2.5%	0.7%	3.7%	1.6%

Table 3.8: Change of Pension Funds' Fixed-Price Equity Holdings across ILLIQ Deciles

This table presents the percent changes of pension funds' fixed-price equity holdings for each ILLIQ decile in two periods, 2008 Q3 & Q4 and 2009 Q1 to 2010 Q1, separately. "Change of holding in 08 Q3 & Q4" is reported as a fraction of the pension funds' equity holdings at the end of 2008 Q2, which is calculated as (holding in 2008 Q4 - holding in 2008 Q2)/(holding in 2008 Q2). "Change of holding from 09 Q1 to 10 Q1" is reported as a fraction of the pension funds' equity holdings at the end of 2008 Q4, which is calculated as (holding in 2010 Q1 - holding in 2008 Q4)/(holding in 2008 Q4).

ãILLIQ Decile	1 liquid	2	3	4	5	6	7	8	9	10 illiquid
Change of holding in 08 Q3 & Q4	-2.8%	0.1%	-1.6%	-5.5%	-4.6%	-4.9%	-2.7%	-6.9%	-2.3%	3.4%
Change of holding from 09 Q1 to 10 Q1	-2.5%	-8.1%	-7.4%	-11.5%	-4.4%	-9.6%	-19.1%	-5.8%	-22.9%	-9.7%

Table 3.9: Hedge Funds' Trading and Stock Characteristics during the Crisis

The table reports the results of 4 stock-level cross-sectional regressions. For Columns (1) and (2), the dependent variable is the change of hedge fund (HF) ownership in 2008 Q3 & Q4 (the change in HFs' total equity holdings in 2008 Q3 & Q4 as a percentage of shares outstanding). In Columns 3 and 4, the dependent variable is the change of HF ownership in 2009 & 2010 Q1 (the change in HFs' total equity holdings in 2009 & 2010 Q1 as a percentage of shares outstanding). The explanatory variables include a set of stock characteristics and previous HF ownership. I calculate the ln value of stock ILLIQ ratio, "ln(ILLIQ)", the standard deviation of daily return, "SD" and the past 6-month returns, "past 6-month return", using the half year data just before the analysis period. The ln value of market capitalization, "ln(size)", the ln value of book-to-market ratio, "ln(book-to-market ratio)" and previous HF ownerships, "Previous HF holdings(%)" are based on the data just before the analysis period. I normalize the mean values of all the stock characteristics to 0 and standard deviations to 1. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Δ HF ownership in 08Q3&Q4(%)		Δ HF ownership in 09&10Q1(%)	
	(1)	(2)	(3)	(4)
ln(ILLIQ)	**0.174*** **	**0.698** **	**-0.446*** **	**-0.669*** **
	(4.27)	(2.32)	(-10.23)	(6.32)
SD	-0.051	-0.128**	0.166***	0.150***
	(-1.24)	(-2.13)	(3.62)	(3.23)
ln(size)		0.496*		-0.249**
		(1.76)		(-2.31)
ln(book-to-market ratio)	-0.026	-0.014	0.134***	0.131***
	(-0.72)	(-0.40)	(3.25)	(3.17)
past 6-month return	0.065*	0.024	0.045	0.061
	(1.88)	(0.58)	(1.07)	(1.43)
Previous HF holdings (%)	-0.239***	-0.239***	-0.269***	-0.272***
	(-31.51)	(-31.57)	(-25.63)	(-25.72)
Constant	-0.047	-0.046	0.622***	0.628***
	(-1.27)	(-1.22)	(14.36)	(14.48)
Observations	3636	3636	3636	3636
Adj R^2	0.2447	0.2452	0.1803	0.1814

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