Dynamic Liquidity Preferences of Mutual Funds*

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Abstract

I examine the relation between expected market uncertainty and the demand for liquidity in open-end mutual funds. The empirical results are consistent with precautionary motives for holding liquid assets, i.e., fund managers tilt their holdings more heavily toward liquid stocks when the market is expected to be more volatile. This dynamic preference for liquid stocks is more pronounced among small fund families, low-load funds, funds whose past performance has been unfavorable, funds with high return volatility, growth-oriented funds, and high-turnover funds. I further show that this type of behavior is valuable for fund investors during high volatility periods because it has led to significantly (both statistically and economically) higher subsequent abnormal returns.

JEL Classification: G11, G20, G30

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1 Introduction

This paper studies the relation between expected market uncertainty and the liquid stock holdings of actively-managed equity mutual funds. In the wake of the financial crisis of 1998, Scholes (2000) underscored the need for financial institutions to build "a dynamic liquidity cushion" to manage liquidity risk. This cushion is particularly valuable during volatile times when the demand for liquidity is high. For mutual funds, periods of high market volatility could be associated with high demand for liquidity through two channels. On the one hand, mutual funds are more likely to experience large withdrawals during volatile periods. This can arise because the probability that the performance of a fund falls below a certain threshold increases with market volatility and such an event may prompt fund investors to withdraw their funds.[1] On the other hand, high volatility in equity markets might not be a curse for fund managers when it presents more investment opportunities. Anecdotal evidence from the popular press often links turbulent markets to investment opportunities for deep-pocket investors.[2] Since market volatility is predictable and high volatility tends to be followed by high volatility, fund managers could be better positioned to meet these liquidity needs if they accumulate more liquid assets in advance, i.e., during times when expected market volatility is high.

This dynamic liquidity preference is in the spirit of precautionary motives for holding liquid assets. As Keynes (1936) originally discussed, a major incentive for holding liquid assets is that it "provide[s] for contingencies requiring sudden expenditure and for unforeseen opportunities of advantageous purchases." Keynes further pointed out that uncertainty is the main explanation for this precautionary liquidity preference. The greater the uncertainty, the more value a liquid balance sheet can add to a firm since liquidity increases a firm's operating options. This precautionary liquidity motive is also influenced by the extent to which a firm has access to external financing. A financially-constrained firm balances the benefit against the cost of holding liquid assets. The benefit of holding liquid assets is that financial flexibility enables a firm to avoid financial distress in the face of negative shocks, and to readily fund profitable investments

[1] Vayanos (2004) built a model based on the idea that withdrawals are more likely during volatile times. The notion of performance-based withdrawals was proposed by Shleifer and Vishny (1997).

[2] A recent example is Chicago hedge fund Citadel Investments' purchase of Sowood Capital Management LP's entire portfolio during the subprime mortgage financial crisis in the summer of 2007. It turns out that "Citadel has made big gains on the investments" (Wall Street Journal, October 27, 2007).

when they arise. The cost includes the opportunity cost of foregoing more profitable projects and the agency costs, i.e., free cash flow problems, associated with liquid assets.

This paper recasts the precautionary story in the mutual fund setting. Since mutual funds provide investors with liquidity services through their open-end structure, fund flows impose significant costs on fund performance (Edelen, 1999). If a fund does not have sufficient liquid assets to cover redemptions, it may be forced to liquidate good investments during inopportune times, which is very costly (Coval and Stafford, 2007). To the extent that expected volatility is associated with future redemptions, fund managers could mitigate the adverse effects of fund flows by tilting to a more liquid portfolio during times when expected volatility is higher. Further, liquid asset holdings during volatile times allow fund managers to capture alpha opportunities when they arise. The cost of holding liquid assets in the mutual fund setting is mainly the opportunity cost, since illiquid stocks have higher risk-adjusted returns than liquid ones. To the extent that agency costs are mitigated by the disciplining effect of withdrawal threats from fund investors (Fama and Jensen, 1983), the mutual fund environment provides a cleaner setting for testing the relation between expected uncertainty and liquid asset holdings.

For fund managers, holding liquid stocks is an attractive alternative to holding cash during periods of high expected volatility. First, liquid stocks offer higher risk-adjusted returns than cash following high expected volatility periods. In the sample period studied in this paper $(1990-2006)$, liquid stocks (bottom 5% in Amihud illiquidity measure) earn a CAPM-adjusted abnormal return, before transaction costs, of 49.4 basis points in the first month (excluding January) immediately subsequent to high expected volatility quarter-ends[3]. Second, equity fund managers have less latitude in adjusting their cash position for various reasons. SEC Rule 35d-1 requires that "an investment company with a name that suggests that the company focuses its investments in a particular type of investment (e.g., the ABC Stock Fund or XYZ Bond Fund) or in investments in a particular industry (e.g., the ABC Utilities Fund or the XYZ Health Care Fund) invest at least 80% of its assets in the type of investment suggested by the name."[4] This puts an upper bound on a fund's cash position. Even if they are not bounded by such regulations, maintaining a large or fluctuating cash position would compromise the managers'

[3] If January is included, the abnormal return is about 80 basis points.

[4] Rule 35d-1 became effective March 31, 2001.

compensation, which usually depends on tracking and beating a benchmark. Additionally, since investors of equity mutual funds expect their managers to hold equities, sitting on a pile of cash would suggest that the manager has no stock ideas. These provide disincentives for mutual funds to increase their cash holdings during volatile periods. Fund managers, however, are not constrained in their holdings of liquid stocks. By definition, liquid securities allow the holder to trade large quantities quickly, at low cost, and without moving the price. Thus, these securities could be converted easily into cash during market stress in order to satisfy heavy redemption requests and to take advantage of investment opportunities without selling less liquid securities in the portfolio.[5]

The purpose of this paper is to examine the preferences of equity mutual funds for liquid stocks across different expected market volatility states as well as the impact of these dynamic preferences on fund performance. Specifically, I ask three questions. First, how do mutual funds' preferences for liquid securities vary across different expected market volatility states? As argued above, we expect that, in aggregate, mutual fund holdings of liquid stocks, as a proportion of their total net assets, increase with expected market volatility.[6]

Second, how is this behavior related to fund characteristics? Since the shift in liquidity demand is a hedge against future redemptions and future investment opportunities, there should be cross-sectional differences among funds with different financial and investment characteristics. This type of preference should be more prevalent among funds with greater likelihood of large redemptions, such as funds from small fund families, low-load funds, funds with unfavorable performance, and funds with high volatility. Funds that tend to incur higher transaction costs in obtaining external financing (e.g., credit lines) or generating internal funds (e.g., by selling off less liquid securities) during volatile periods should also accumulate more liquid assets

[5] The disadvantage of holding liquid stocks instead of cash, however, is that it incurs transaction costs. Thus, fund managers face a trade-off when deciding between using cash or liquid stocks to fulfill their liquidity needs. In this study, I view liquid stock holdings and cash holdings as substitutes to each other. Massa and Phalippou (2005) and Yan (2006) present evidence that the cash holdings of a mutual fund are significantly and negatively related to the liquidity of the fund's equity portfolio. In the robustness check section, I explicitly control for fund cash position and the results still hold up.

[6] To increase their asset weight in liquid stocks, fund managers can either allocate a larger fraction of their inflows into purchasing liquid securities, or sell off some of their illiquid stock holdings and use the proceeds to buy liquid stocks. Selling illiquid stocks prematurely is costly, but it is less costly during normal periods than during market downturns when liquidity deteriorates precipitously for illiquid securities, which is often referred to as "flight to liquidity." See, for example, Acharya and Pedersen (2005).

for precautionary purposes. Furthermore, since the increase in holdings of liquid stocks is also a hedge for future investment opportunities, I expect this behavior be more prevalent among funds with better investment opportunities during volatile times. Intuitively, there is greater uncertainty about fundamentals during volatile times than during normal times, which gives rise to greater chances of mispricing.[7] As such, the distribution of alphas is more spread out during such times. Fund managers with better skills in identifying positive alpha opportunities are expected to exhibit stronger liquidity preferences during periods of high expected volatility.

Third, if fund managers invest a large fraction of their assets in liquid stocks during periods of high expected volatility, does this behavior in fact add value for investors?[8] A premise of the precautionary motive for holding liquid assets is that it creates value for the firm by providing options. However, there is no evidence that liquid asset holdings during uncertain times lead to improved performance. This paper bridges the gap by examining the relation between the precautionary liquidity holdings of mutual funds and subsequent abnormal fund returns. If a fund with a high proportion of its assets in liquid stocks during high expected volatility periods fares better than funds that are not hedging the uncertainty, it provides direct support for the notion that financial flexibility during times of uncertainty adds value.

Using a sample of all NYSE, AMEX, and NASDAQ common stocks and $1,962$ domestic equity mutual funds from 1990 to 2006, I examine the dynamic liquidity preference of mutual funds as well as its implications for fund performance. I first show that higher expected volatility is followed by both a greater probability of withdrawals and more investment opportunities. This evidence suggests that a liquidity cushion is valuable for fund managers during periods of high expected volatility. The main findings of this paper can be summarized as follows: First, in aggregate, equity mutual fund managers hold a larger proportion of their assets in liquid stocks when expected market volatility is higher. This finding is robust to controls for fund-specific characteristics, and a number of specification checks and changes in the sample. Additionally, difference-in-difference tests show that the stocks bought (relative to those sold) by mutual

[7] Here, we depart from the efficient market paradigm.

[8] A related question is how fund managers' portfolio rebalancing (the change in liquid stock holdings) during high volatility times affects subsequent fund performance. The current paper does not examine this question. The reason is that the precautionary story hinges on the benefit of the *level*, not the change, of liquid asset holdings during uncertain times.

funds during periods when expected volatility increases (relative to periods when expected volatility decreases) are significantly more liquid. This suggests that fund managers reallocate their portfolios to achieve the optimal liquidity level in anticipation of market turmoil. Second, dynamic liquidity preference is more prevalent among funds from small fund families, low-load funds, funds with unfavorable performance, funds with high volatility, growth funds, and high-turnover funds. Combined with the evidence that these fund characteristics are associated with outflows or investment opportunities during volatile times, the results are consistent with the notion that the benefits of precautionary liquidity holdings are greater for these funds. Last, precautionary liquidity holdings during high expected volatility periods are associated with statistically and economically significant abnormal fund returns in the subsequent period.

This study contributes to the literature in several ways. First, the paper presents the first evidence that financial flexibility, i.e., liquid asset holdings, under highly uncertain environments, adds value. Second, the paper contributes to our understanding of mutual fund liquidity management. While the existing literature mainly focuses on the transaction motives and thus shows that mutual funds have time-invariant preferences for liquid stocks, this paper demonstrates that mutual funds exhibit dynamic liquidity preferences for precautionary motives as well. Last, the dynamic liquidity preference findings offer insights into the dynamics of the liquidity premium in stock returns.[9]

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 describes the data. Section 4 explores the link between the expected volatility measure (the VIX) and future redemptions, and that between the VIX and future investment opportunities. Section 5 uses both fund-level and stock-level analyses to examine the impact of expected market volatility on mutual funds' preferences for liquid stocks. The effect of fund characteristics on the dynamic liquidity preference is also examined therein. Section 6 tests the impact of mutual funds' dynamic liquidity preferences on fund performance in the subsequent period. Section 7 offers robustness checks and Section 8 concludes.

[9] As pointed out by Scholes (2000), the "liquidity premium varies considerably over time as a function of preferences", and "[t]he dynamics of the liquidity premium depend on institutional reactions to financial crises."

2 Related Literature

This study is closely related to two theoretical studies on the liquidity preferences of mutual funds, with the first being Vayanos (2004). In this model, investors are fund managers and subject to performance-based withdrawals. The model generates a liquidity preference that is time-varying and increasing with volatility. A key premise to Vayanos (2004) is that withdrawals become more likely during volatile times. The present paper complements Vayanos' paper by empirically showing the following: (1) withdrawals increase following high expected volatility periods, (2) fund managers increase their preferences for liquid stocks during times when expected volatility is high, and (3) mutual funds with large liquid stock holdings perform better during times of high volatility. Chordia (1996) theorizes that the cash holdings of open-end funds cash holdings are positively related to uncertainty about redemptions, which arises because redemptions impose significant costs on mutual funds. Using redemption variance as a proxy for redemption uncertainty, he provides evidence that funds with greater redemption uncertainty hold more cash. My paper differs from Chordia (1996) in several important ways. First, while Chordia focuses on the static cross-sectional implication of precautionary holdings, I exploit the time-series implication and also interact fund characteristics with expected volatility in order to examine heterogeneity in the dynamic liquidity preference across funds. Second, while the uncertainty in Chordia (1996) is only about investor redemptions, my paper also considers uncertainty about the market. As I show in Section 4, higher levels of expected market volatility are associated with a greater likelihood of large redemptions in the future *and* increased attractiveness of future investment opportunities. Third, instead of examining cash holdings, I focus on liquid stock holdings and I also explore the implications of dynamic preferences on fund performance. Last, while Chordia (1996) conducts his study at the fund level, this paper implements tests at both the fund level and the stock level. Specifically, I examine how liquid stock holdings by mutual funds vary with expected market volatility and how mutual fund ownership of liquid stocks varies with expected market volatility states. The latter could avoid noise introduced by fund specific events, such as house cleaning by new managers.[10]

[10] Jin and Scherbina (2006) documents that when new managers take over mutual fund portfolios, they tend to sell losers (less liquid) at a faster rate than winners. A story one can tell is that the fund-level precautionary results could be driven by new managers' house cleaning activities, i.e., reallocation of portfolios towards winners

The paper is also related to the extensive literature on mutual fund performance and timing abilities. The central message of Jensen (1968) and the subsequent literature is that on average the portfolio management skills provided by mutual fund managers are of little value to investors. Edelen (1999) attributes mutual funds' underperformance to the liquidity service that fund managers provide investors. In particular, to avoid large and random fluctuations in the cash position of the fund, fund managers must engage in liquidity trading, which contributes to negative performance. The present paper suggests that the adverse effect induced by fund flows could, to some extent, be moderated by fund managers' active management of their liquid stock holdings. By hoarding liquid stocks in response to an increase in expected future market volatility, fund managers could be better positioned to withstand flow shocks while maintaining a stable cash balance. Busse (1999) documents that mutual funds' volatility timing, i.e., reducing market exposure during times of high expected market volatility, leads to higher risk-adjusted returns in the contemporaneous period, suggesting that mutual funds provide investors with a valuable volatility hedge. This paper complements Busse's study by showing a different form of volatility hedge, which is also valuable for investors.

There is a parallel literature in corporate finance investigating the precautionary cash holdings of publicly traded firms. Several papers use cash flow volatility proxies constructed from accounting data and present evidence that a firm's investment in liquid assets increases with its cash flow uncertainty (Kim, Mauer, and Sherman, 1998 and Opler, Pinkowitz, Stulz, and Williamson, 1999). These papers share the common feature that they examine the static cross-sectional implication of the precautionary liquidity motives, i.e., firms with different cash-flow uncertainty profiles tend to choose different cash-holding policies. The time-series implication, i.e., firms increase their liquid asset holdings in response to increases in expected uncertainty, is not examined in the literature. The present paper fills this void by applying the idea to the mutual fund context. Instead of using accounting information to construct volatility measures, I use the implied volatility from index options. The implied volatility measure is forward-looking and can be easily measured at a relatively high frequency.

(more liquid stocks).

3 Data and Summary Statistics

3.1 Data

The primary data source on mutual funds is the merged CRSP Survivor-Bias Free Mutual Fund Database and Thomson Financial CDA/Spectrum Mutual Fund Holdings Database (Wermers, 2000). This database merges information about individual fund managers and the quarterly stock holdings of each fund. The original source of the holdings data is Form N-30D, which U.S. mutual funds are required to file with the SEC at the middle and end of their fiscal years. I collect the holdings data for the time period starting from the first quarter of 1990, when the CBOE VIX index became available, through the last quarter of 2006. Quarterly holdings data are available for 62.46% of the sample while 31.99% of the holdings are observed semi-annually. To focus my analysis on open-end domestic equity mutual funds, for which the holdings data are most complete and reliable, I eliminate balanced, bond, money market, international, and unclassified funds. I also exclude funds which hold less than 10 stocks. In addition, I exclude index funds in order to focus on actively managed mutual funds.[11] Following Chen et al. (2004), I require a fund to have a TNA greater than $15 million and to have at least one year of reported returns. Finally, I aggregate different share classes of a mutual fund into one single fund, instead of discarding them as redundant observations, in order to minimize the loss of information.[12] There are $1,962$ distinct fund entities and a total of $45,583$ fund-quarter observations in the analysis. The number of mutual funds included in the sample ranges from 402 in 1993Q3 to $1,119$ in 2000Q2.

To measure expected market volatility, I use the S&P500 Volatility Index (VIX) constructed by the Chicago Board Options Exchange (CBOE). The VIX provides a snapshot of expected stock market volatility over the next 30 calendar days. Compared to volatility estimates calculated based on historical data, the VIX has the advantage that it is a quantity backed out from an option-pricing model and does not suffer from sampling errors. This forward-looking

[11] A fund is identified as an index fund if its fund name provided by Thomson Financial has the word "index."

[12] Specifically, I sum the TNA of each share class to obtain the TNA for the fund. I use the inception date of the initial fund class to calculate fund age. For other fund characteristics, such as turnover, expenses, and load, I use the TNA-weighted average across all share classes.

volatility index has been widely accepted as a measure of expected volatility by both practitioners and academic researchers.[13] Ideally, one would like to use the VIX on the last day of the quarter so that it's the most up-to-date forecast for the next period's volatility. However, considering that fund managers are more likely to adjust their positions slowly to reduce price impact, I calculate the expected volatility of each quarter as the average VIX of the last 21 trading days in that quarter. The results are robust to using a shorter window, e.g. the last 3 trading days of each quarter. The mean level of the quarterly VIX series is 18.9%, and its standard deviation is 6.4%. To examine the effect of changes in expected volatility on mutual funds' trading behavior, I also construct an innovation in the VIX series by fitting an AR(3) model to the VIX, and measure innovations relative to the AR(3) specification. The VIX innovation series has a mean of -0.1% (statistically indistinguishable from 0) and a standard deviation of 4.4%. Figure I plots the VIX series (Panel A) and the VIX innovation series (Panel B), with the bars indicating quarters where the VIX level or the innovation in VIX is higher than the median.

[Insert Figure I about here]

3.2 Mutual Fund Characteristics

For the fund-level analysis, I consider various fund characteristics suggested by the literature as controls. I retrieve TNA and fund returns from the CRSP Mutual Fund monthly file and other characteristics from the quarterly file. Since the holdings information is available only at a quarterly frequency, I measure fund characteristics at the end of each quarter. Fund size is the total net assets (TNA) of the fund, while fund family size is measured as the log of one plus the cumulative TNA of the other funds in the fund's family. Net flow is the percentage of new fund flow into the mutual fund over the past year (described below). Variance of net flows is measured as the variance of the previous 12 months of net flows. Total load is the sum of front- and rear-end load fees. Turnover is defined as the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA. Age is the number of years since the

[13] See, for example, Fleming, Ostdiek and Whaley (1995), Blair, Poon, and Taylor (2001), and Connolly, Stivers and Sun (2005).

initiation of the fund. Expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses. Portfolio concentration is the inverse of the number of stocks held by the fund. Liquid stock beta is the average beta of liquid stocks in the fund's portfolio, weighted by the dollar amount invested. Lag return is the buy-and-hold fund return over the past 12 months. Return volatility is the standard deviation of the monthly fund return over the past 12 months.

The percentage net flow to fund i during year t is measured as follows:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) - MergeTNA_{i,t}}{TNA_{i,t-1}}$$

where $TNA_{i,t}$ is the TNA at the end of year t, $R_{i,t}$ is the fund's return for year t, and $MergeTNA_{i,t}$ is the increase in the TNA due to mergers during year t.

Table I reports summary statistics on the mutual fund sample. Fund size measured by TNA has a mean of $\$1,349.39$ million and a median of $\$293.15$ million, suggesting a highly skewed distribution. The average one-year net flow into funds is 12.9% of fund assets. The average fund has an annual portfolio turnover rate of 88.5% and an expense ratio of 1.3%. The average fund portfolio contains 62 stocks (1/0.0162).

[Insert Table I about here]

3.3 Stock Characteristics

I calculate mutual fund ownership (MFO) for a specific stock in a given quarter by summing the reported holdings of the sample mutual funds and dividing by the total shares outstanding for the firm. If a stock is not held by any reporting mutual fund, then I set MFO to zero. The results are robust to the exclusion of stocks with zero mutual fund ownership. Security characteristics data, such as stock returns, price, industry classification, and trading volume are gathered from the CRSP monthly stock file. I obtain accounting information from CompuStat. All common stocks traded on NYSE, AMEX, and NASDAQ with adequate CRSP/CompuStat data are included in the analysis.

Following Gompers and Metrick (2001) and Bennett, Sias, and Starks (2003), I focus on four categories of stock characteristics: three measures of liquidity (firm size, price, and turnover), two proxies for prudence (firm age and dividend yield), three proxies for risk (return volatility, beta, and firm-specific risk), and one measure to capture momentum trading (lagged return). Firm size is measured as the quarter-end market capitalization. Share price is measured as the quarter-end price per share. Share turnover is defined as the average ratio of monthly volume to number of shares outstanding in the current quarter. Firm age is measured as the number of months since a stock first appears in CRSP monthly stock file. Dividend yield is measured as the cash dividends for the fiscal year ending at least three months before the current quarter-end, divided by size as of December 31 during that fiscal year. Return volatility is estimated as the standard deviation of monthly returns over the previous two years. Beta is estimated as the sum of the coefficients in a regression of the firm's monthly return on the contemporaneous and lagged one-month CRSP NYSE/AMEX value-weighted index over the previous $24 - 60$ months. Firm-specific volatility is measured as the three-month average of the Campbell, Lettau, Malkiel, and Xu (2001) monthly firm-specific risk measure over the current quarter. Lag return is measured as the six-month cumulative gross returns prior to the beginning of the quarter.

As a complement to the three measures of liquidity, I also employ Amihud's (2002) illiquidity ratio. For stock i in month m, the illiquidity measure is defined as:

$$ILLIQ_{i,m} = \frac{1}{D_{i,m}} \sum_{t=1}^{D_{i,m}} \frac{|r_{i,t}|}{dvol_{i,t}}$$

where $D_{i,m}$ is the number of days for which data are available for stock i in month m, r_t is the stock return on day t, and $dvol_{i,t}$ is the CRSP-reported dollar volume for the stock on day t. The average is computed over all days with non-zero volume in the month for which return data are available. Intuitively, if a stock's price moves a lot in response to little volume, the stock is illiquid, i.e., has a high value of $ILLIQ$. Amihud (2002) shows empirically that the illiquidity ratio is positively related to measures of price impact and fixed trading costs. Similarly, Hasbrouck (2006) reports that "[a]mong the daily proxies, the Amihud illiquidity measure is most strongly correlated with the TAQ-based price impact coefficient." The illiquidity ratio is widely employed in the empirical literature as a liquidity measure, such as, Acharya and Pedersen (2005), Hou and Moskowitz (2005), and Avramov, Chordia, and Goyal (2006). Following Acharya and Pedersen (2005), I use the normalized Amihud illiquidity ratio,

$$ILLIQ_{i,m}^{n} = \min(0.25 + 0.30 * ILLIQ_{i,m} * M_{t-1}, 30.00)$$

where M_{t-1} is the ratio of the capitalization of the market portfolio at the end of month $t-1$ to that of the market portfolio at the end of July 1962. The illiquidity ratio is measured as the three-month average of the monthly normalized illiquidity measure over the current quarter.

Table II presents summary statistics for mutual fund ownership and other stock characteristics. The average MFO for stocks is 5.78%. Firm size measured by market capitalization has a mean of $\$1,694$ million and a median of \$196 million. The year-by-year summary statistics (not reported) show some interesting patterns. For example, mutual fund ownership of the average stock increases steadily over time, and the liquidity of the average stock improves significantly.[14]

[Insert Table II about here]

For the stock-level analysis, I first estimate 68 separate cross-sectional regressions of mutual fund ownership on firm characteristics, one for each quarter. I then compare the coefficients of the test variables across high- and low-expected-volatility quarters. Since the magnitude of an ordinary regression coefficient depends on the scale of both the dependent variable and independent variables, which in this setting are time-varying, we cannot directly compare the coefficients using the raw data.[15] Another issue with regressing mutual fund ownership on firm characteristics is that the relationship could be non-linear (Falkenstein, 1996). To tackle

[14] For example, the normalized Amihud illiquidity ratio for the average stock at the end of the sample period drops to half of its beginning of the period value, and turnover for the average stock increases from 5.76% in 1990Q1 to 16.36% in 2006Q4.

[15] Consider an example where mutual funds have constant liquidity preference over different volatility states. If the average MFO during the high VIX state is twice as large as the average MFO during the low VIX state and the liquidity characteristics of the average stock does not change, the coefficient estimates from the regression of raw MFO on raw stock characteristics will simply double during the high VIX state. Similarly, the independent variables in such regressions, i.e., the stock characteristics, are also time-varying. This could also lead to time-series variation in raw coefficient estimates.

these problems, I transform all of the independent and dependent variables into standardized percentile ranks, ranging from 0 to 1.[16] Specifically, in each quarter, I rank stocks based on the levels of a variable and assign percentile ranks to stocks, then dividing these percentile ranks by 100. In this way, all variables are transformed into values evenly spread between 0 and 1, where 0 represents the minimum and 1 represents the maximum.

4 Why Should Fund Managers Care About Expected Volatility?

The paper proposes a story where high expected market volatility could pressure fund managers to increase their liquid stock holdings through: (1) the link between expected volatility and fund outflows, and (2) the link between expected volatility and investment opportunities. As a starting point for the empirical work, this section presents evidence on these links.

4.1 Expected Volatility and Mutual Fund Flows

To examine the relation between the VIX and future fund flows, I calculate the one-month-ahead mutual fund net flows at each quarter-end. Panel A in Figure II plots the frequency distribution of mutual fund net flows following high versus low VIX states. Focusing on the left side of the graphs, we see that there are more realizations of large redemptions (negative net flows) following high VIX quarter-ends. For outflows greater than 2.5% of a fund's total net assets[17], the cumulative density is 14.6% for high VIX states versus 12.3% for low VIX states. A Wilcoxon rank-sum test easily rejects the null hypothesis that the probability of these large redemptions across the two states is the same with a p-value well below 0.01.

I also sort the one-month-ahead fund flows into deciles and examine the probability of falling into the bottom decile[18] following high versus low VIX quarter-ends. Panel B in Figure II shows that mutual funds enter disproportionately into the bottom (outflow) decile following periods of

[16] This is similar to Chan, Jegadeesh, and Lakonishok (1996).

[17] To put the number into some perspective, note that a typical fund's cash position is around 5% of its TNA. Hence, a 2.5% redemption in one month is economically large.

[18] The 10th percentile of the distribution for net flows is -3.08%.

high expected volatility. The probability of falling into the bottom decile is 10.9% for high VIX periods, while that for low VIX periods is 8.9%. Again, the difference is statistically significant. This presents the first evidence consistent with Vayanos' intuition that withdrawals are more likely during times of high volatility.[19]

[Insert Figure II about here]

While I find a positive relation between outflows and expected volatility, I expect some heterogeneity in the strength of the correlation across funds. Since the likelihood of underperformance and/or withdrawal can differ across funds, funds will vary in their susceptibility to outflows. In particular, the following fund characteristics are expected to be associated with a stronger correlation between withdrawals and volatility: low load, small fund family association, poor past performance, and high return volatility.

To examine the heterogeneity of the relation across funds, I first sort one-month-ahead fund flows into deciles. I then sort funds into quartiles based on each characteristic at each quarter-end. In particular, the bottom quartile (Q1) consists of funds with the lowest values of a characteristic considered and the top quartile (Q4) consists of funds with the highest values of the characteristic. For each quarter-end, I calculate the cross-sectional mean statistics of the probability of entering into the bottom fund flow decile across funds in Q1 and Q4 for each characteristic. Table III reports the time-series average of these mean statistics across high and low VIX quarters and the results of a Wilcoxon rank-sum test of the null hypothesis that the probability of falling into the bottom fund flow decile is identical across high and low VIX states for funds with a particular characteristic. The table also reports Wilcoxon rank-sum test statistics resulting from a difference-in-difference test of whether the difference between high and low VIX regimes is significantly different across Q1 and Q4 funds.

The difference-in-difference test shows that, relative to funds with opposite characteristics, those from small fund families, low-load funds, and underperforming funds are more likely to incur large outflows during high volatility periods than during normal periods. Interestingly,

[19] In Vayanos (2004), withdrawals are more likely when *realized* volatility is higher. If I replace the forward-looking VIX measure with realized volatility, the results still hold. This is not surprising, given that implied volatility is a good predictor of future realized volatility.

highly volatile funds are not significantly different from less volatile funds in terms of the flow-VIX relation. In addition to these four characteristics, I also consider investment style and fund turnover. The results show that, relative to income funds, growth funds are less likely to have outflows during high volatility periods, and high-turnover funds are not significantly different from low-turnover funds. Considering that growth funds and high-turnover funds incur high price impact costs (Chan and Lakonishok, 1995), it is reasonable to assume that these two types of funds incur high transaction costs in obtaining funds (by selling their holdings) during high volatility periods when transaction costs for their holdings shot up. Thus, growth funds and high-turnover funds are, to some extent, financially constrained. Given that they face the same (or even less) pressure from investor redemptions, this financial constraint could potentially provide them an incentive to hold more liquid stocks.

[Insert Table III about here]

4.2 Expected Volatility and Investment Opportunities

I use the realized stock return to examine the relation between expected volatility and future investment opportunities. More stocks experiencing high alphas following a high VIX quarter-end than a low VIX one may indicate that there are more investment opportunities during volatile markets. I use two measures of risk-adjusted returns of stocks: the CAPM alpha and the Fama-French three-factor alpha. Both alphas are measured over the 6-month period subsequent to a quarter-end.[20] I sort the six-month-ahead alphas into deciles and examine the probability of falling into the top decile during high versus low VIX periods.[21]

Figure III plots the frequency distribution of CAPM (Panel A) and three-factor alphas (Panel B) following high and low VIX quarters. For both measures, the probability of entering into the top decile is significantly higher following high VIX quarter-ends compared to low VIX quarter-ends. For example, 12.4% of stocks deliver top decile three-factor alphas subsequent to high VIX quarter-ends, compared to 7.3% following low VIX quarter-ends. The difference

[20] I use monthly returns during the four-year period before the event month, i.e., month [-59, -12], to estimate betas.

[21] The 90th percentiles of the distribution for CAPM alphas and three-factor alphas are 7.51% and 7.55%, respectively.

is statistically significant at the 1% level. The results using CAPM alphas are even stronger. This lends support to the notion that there are more investment opportunities during volatile markets.[22]

[Insert Figure III about here]

Given that volatile markets are associated with attractive investment opportunities, I expect fund managers with better stock picking skills to capture these profitable opportunities. Wermers (2000) and Chen, Jegadeesh, and Wermers (2000) show that high-turnover funds and growth funds have better stock picking talents, thus these funds could take advantage of the alpha opportunities during volatile periods if they have sufficient liquidity.

In sum, fund managers react to expected volatility because higher expected volatility periods are followed by: (1) a higher probability of fund outflows and (2) a greater proportion of stocks with positive alphas. I also show that funds with the following characteristics are associated with greater outflows or better investment opportunities during highly volatile periods: funds from small fund families,[23] low-load funds, poorly performing funds, funds with high return volatility, growth funds, and high-turnover funds. As such, these funds should have stronger preferences for liquid stocks during periods of high expected volatility.

[22] Interestingly, the distribution of alphas has fatter tails during volatile periods than during normal periods. That is, there are greater chances of both positive alphas and negative alphas during volatile periods. Because only a very small fraction of mutual funds sell short, positive alpha opportunities are more relevant for fund managers.

[23] An additional rationale for small-family funds to exhibit greater preference for liquid securities is that they have higher costs in getting outside funds in the form of credit lines and fund-family borrowing when in trouble. Gaspar, Massa, and Matos (2006) document that large mutual fund families have greater latitude in allocating resources across their funds. Chen et al. (2004) argue that large fund families have economies of scale associated with marketing, trading commissions, and stock lending fee. Nanda, Wang, and Zheng (2004) show that a fund family with lower correlation between fund returns in the family, presumably large families, have a greater probability of producing stars, and there exists a flow spillover within these fund families that possess a star fund.

5 Changes in Liquidity Preferences of Mutual Funds across Market States

This section examines the relation between mutual fund liquid stock holdings and expected volatility. I first conduct tests on the fund level, examining how mutual funds' liquid stock holdings vary with expected market volatility. Section 5.1.1 and 5.1.2 present univariate and multivariate results, respectively. Section 5.1.3 examines the effect of fund characteristics on the relation between liquid stock holdings and expected volatility. I then switch to stock-level analysis. Section 5.2.1 examines the liquidity characteristics of stocks bought and sold by mutual funds during high versus low VIX innovation periods. Section 5.2.2 uses stock-level regressions to examine how mutual fund ownership of liquid stocks changes during high versus low VIX states. Section 5.2.3 examines the effect of fund characteristics on the relation between liquid stock holdings and expected volatility on the stock level.

5.1 Fund-Level Analysis

5.1.1 Liquid Stock Holdings of Mutual Funds: Univariate Analysis

In this subsection, I test whether the proportion of liquid stocks in a fund's assets is related to expected volatility. I use both level-on-level and change-on-change tests. The level-on-level test examines how the fraction of liquid stock holdings in mutual funds' assets (termed "liquidity weight" hereafter) varies with the level of the VIX. Specifically, the liquidity weight is measured by the ratio of the total dollars invested in liquid stocks to the total net assets. For this test, I calculate the liquidity weight for each manager at each quarter-end, then calculating the mean weight across all funds at each quarter-end. Panel A in Table IV reports the time-series average of the cross-sectional mean weight for high and low VIX quarters. I use three different cutoffs for the Amihud illiquidity ratio–bottom 1%, bottom 5%, and bottom 10%–to identify liquid stocks. For all three cutoffs, the average fund manager holds a significantly larger fraction of liquid stocks in the portfolio during high VIX times compared to during low VIX times. For example, the top 5% liquid securities constitute 39.0% of the average fund manager's total net assets during high VIX periods versus 33.7% during low VIX periods. The difference between these two states is statistically and economically significant.

The change-on-change test examines how the change in the liquidity weight of mutual funds varies with the change in the VIX. I calculate the change in the liquidity weight for each fund at each quarter-end by subtracting the liquidity weight of the previous quarter-end from that of the current quarter-end. The change in the VIX is obtained as the residual in AR(3) regression of the VIX series. Similar to the level-on-level test, I first calculate the cross-sectional mean change in liquidity weights at each quarter-end, and then compute the time-series average for high and low VIX innovation quarters separately. Panel B in Table IV reports the results. The magnitude of changes in liquidity weight is not as large as that observed in Panel A, suggesting that the level results could be caused by high valuation of liquid stocks relative to illiquid stocks during periods of high volatility. Nevertheless, when the 5% and 10% cutoffs are used to identify liquid stocks, we see that mutual funds significantly increase their liquid stock holdings during high VIX innovation quarters relative to low VIX innovation quarters. In fact, they increase their liquidity weight when the VIX increases, and decrease their liquidity weight when the VIX decreases. The result for the 1% cutoff is weaker, but in the same direction.

[Insert Table IV about here]

5.1.2 Liquid Stock Holdings of Mutual Funds: Multivariate Analysis

While the univariate results are consistent with the hypothesis that fund managers tilt their holdings toward liquid stocks during high VIX times, this tilting could also be driven by other factors. As is mentioned above, the overall valuation of liquid stocks relative to illiquid stocks could be one explanation. Alternatively, as documented by Busse (1999), fund managers tend to time market volatility by decreasing market exposure during times when market volatility is high. If liquid stocks tend to be low-beta stocks, then the univariate analysis may just be picking up volatility timing. Thus, it is important to control for the market exposure of liquid stocks. In addition, mutual fund managers could be timing market liquidity as suggested by Cao, Simin, and Wang (2007). That is, fund managers reduce market exposure in illiquid markets. If high volatility periods are accompanied by market illiquidity and liquid stocks have low betas, we could also find a positive relation between liquid stock holdings and market volatility.

I explicitly control for these alternative possible influence on mutual funds' liquid stock holdings by estimating a fixed-effect panel regression,[24]

$$LiqWt_{i,q} = \mu + \nu_i + \phi VIX_q + \delta MktLiqWt_q + \gamma MktIlliq_q + \theta \mathbf{X}_{i,q} + \varepsilon_{i,q}$$

where $LiqWt_{i,q}$ is fund i's liquid stock holdings as a fraction of its total assets at the end of quarter q, ν_i is the unobservable fund effect, VIX_q is the average VIX of the last 21 trading days in the quarter, $MktLiqWt_q$ is the ratio of the capitalization of liquid stocks to that of the market portfolio at the end of quarter q, $MktIlliq_q$ is the value-weighted average Amihud illiquidity ratio of the market portfolio at the end of quarter q, $\mathbf{X}_{i,q}$ is a set of fund characteristics measured at the end of quarter q including fund size, fund family size, age, average beta of liquid stocks in a fund's portfolio, and so on. Panel A in Table V reports the results for all three cutoffs. The estimated impact of VIX is statistically significant at the 1% confidence level in all specifications, and the economic magnitude is large as well. The results in Column 2 (for the top 5% liquid stocks) suggest that a 10 percentage point increase in the VIX (for example, from 15 to 25) could increase the average mutual fund's liquidity weight by 0.6% (for example, from 30% to 30.6%). The number is comparable to that in Panel B of Table IV. When translated into dollar terms, this means that the mutual fund industry reallocated \$6.2 billion dollars to liquid stocks during high VIX quarters.[25]

Since a fund's position in liquid stocks is likely to be persistent over time and fund managers might slowly adjust their positions to achieve the optimal liquidity, I include lagged liquidity weights as controls and re-estimate the baseline regression. For such panel-dynamic models, the least-squares dummy variable estimator is inconsistent, but the maximum likelihood estimator is consistent for random-effects models. Thus, I treat unobservable effects as random and

[24] In the baseline specification, I assume that time-specific effects are fully captured by fund-invariant variables including the VIX, market valuation of liquid stocks, and market illiquidity. The assumption is admittedly quite strong. In Section 5.1.3, I relax this assumption by adding time fixed effects and focus on the interaction effects.

[25] To get the number, multiply 0.6% by the average TNA (\$1,331 million), then by the average number of funds (775) at each quarter-end.

estimate the model using MLE. Panel B of Table V presents the results using 5% as the cutoff to identify liquid stocks. The results for other cutoffs are qualitatively similar. The coefficients of the lagged liquidity weights are highly significant, suggesting persistence in a fund's holdings of liquid securities. The coefficient for the VIX is still highly significant, and the magnitude is comparable to the baseline case.

Table V also reveals a number of other interesting findings. Large funds favor a high liquidity weight. This could be driven by their transaction cost considerations because they hold large positions in individual stocks. Funds experiencing large outflows in the past year tend to maintain a high liquidity weight, which is reasonable if past redemptions are a good proxy for future redemptions. Funds in which the principal-weighted beta of liquid stocks is high tend to keep a high liquidity weight. Thus the relation between the VIX and liquidity weight is robust to the inclusion of liquid stock betas as controls, suggesting that the results are not driven by volatility timing. High-expense funds hold less liquid stocks. Mutual funds' asset weights in liquidity stocks are significantly positively related to the weight of liquid stocks in the market portfolio in the baseline specification. However, they change signs and become insignificant when we control for lagged liquidity weights in the dynamic specification. Similarly, fund managers' liquidity weight is significantly and negatively related to market illiquidity in the baseline specification, but it becomes positive in the dynamic specification. Two possible reasons for these changes are that: (1) I do not assume fund fixed effects in the dynamic model, and (2) the lagged liquidity weight is correlated with these variables and thus absorbs some of the effects.

[Insert Table V about here]

5.1.3 The Effect of Fund Characteristics

As discussed in Section 4, some fund characteristics are associated with outflows or investment opportunities during periods of high volatility. To gauge the effect of these fund characteristics on precautionary liquidity holdings, I include an interaction term combining the VIX and fund characteristic variables in the panel regression. Unlike the baseline specification where time effects are assumed to be fully captured by the fund-invariant variables, I include both fund and time dummies to focus on the interaction effect. Time dummies are intended to capture any time specific effects such as the VIX, market valuation of liquid stocks, market illiquidity, etc.

For the effect of fund family associations, I use a dummy for small fund families, which is defined as the bottom 90% in terms of family size measured by the TNA of all funds under the same management company at each quarter-end. I use the investment objective code (*ioc*) provided by Thomson Financial to identify growth funds and income funds. Funds with $ioc = 2$ and 3 are identified as growth funds and funds with $ioc = 4$ are identified as income funds.[26] I use the raw measure for the following characteristics: total loads, past returns, return volatility, and fund turnover. For fund characteristics such as small family, high return volatility, high turnover, and growth oriented, a significant positive coefficient on the interaction term is evidence that funds with these characteristics have a greater tendency to tilt their portfolios toward liquid stocks during times when the VIX is higher. For funds with poor past returns or low loads, a significant negative coefficient on the interaction term is expected.

Table VI summaries the results with the bottom 5% stocks in Amihud illiquidity ratio identified as liquid stocks. The results for other cutoffs are qualitatively similar. The coefficients of our variable of interest, the interaction term, have the expected sign and are statistically significant. The only exception is the interaction term with total loads, which is insignificant and negative. In fact, this interaction term is significant and negative when the bottom 1% stocks in Amihud illiquidity ratio are used to identify liquid stocks.

Among the characteristics considered, fund return volatility and investment style have the largest impact. For a 10 percentage point increase in the VIX, funds at the 75th percentile in return volatility increase their liquid stock holdings by 0.9 $((5.11\% - 3.29\%) * 4.942 * 10)$ percentage points higher than funds at the 25th percentile in return volatility. Growth funds also tilt their portfolios to liquid stocks significantly; the increase in liquidity weights for growth funds is 0.8 percentage points higher than that for value funds. Other characteristics, such

[26] This classification is similar to Chen, Jegadeesh, and Wermers (2000). The only difference is that I do not include balanced funds in my sample.

as poor past performance, high turnover, and small family association, are associated with 0.2 to 0.3 percentage point increases in their liquidity weights than funds with the opposite characteristics. Recall that the same magnitude of changes in the VIX leads to a 0.6 percentage point increase in the liquidity weight for the average fund. Thus, the effect of fund characteristics on funds' precautionary liquidity holdings is economically significant as well.

[Insert Table VI about here]

5.2 Stock-Level Analysis

5.2.1 Mutual Fund Trading, Expected Volatility and Stock Characteristics

The stock-level analysis starts out by examining the liquidity characteristics of stocks traded by fund managers during high versus low VIX innovation periods. An implication of the precautionary story is that fund managers buy liquid stocks and sell illiquid stocks during periods when expected volatility increases and vice versa. In this subsection, I test whether stocks bought (versus sold) by mutual funds during high (versus low) VIX innovation times are more liquid. This is similar to a change-on-change test on the stock level.

For this test, I infer mutual fund trading activity from the quarterly holdings data. Following Gibson, Safieddine, and Titman (2000), for stock i in quarter q, the net change in mutual fund ownership, $\triangle MFO$, is measured as,

$$\begin{aligned}\triangle MFO_{i,q} = &\sum_{j=1}^{N} \frac{\text{shares owned of stock } i \text{ by fund } j \text{ at the end of quarter } q}{\text{shares outstanding of stock } i \text{ at the end of quarter } q} \\ &- \sum_{j=1}^{N} \frac{\text{shares owned of stock } i \text{ by fund } j \text{ at the end of quarter } q-1}{\text{shares outstanding of stock } i \text{ at the end of quarter } q-1}\end{aligned}$$

where N is the number of mutual funds that report their holdings of stock i at the end of quarter $q-1$ plus the number of funds that initiate their holdings of stock i during quarter q.

At each quarter-end, I sort stocks into deciles by the net change in mutual fund ownership: the bottom decile (D1) consists of the most heavily sold stocks and the top decile (D10) consists of the most heavily bought stocks by mutual funds. I examine various liquidity characteristics of the bottom versus the top decile stocks during high and low VIX innovation times. In particular, for each quarter-end, I calculate the cross-sectional mean statistics of the four liquidity measures (price, turnover, size, and Amihud illiquidity ratio) across stocks in D1 and D10 deciles separately. Table VII reports the time-series average of these mean statistics across high and low VIX innovation quarters and the results of a Wilcoxon rank-sum test of the null hypothesis that the liquidity characteristics in the two deciles are identical. The Wilcoxon rank-sum test statistic resulting from a difference-in-difference test of whether the difference between D1 and D10 is significantly different across high and low VIX innovation regimes is also reported.

For both rank (Panel A) and raw (Panel B) measures of liquidity, the difference-in-difference test shows that the difference between D1 and D10 in regards to the stock price, size, and Amihud illiquidity ratio is significantly greater during the high VIX innovation period than during the low VIX innovation period. The result seems to be driven mainly by the liquidity difference of D1 and D10 stocks during high VIX innovation periods. Specifically, D10 (heavily bought) stocks have significantly higher prices, larger sizes, and lower Amihud illiquidity ratios than D1 (heavily sold) stocks during high VIX innovation periods. This is consistent with fund managers reallocating their portfolios toward more liquid assets during times when the VIX increases. Turnover is the only variable that does not differ significantly for D1 and D10 stocks during both high and low states. One reason could be that turnover is not an exogenous characteristic because mutual fund trading (purchasing and selling) contributes to higher turnover. A similar argument could be applied to price, which is significantly higher for D10 stocks than D1 stocks during both high and low states. This could arise because mutual fund trading exerts price pressure on stocks or because mutual fund trading is informative.

Overall, the evidence is consistent with fund managers reallocating assets to liquid stocks during times when the market is expected to be more volatile.

[Insert Table VII about here]

5.2.2 Mutual Fund Ownership of Liquid Stocks: Multivariate Test

In the stock-level multivariate test, I run cross-sectional regressions of mutual fund ownership on stock liquidity (size, price, turnover, and Amihud illiquidity ratio) and other characteristics. The idea is that if fund managers hold more liquid stocks during periods of high expected volatility, the coefficients of the liquidity variables should be greater for high VIX periods than for low VIX periods.

As the first step, I follow Gompers and Metrick (2001) and estimate a cross-sectional regression of MFO on the stock characteristics for each quarter. The average coefficients for 68 OLS regressions are reported in Table VIII. I use two specifications. The first specification (Panel A) uses price, turnover, and size as liquidity measures. The second specification (Panel B) uses size and Amihud illiquidity ratio as liquidity measures.[27] The results show that, over the entire sample period, mutual fund ownership is positively related to all three liquidity measures and negatively related to the illiquidity measure, the risk measures, and lagged returns. These results are generally consistent with Gompers and Metrick (2001) and Bennett, Sias, and Starks (2003), except those for volatility and specific risk.[28]

[Insert Table VIII about here]

To examine the hypothesis that mutual fund managers' preferences for liquidity vary across market volatility states, I compare the aggregated coefficients of the liquidity measures across high and low VIX periods using the Wilcoxon rank-sum test. The results reported in Table IX show that all coefficients of the liquidity measures are larger in the high expected volatility period than in the low expected volatility period. In the first two columns, I test the null hypothesis that the sum of the coefficients of price, turnover, and size is not significantly different

[27] Gompers and Metrick (2001) suggest that failing to control for size could lead to serious omitted-variable bias.

[28] The two papers, by Gompers and Metrick (2001) and Bennett, Sias, and Starks (2003), show positive coefficients for volatility and specific risk, while I find significantly negative coefficients. The discrepancy could be due to: (1) the dependent variable in the two papers is institutional ownership, not mutual fund ownership; (2) although Bennett, Sias, and Starks (2003) also examine mutual fund ownership, their data source (13F) is different from that used in this paper and the sample period is more recent in this paper; and (3) the two papers do not consider possible nonlinearity in the relation between institutional ownership and the risk measures, while my paper takes this into account by using the rank measure.

across the two states. In the last two columns, the null hypothesis is that the difference between the coefficients of size and Amihud illiquidity ratio ($\beta_{Size} - \beta_{IlliquidityRatio}$) is not significantly different in the two states. The Wilcoxon rank-sum test statistics reject both nulls at the 1% level. To get some sense of economic significance, consider a stock moving from the lowest liquidity centile (in terms of size and illiquidity ratio) to the highest liquidity centile. Controlling for other characteristics, the MFO rank of the stock will move up by 60 out of 100 in the low expected volatility state, while it will move up by 68 out of 100 in the high expected volatility state.

Table IX also presents evidence consistent with volatility timing by fund managers. The coefficient on beta is significantly smaller during high VIX times than during low VIX times, which suggests that fund managers decrease their market exposure during high volatility times.

[Insert Table IX about here]

5.2.3 The Effect of Fund Characteristics

To examine the effect of fund characteristics on the dynamic preference of mutual funds, I first divide funds at the end of a given quarter into high- and low-type groups based on their characteristics. I then calculate mutual fund ownership measures for each stock at each quarter, separately for high- and low-type funds. I use the stock-level multivariate test to examine the heterogeneity of liquidity preferences for liquidity stocks across high- and low-type funds. Table X reports the results. To save space, I only report the aggregated liquidity coefficient on size and the Amihud illiquidity ratio (i.e., $\beta_{Size} - \beta_{IlliquidityRatio}$) along with the associated Wilcoxon test statistics.[29] The results are generally consistent with the fund-level results. Specifically, difference-in-difference tests show that, relative to funds with opposite characteristics, small-family, low-load, high-volatility, and growth funds increase their liquid stock holdings significantly during high VIX periods relative to low VIX periods. The results for the other two fund characteristics, i.e., past performance and fund turnover, are insignificant.

[Insert Table X about here]

[29] The unreported results using size, price, and turnover as liquidity measures are remarkably similar.

To summarize, both fund- and stock-level tests show that mutual fund managers tend to hold a large proportion of their assets in liquid securities under highly uncertain market conditions. They achieve the desired liquidity level through purchasing liquid stocks and selling illiquid stocks. This dynamic liquidity preference is more prevalent for small-family, low-load, poorly-performing, high-volatility, growth-oriented, and high-turnover funds. The evidence is consistent with the notion that the benefit of precautionary liquidity holdings is greater for these funds.

6 Precautionary Liquidity Holdings and Fund Performance

The evidence thus far shows that fund managers invest a larger fraction of their assets in liquid stocks when expected market volatility is higher. A natural question to ask is how this affects mutual fund performance. Since liquid stocks earn lower expected returns than illiquid stocks on average, fund performance could be adversely impacted if managers hold more liquid stocks. However, there are several reasons why this behavior could result in superior returns. First, the precautionary liquidity holdings serve as shock absorber when large redemptions occur, thus mitigating the adverse effect of liquidity service that a fund has to provide investors. Second, liquid stock holdings provide "dry powder" for bargain hunting, which should show up in abnormal fund returns if and when the price of those distressed stocks reverses. Last, if liquid stocks earn higher contemporaneous returns than less liquid ones during turbulent markets, fund managers who hold on to their liquid stocks could capture the liquidity premium.

To gauge the effect of precautionary liquidity holdings on fund performance, I run multivariate panel regressions to examine whether precautionary liquidity holdings predict abnormal fund performance in the subsequent period. I use five benchmarks to adjust for fund performance, i.e., the market model, the CAPM, the Fama-French three-factor model, the Fama-French-Carhart four-factor model, and the conditional model proposed by Ferson and Schadt (1996). The conditional model uses predetermined conditioning variables, including the dividend yield of the CRSP index, a Treasury yield spread, a corporate bond yield spread, and a short-term Treasury bill rate, to account for time-varying risk premiums and time-varying betas.

I follow Chen et al. (2004) to estimate factor loadings. I first sort all funds into five quintiles by lagged TNA at the beginning of each quarter. I then track these five portfolios for one quarter and use the entire time-series of their monthly returns to estimate the loadings to various factors for each of the five portfolios. For each month, each fund inherits the loadings of one of these five fund size quintiles that it belongs to. The one-month-ahead expected fund return is then calculated by using the above factor loadings along with the realized factor returns (including return on the risk-free asset) for the next month. Finally, the risk-adjusted return is calculated as the difference between the realized fund return and the expected fund return.

I test the hypothesis that liquid stock holdings of mutual funds in high VIX periods contribute to abnormal performance in the next period by adapting the methodology used by Chen et al. (2004). Specifically, I use a fixed-effect panel model and regress next month's abnormal fund net returns on the fund's liquidity weight, an interaction term combining the VIX and the liquidity weight, and other fund characteristics measured at the end of the current quarter[30]:

$$AR_{i,q+1} = \mu + \nu_i + \tau_q + \delta LiqWt_{i,q} + \gamma VIX_q \cdot LiqWt_{i,q} + \theta \mathbf{X}_{i,q} + \varepsilon_{i,q}$$

where $AR_{i,q+1}$ is the abnormal net return for fund i in the first month following the end of quarter q, ν_i is the unobservable fund effect, τ_q is the fixed time effect, VIX_q is the average VIX of the last 21 trading days in the quarter, $LiqWt_{i,q}$ is the fraction of liquid securities in fund i's assets at the end of quarter q, $\mathbf{X}_{i,q}$ is a set of fund characteristics measured at the end quarter q including fund size, fund family size, age, lagged returns, return volatility, turnover, expenses, load fees, and so on. The variable of interest is the coefficient of the interaction term, which is a difference-in-difference estimate of whether the performance difference of funds with high liquidity holdings versus low liquidity holdings is significantly different across high and low VIX periods.

Table XI reports the results. Notice that the coefficients in front of the interaction terms are positive and significant across the five performance measures. The coefficients are around 0.001 with robust t-statistics of about 14. To get some economic sense, consider a fund manager who

[30] Since I also include year fixed effects in the panel regression, all fund-invariant variables, such as the VIX, are not identified and are thus omitted.

responds to a two standard deviation shock of VIX by increasing her liquid stock holdings by two standard deviations. The abnormal return, net of fees and expenses, in the subsequent month would increase by 72.4 basis points (0.001% times 13.4 times 54.0). Thus, the evidence provides strong support for the notion that liquid stock holdings during high VIX times contribute to statistically and economically significant abnormal fund returns in the subsequent period.

The table also shows several other interesting results. The coefficient in front of liquid stock holdings ($LiqWt$) is significantly negative, which is consistent with liquid securities having lower returns than less liquid ones during normal times. Consistent with Chen et al. (2004), fund size is a significantly negative predictor of fund performance, but fund family size is not significant, although it has the same sign as Chen et al. (2004). Turnover is positive and significant, suggesting that high-turnover funds might have better stock-picking skills (Wermers, 2000).

[Insert Table XI about here]

7 Robustness Tests

7.1 Cash Holdings

The paper examines how active mutual fund managers use liquid stocks to fulfill their liquidity needs during highly volatile times. A natural question to ask is: How are cash holdings (the most liquid assets) related to the big picture?

Since information on quarterly cash holdings (fraction of a mutual fund's assets in cash) is available from the CRSP starting from March 2000, the following tests are implemented with a sub-sample for which cash position data is available. The first test simply includes cash holdings as a control in the fund-level panel regressions. The purpose is to see whether cash holdings affect fund managers' liquidity needs, and in particular, whether cash holdings could muffle the effect of the VIX on their liquid stock holdings. As it turns out (Column 1 of Table XII), cash holdings have a negative and significant impact on a fund's liquid stock holdings, suggesting that the two are substitutes. Nevertheless, the effect of the VIX on liquid stock holdings is still highly significant when cash holdings are included. Note that, because the test uses only the latter period of the sample where cash information is available, the results are not directly comparable to those obtained using the baseline model and the full sample.

A second test uses cash holdings as the dependent variable in a multivariate panel regression to examine whether fund managers use cash to meet their liquidity needs during high VIX periods. Interestingly, when cash holdings as a fraction of total net assets are regressed on the VIX and other fund characteristics, the coefficient in front of the VIX is insignificant (Column 2 of Table XII). This suggests that fund managers do not adjust their cash positions in response to changes in expected volatility during the post-2000 era.

The last test explores whether a large proportion of holdings in cash during high VIX times leads to superior fund performance in the next period. In unreported results where I replace liquid stock holdings with cash holdings in the performance panel regression, the interaction term is insignificant. This indicates that cash holdings in advance of market turmoil might not be as valuable as liquid stock holdings for fund investors.

[Insert Table XII about here]

7.2 Excluding Flight-to-Liquidity Episodes

The paper shows that mutual fund holdings of liquid stocks increase during periods of high expected volatility. One possibility is that fund managers anticipating liquidity needs in the future respond by accumulating liquid stocks today. Another possibility is that the evidence is driven by some extreme episodes associated with "flight to liquidity".[31] That is, fund managers rebalance their portfolios toward more liquid securities when the market is actually (as opposed to being expected to be) in turmoil. However, the precautionary explanation and this alternative flight explanation are not mutually exclusive. The flight to liquidity behavior could be driven by fund managers' expectation that the crisis still needs time to unfold, which gives them an

[31] "Flight to quality" is not a big concern here because I controlled for risk (market betas) in the *stock*-level cross-sectional regressions. If mutual funds flock to stocks with low betas during times of market stress, this effect will be captured by a smaller coefficient in front of beta for high VIX periods. This is exactly what is seen in Table X.

incentive to hold liquid securities for precautionary reasons. Nevertheless, to disentangle these two explanations, I re-estimate the regressions in Section 5.1.2 after excluding fund/quarter observations which are likely to be associated with flight-to-liquidity episodes. Since flight-to-liquidity episodes are generally characterized by market downturns and illiquid markets, I identify flight periods as quarters with high VIX, low market returns, and high market illiquidity. There are 7 quarters in the sample that have a higher-than-median VIX and market illiquidity, and a lower-than-median market return. For example, the third quarter of 1998 is picked up, which is an extreme episode of flight to liquidity with the collapse of Long-Term Capital Management. The results obtained when the observations associated with flight events are excluded should capture only the "precautionary" effect.

Column 3 in Table XII reports the panel regression results using only fund/quarter observations that are not flight-related. The coefficient in front of the VIX is still highly significant, and the magnitude is greater than in the baseline case, which suggests that the findings of precautionary liquidity preferences are not driven by flight episodes.

I also use stock-level analysis to examine this alternative hypothesis. After estimating the cross-sectional regressions, I compare the coefficients from the non-flight high VIX quarters with those from the low VIX ones. The results (not reported) confirm the fund-level results.

7.3 Subperiod Results

Bennett, Sias, and Starks (2003) present evidence that institutional preferences have changed over time. To ensure that the results presented here are not driven by mutual funds' shift in preferences over time, I separate the full sample into two equal subperiods, each with 34 quarters. Again, I use both fund- and stock-level analyses for each subperiod. The results for fund-level panel regressions are reported in Columns 4 and 5 of Table XII. Notice that, in both subperiods, the coefficients of the VIX are highly significant. The magnitude in the latter half of the sample is higher than in the first half. The results for stock level regressions, not reported, are qualitatively similar to the full sample results.

8 Conclusions and Discussion

This paper is the first in the literature to examine the dynamic liquidity preferences of mutual funds and the impact of such preferences on fund performance. Consistent with the precautionary view of liquidity preferences, I find evidence that fund managers tilt their holdings more heavily toward liquid securities when expected market volatility is higher. The findings are robust to a number of specification checks and changes in the sample, such as the inclusion of cash holdings as controls, exclusion of flight-to-liquidity episodes, use of different volatility estimators, and different subperiods. Mutual fund managers tend to buy liquid stocks and steer clear of illiquid stocks during times when innovation in the VIX is high. Stock-level analysis also shows that mutual funds' preferences for liquid stocks are significantly greater during times when market volatility is expected to be higher. This type of liquidity preference is more pronounced among small-family funds, low-load funds, funds with unfavorable past performance, funds with high volatility, growth funds, and high-turnover funds. I also show that these fund characteristics are associated with withdrawals and investment opportunities during times of high volatility. Thus, the evidence is consistent with the notion that the benefits of precautionary liquidity holdings tend to be greater for these fund types.

The paper also finds strong empirical evidence that funds with high liquid stock holdings during times of high expected market volatility have better risk-adjusted performance in the subsequent period. This provides the first evidence that financial flexibility, in the form of liquid asset holdings under a highly uncertain environment, adds value. From the perspective of fund investors, this suggests that actively managed funds could provide a valuable hedge against expected market volatility.

The study has several implications. First, if mutual fund managers' preferences for liquid stocks are time-varying, liquidity-based asset pricing models where agents are assumed to have time-invariant preferences for liquid stocks should be adjusted. Second, it might appear that mutual funds are herding when they exhibit such dynamic preferences, i.e., trade the same type of stocks (liquid versus illiquid stocks) at the same time (high versus low expected market volatility). However, they are actively managing their portfolio liquidity. Thus, it is important to control for the effect of precautionary liquidity holdings when examining mutual fund herding. Last, since mutual funds are becoming a dominant force in the equity market, how their trading induced by this change in liquidity preferences affects asset prices and asset liquidity deserves further inquiry.

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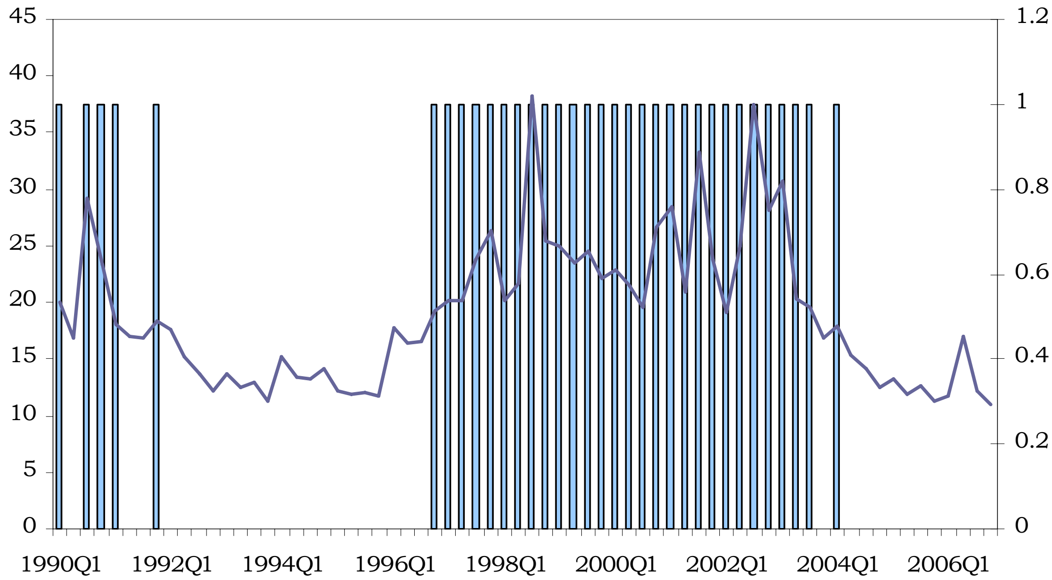
Figure I

This figure plots the CBOE VIX series and the VIX innovation series (both in percentage points, left scale) from 1990Q1 to 2006Q4. The VIX of each quarter is calculated as the average VIX of the last 21 trading days in that quarter. The innovation in VIX is obtained as the residual in AR(3) regression of the VIX series. Panel A presents the VIX series, with the bars indicating high VIX quarters. Panel B presents the VIX innovation series, with the bars indicating high VIX innovation quarters.

Panel A: The VIX Level Series



Panel B: The VIX Innovation Series

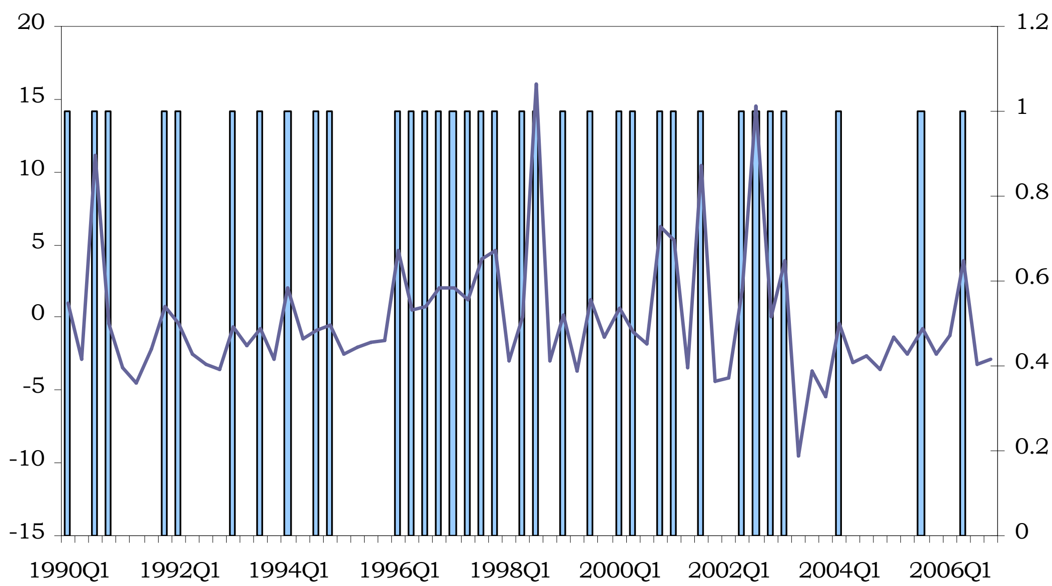
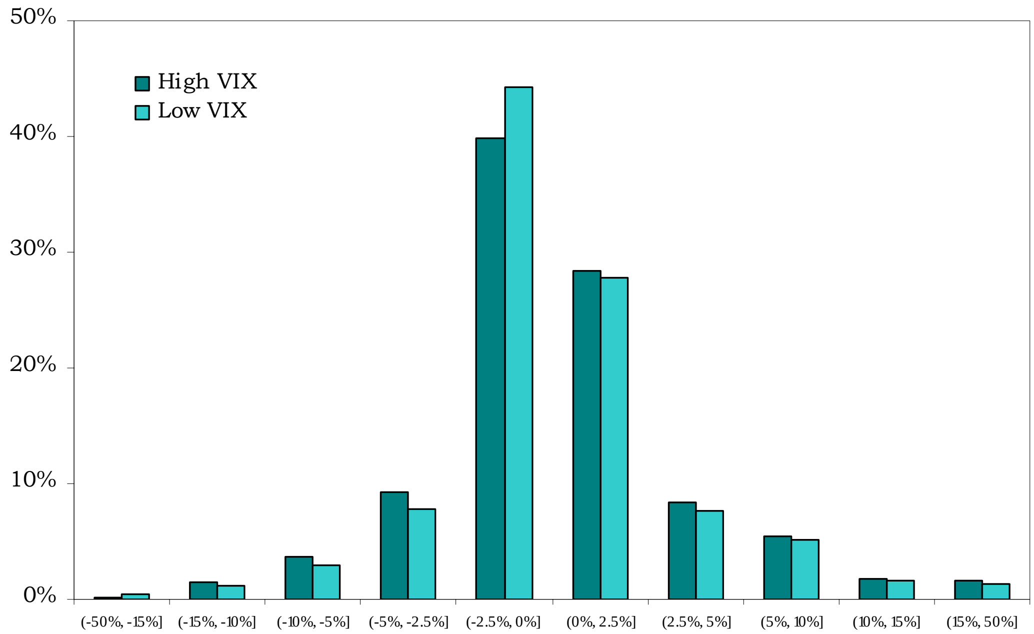


Figure II

This figure presents the frequency distribution of one-month-ahead fund net flows at high versus low VIX quarter-ends. The horizontal axis shows fund flow bins, with the left tail representing outflows and vice versa. In Panel A, the distribution of fund net flows, as percentage of lagged NAV, is divided into discrete bins based on pre-specified cutoffs. In Panel B, the distribution is sorted into deciles where extreme outflows are in D1 and vice versa.

Panel A: Pre-specified Cutoffs



Panel B: Decile Cutoffs

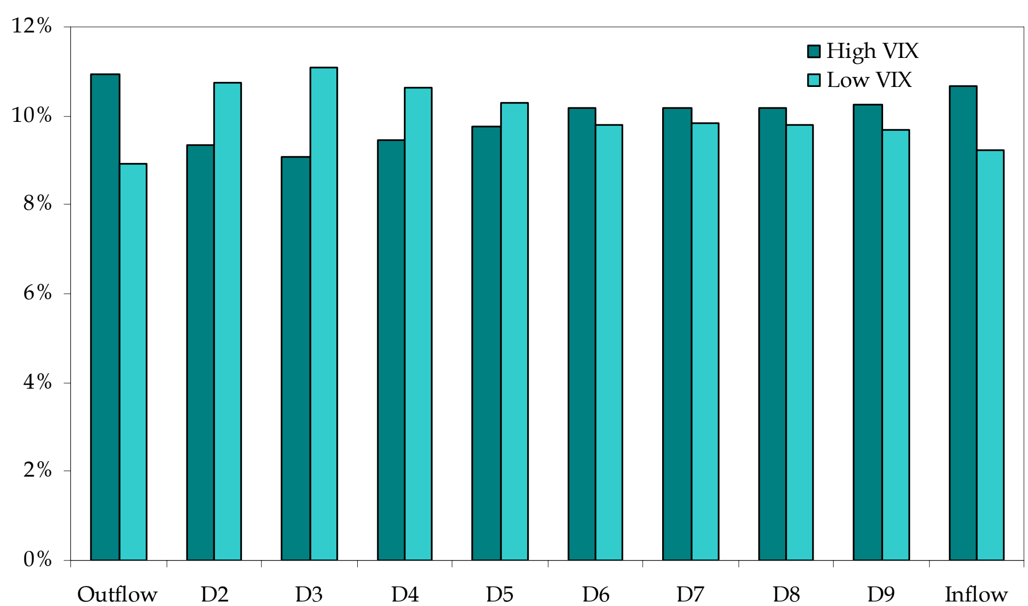
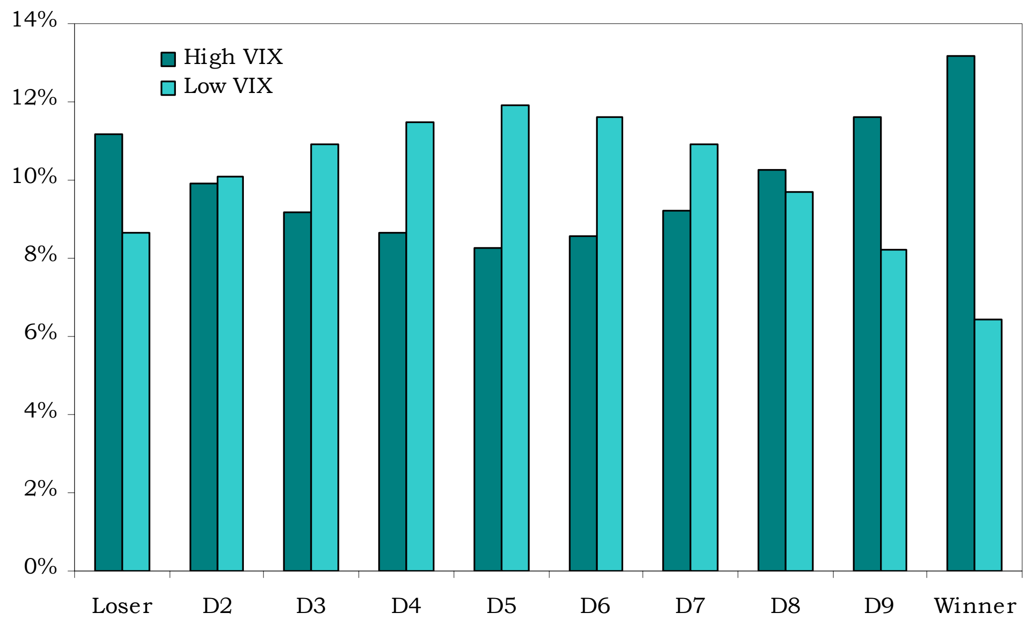


Figure III

This figure presents the frequency distribution of six-month-ahead abnormal stock returns at high versus low VIX quarter-ends. The horizontal axis shows decile bins based on stock performance, with the left tail representing loser stocks and vice versa. Abnormal returns are obtained using the CAPM (Panel A) and the Fama-French three-factor model (Panel B).

Panel A: CAPM Alpha



Panel B: Fama-French Three-Factor Alpha

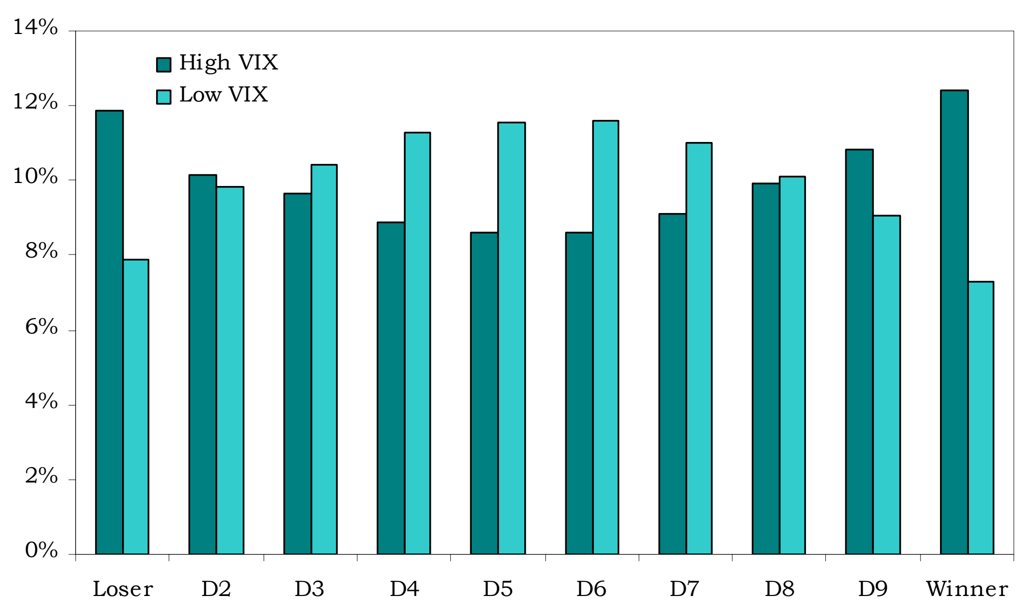


Table I

Summary Statistics for Mutual Fund Sample

The table presents summary statistics on the mutual fund sample obtained from the merged CRSP Survivor-Bias Free U.S. Mutual Fund Database and Thomson Financial CDA/Spectrum Mutual Fund Holdings Database. The sample consists of 1,962 distinct fund entities comprising 45,583 fund-quarters. TNA is the total net assets of the fund. Family Size is measured as the log of one plus the cumulative TNA of the other funds in the fund's family. Net Flow is the percentage new fund flow into the mutual fund over the past 12 months. Variance of Net Flows is measured as the variance of the monthly net flows over the past 12 months. Total Load is the sum of front-end load fees and rear-end load fees. Liquid Stock Beta is the average beta of the top 5% liquid stocks in the fund's equity portfolio, weighted by the dollar amount invested. Portfolio Concentration is the inverse of the number of stocks held by the fund. Turnover is defined as the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA. Age is the number of years since the initiation of the fund. Expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses. Lagged Return is the buy-and-hold fund return over the past 12 months. Return Volatility is the standard deviation of the monthly fund return over the past 12 months. For each item, I first compute the cross-sectional statistics in each quarter from 1993 to 2006. The reported statistics are time-series averages of the cross-sectional figures.

	Mean	Median	25th Percentile	75th Percentile	Standard Deviation
TNA ($million)	1,349.39	293.15	98.70	958.55	4,142.06
Log(TNA)	5.73	5.62	4.55	6.79	1.57
Log(FamSize)	8.04	8.52	6.80	9.92	2.90
Variance(Net Flows)	40.74	7.98	5.50	18.52	158.89
Net Flows (%)	12.89	-2.03	-14.00	19.19	56.22
Liquid Stock Beta	1.02	1.02	0.78	1.29	0.59
Portfolio Concentration (x100)	1.62	1.40	0.92	2.05	1.11
Total Load (%)	2.31	1.38	0.00	4.76	2.39
Turnover (%)	88.50	65.86	36.09	110.46	166.54
Age (years)	13.31	9.04	5.86	16.74	10.50
Expenses (%)	1.28	1.22	0.98	1.52	0.44
Lagged Return (%)	11.18	10.08	3.46	17.54	12.32
Return Volatility (%)	4.34	3.99	3.29	5.11	1.62

Table II

Summary Statistics for Stock Sample

The table reports summary statistics for the stocks in the sample. All common stocks traded on NYSE, AMEX, and Nasdaq with adequate CRSP/CompuStat data are included in the sample. Mutual Fund Ownership (MFO) is calculated by summing the reported holdings of the sample mutual funds at each quarter-end and divide by the total shares outstanding for the firm. Amihud illiquidity ratio is the normalized Amihud illiquidity ratio as suggested by Acharya and Pedersen (2005). Firm size is measured as the quarter-end market capitalization. Share price is measured as the quarter-end price per share. Share turnover is defined as the average ratio of monthly volume to number of shares outstanding in the current quarter. Firm age is measured as the number of months since a stock first appears in CRSP monthly stock file. Dividend yield is measured as the cash dividends for the fiscal year ended at least three months before the current quarter-end, divided by size as of December 31 during that fiscal year. Return volatility is estimated as the standard deviation of monthly returns over the previous two years. Beta is estimated as the sum of the coefficients in a regression of the firm's monthly return on the contemporaneous and laggedone-month CRSP NYSE/AMEX value-weighted index over the previous 24-60 months. Firm-specific volatility is measured as the three-month average of the Campbell, Lettau, Malkiel, and Xu (2001) monthly firm-specific risk measure over the current quarter. Lagged return is measured as the six-month cumulative gross returns prior to the beginning of the quarter. For each item, I first compute the cross-sectional statistics in each quarter from 1990 to 2006. The reported statistics are time-series averages of the cross-sectional figures.

	Mean	Median	25th Percentile	75th Percentile	Standard Deviation
MFO (%)	5.78	4.10	0.84	9.14	5.77
Amihud Illiq. Ratio	5.90	0.95	0.31	7.28	9.20
Price ($)	18.80	13.93	5.23	26.99	17.56
Turnover (%)	10.97	6.95	3.49	13.43	12.12
Size ($million)	1,693.58	195.89	51.76	854.71	5,245.63
Log(B/M)	-0.66	-0.56	-1.11	-0.12	0.80
Beta	1.39	1.20	0.64	1.95	1.10
Specific Risk	4.02	1.80	0.79	4.27	6.39
Volatility	14.14	12.66	8.72	17.91	7.07
Yield (%)	1.05	0.00	0.00	1.71	1.70
Lagged Return (%)	9.23	7.04	-11.05	26.38	37.60
Age (months)	199.07	135.43	78.63	257.63	174.19

Table III
The Effect of Fund Characteristics on the Relation between Expected Volatility and Fund Outflows

The table presents the probability of falling into the bottom decile of fund flows subsequent to high versus low VIX periods for a number of fund characteristics. I first sort one-month-ahead fund flows into deciles. I then sort funds into quartiles based on characteristics at each quarter-end. I consider the following fund characteristics: fund family size, total load, past returns, return volatility, investment style (growth versus value), and fund turnover. The bottom quartile (Q1) consists of funds with the lowest values of a characteristic considered and the top quartile (Q4) consists of funds with the highest values of the characteristic. For each quarter-end, I calculate the cross-sectional mean statistics of the probability of entering into the bottom fund flow decile across funds in Q1 and Q4 for each characteristic. The table reports the time-series average of these mean statistics across high and low VIX quarters, and the Wilcoxon rank-sum test of the null that the probability of entering into the bottom decile is identical following high and low VIX quarter-ends. The last row in each panel reports Wilcoxon rank-sum test statistics resulting from difference-in-difference tests of whether the difference between high and low VIX regimes is significantly different across Q1 and Q4 funds.

	High VIX	Low VIX	*z*-statistic	*p*-value
Panel A: Fund Family Size				
Small Fund Family (Q1)	12.84%	9.07%	3.55	(0.00)
Large Fund Family (Q4)	9.97%	9.09%	0.20	(0.84)
Diff-in-Diff			2.39	(0.02)
Panel B: Total Load				
Low Load (Q1)	12.81%	8.80%	3.13	(0.00)
High Load (Q4)	7.57%	4.94%	1.21	(0.22)
Diff-in-Diff			1.82	(0.07)
Panel C: Past Returns				
Loser (Q1)	20.35%	14.25%	1.76	(0.08)
Winner (Q4)	6.92%	6.48%	0.14	(0.89)
Diff-in-Diff			1.76	(0.08)
Panel D: Return Volatility				
Low Volatility (Q1)	8.59%	5.97%	1.48	(0.14)
High Volatility (Q4)	14.94%	13.28%	0.47	(0.64)
Diff-in-Diff			0.17	(0.87)
Panel E: Investment Style				
Growth (Q1)	8.51%	10.15%	-0.98	(0.16)
Income (Q4)	13.97%	7.63%	3.81	(0.00)
Diff-in-Diff			-3.98	(0.00)
Panel F: Fund Turnover				
Low Turnover (Q1)	8.38%	5.69%	1.97	(0.05)
High Turnover (Q4)	13.63%	12.79%	0.17	(0.86)
Diff-in-Diff			0.93	(0.35)

Table IV

Liquid Stock Holdings of Mutual Funds in High vs. Low VIX Quarters

The table reports the summary statistics for mutual funds' liquidity weights (liquid stock holdings as a proportion of TNA, in percentage). I use three cutoffs to identify liquid stocks, i.e., bottom 1%, 5%, and 10% in Amihud illiquidity ratio. For each cutoff, I first compute the cross-sectional mean of liquidity weights (LiqWt) and changes in liquidity weights (ΔLiqWt) in each quarter from 1993 to 2006. Panel A reports time-series averages of the cross-sectional means of liquidity weights for the full sample period (All), the high and the low VIX period. The last two rows in Panel A report the z-statistic of the Wilcoxon rank-sum test of the null hypothesis of no difference between liquid stock holdings during high versus low VIX quarters and the associated one-tail p-values. Panel B reports time-series averages of the cross-sectional means of changes in liquidity weights for the full sample period (All), the high VIX innovation period, and the low VIX innovation period. The last two rows in Panel B report the z-statistic of the Wilcoxon rank-sum test of the null hypothesis of no difference between changes in liquid stock holdings during high versus low VIX innovation quarters and the associated one-tail p-values.

Panel A: Level-on-Level

	LiqWt $^{(1\%)}$	LiqWt $^{(5\%)}$	LiqWt $^{(10\%)}$
All	15.84	35.99	47.45
High VIX	17.53	38.65	49.89
Low VIX	14.20	33.42	45.10
z-statistic	4.24	4.54	4.24
(p-value)	(0.00)	(0.00)	(0.00)

Panel B: Change-on-Change

	ΔLiqWt $^{(1\%)}$	ΔLiqWt $^{(5\%)}$	ΔLiqWt $^{(10\%)}$
All	0.13	0.17	0.21
High VIX Innovation	0.30	0.47	0.49
Low VIX Innovation	-0.05	-0.15	-0.09
z-statistic	1.00	1.82	1.64
(p-value)	(0.16)	(0.03)	(0.05)

Table V

Liquid Stock Holdings of Mutual Funds and Expected Volatility: Multivariate Regressions

The table reports the coefficients of the quarterly panel regressions using mutual funds' liquidity weight (LiqWt, liquid stock holdings as a proportion of TNA, in percentage) as dependent variables. Market Weight is the ratio of liquid stock market capitalization to overall market capitalization. Market Illiquidity is the value-weighted average Amihud illiquidity ratio of all stocks in the market portfolio at a given quarter-end. See Table I for the definition of other variables. For the baseline regression (Panel A), I treat fund specific effects as fixed. The associated *t*-statistics using robust standard errors are reported in parentheses. For the dynamic panel model with lagged dependent variables (Panel B), I use an MLE estimator with random effects for each fund. The *t*-statistics using bootstrapped standard errors are reported in parentheses. Significance on a ten percent (*), five percent (**), or one percent level (***) is indicated.

Panel A: Baseline Fixed Effects

	LiqWt (1%) (1)	LiqWt (5%) (2)	LiqWt (10%) (3)
VIX	0.041	0.059	0.069
	(5.28)***	(5.46)***	(6.30)***
Var(Net Flows) (x100)	0.107	0.069	0.008
	(2.83)***	(1.62)	(0.19)
Net Flows (x100)	-0.043	-0.381	-0.670
	(0.55)	(3.70)***	(6.36)***
Market Weight	0.424	0.671	0.825
	(38.17)***	(43.09)***	(39.03)***
Market Illiquidity	-8.311	-23.171	-18.517
	(2.38)**	(4.75)***	(3.65)***
Log(TNA)	0.290	0.517	0.175
	(4.23)***	(5.62)***	(1.82)*
Log(FamSize)	0.053	-0.086	-0.229
	(1.30)	(1.60)	(4.25)***
Liquid Stock Beta	0.834	0.869	0.200
	(13.41)***	(9.12)***	(1.87)*
Portfolio Concentration	21.540	15.182	-24.177
	(2.50)**	(1.22)	(1.78)*
Turnover (x100)	-0.005	-0.015	-0.002
	(1.79)*	(2.83)***	(0.40)
Age	0.191	0.308	0.463
	(5.85)***	(6.79)***	(9.68)***
Expenses	-0.597	-0.968	-1.368
	(2.13)**	(2.49)**	(3.48)***
Total Load (x100)	0.014	0.020	0.017
	(0.84)	(0.73)	(0.47)
Lagged Return	-0.539	-0.869	0.196
	(2.57)**	(2.86)***	(0.61)
Return Volatility	-20.443	-20.219	-6.426
	(7.77)***	(5.27)***	(1.56)
Constant	-0.819	-6.010	-15.446
	(0.45)	(2.33)**	(5.43)***
Fund FE	Yes	Yes	Yes
Observations	41,691	41,691	41,691
R-squared	0.11	0.15	0.15

Panel B: Dynamic Random Effects (Dependent Variable = LiqWt (5%))

	With 1 Lag (1)	With 2 Lags (2)
VIX	0.057	0.053
	(7.61)***	(5.74)***
Var(Net Flows) (x100)	0.026	-0.030
	(0.62)	(0.68)
Net Flows (x100)	0.104	0.215
	(1.92)*	(3.05)***
Market Weight	-0.017	-0.015
	(1.84)*	(1.32)
Market Illiquidity	5.874	8.846
	(5.14)***	(7.17)***
Log(TNA)	0.021	0.016
	(0.71)	(0.53)
Log(FamSize)	-0.013	-0.007
	(1.06)	(0.50)
Liquid Stock Beta	0.223	0.076
	(4.27)***	(1.72)*
Portfolio Concentration	3.219	2.624
	(0.78)	(0.60)
Turnover (x100)	-0.011	-0.080
	(0.24)	(2.18)**
Age	0.005	0.007
	(1.42)	(1.98)**
Expenses	-0.301	-0.072
	(3.49)***	(0.66)
Total Load (x100)	0.781	-1.345
	(0.45)	(0.71)
Lagged Return	0.298	0.411
	(1.89)*	(1.93)*
Return Volatility	-5.196	-5.249
	(2.94)***	(2.48)**
Lag(LiqWt)	0.980	0.787
	(825.76)***	(57.03)***
Lag2(LiqWt)		0.199
		(14.44)***
Constant	-0.952	-2.262
	(1.43)	(2.77)***
Observations	27,636	22,631
Log Likelihood	-86,287.14	-69,642.03

Table VI

The Effect of Fund Characteristics on the Relation between Liquid Stock Holdings of Mutual Funds and Expected Volatility: Multivariate Regressions

The table reports the coefficients of the quarterly panel regressions using mutual funds' liquidity weights (liquid stock holdings as a proportion of TNA) as dependent variables. Liquid stocks are defined as the bottom 5% in Amihud illiquidity ratios. Small Family is a dummy variable that equals 1 if the fund belongs to a family that is in the bottom 90% in terms of family size measured by the TNA of all funds under the same management company at each quarter-end. Growth is a dummy that equals 1 if the fund is classified as "aggressive growth" or "growth" by Thomson Financial. See Table I and V for the definition of other variables. The specification is similar to the baseline specification in Table V, except that year fixed effects are included and thus fund-invariant variables, such as the VIX, are excluded. All regressions include both fund dummies and time dummies. The associated *t*-statistics using robust standard errors are reported in parentheses. Significance on a ten percent (*), five percent (**), or one percent level (***) is indicated.

	(1)	(2)	(3)	(4)	(5)	(6)
VIX*SmallFamily	0.027 (3.43)***					
VIX*TotalLoad (x100)		-0.010 (1.07)				
VIX*LagReturn			-0.195 (3.02)***			
VIX*ReturnVolatility				4.942 (10.34)***		
VIX*Growth					0.076 (4.54)***	
VIX*Turnover (x100)						3.282 (2.33)**
Var(Net Flows) (x100)	0.087 (2.07)**	0.087 (2.06)**	0.088 (2.08)**	0.086 (2.03)**	0.087 (2.07)**	0.078 (1.90)*
Net Flows (x100)	-0.379 (3.66)***	-0.376 (3.63)***	-0.397 (3.82)***	-0.409 (3.94)***	-0.394 (3.81)***	-0.372 (3.59)***
Log(TNA)	0.660 (7.09)***	0.629 (6.80)***	0.619 (6.68)***	0.669 (7.22)***	0.650 (7.01)***	0.628 (6.79)***
Log(FamSize)	-0.009 (0.16)	-0.023 (0.43)	-0.023 (0.43)	-0.022 (0.41)	-0.022 (0.41)	-0.025 (0.47)
Liquid Stock Beta	0.943 (9.74)***	0.947 (9.77)***	0.949 (9.79)***	0.985 (10.17)***	0.955 (9.83)***	0.953 (9.83)***
Portfolio Concentration	14.577 (1.17)	15.103 (1.22)	15.183 (1.22)	16.036 (1.29)	15.361 (1.24)	15.193 (1.22)
Turnover (x100)	-0.017 (2.99)***	-0.017 (2.97)***	-0.017 (2.99)***	-0.018 (3.03)***	-0.017 (2.97)***	-0.616 (2.28)**
Age	0.290 (2.55)**	0.295 (2.60)***	0.294 (2.59)***	0.283 (2.50)**	0.306 (2.69)***	0.297 (2.61)***
Expenses	-1.476 (3.73)***	-1.518 (3.84)***	-1.491 (3.77)***	-1.488 (3.76)***	-1.488 (3.76)***	-1.490 (3.77)***
Total Load (x100)	0.038 (1.35)	0.192 (1.44)	0.039 (1.41)	0.043 (1.58)	0.038 (1.39)	0.039 (1.41)
Lagged Return	-0.141 (0.37)	-0.141 (0.37)	4.286 (2.80)***	0.720 (1.84)*	-0.073 (0.19)	-0.121 (0.32)
Return Volatility	-19.295 (4.70)***	-19.413 (4.73)***	-21.633 (5.19)***	-139.619 (11.12)***	-21.308 (5.17)***	-20.371 (4.94)***
Constant	27.023 (10.78)***	27.527 (11.00)***	27.336 (10.92)***	29.132 (11.64)***	21.173 (15.14)***	27.697 (11.05)***
Fund/Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,691	41,691	41,691	41,691	41,678	41,691
R-squared	0.16	0.16	0.16	0.16	0.16	0.16

Table VII

Liquidity Characteristics of Stocks in the Top and Bottom Mutual Fund Net Buying Decile

The table reports the liquidity characteristics of stocks most heavily bought and most heavily sold by mutual funds during high and low VIX innovation periods. I infer mutual fund trading from holdings data and sort stocks into deciles at each quarter-end by the net changes in mutual fund ownership. The lowest decile (D1) consists of the most heavily sold stocks and the highest decile (D10) consists of the most heavily bought stocks at each quarter-end by mutual funds. For each quarter-end, I calculate the cross-sectional mean statistics of the four liquidity measures (price, turnover, size, and Amihud illiquidity ratio) across stocks in D1 and D10 separately. The table reports the time-series average of these mean statistics across high and low VIX innovation quarters, and the results of a Wilcoxon rank-sum test of the null hypothesis that the liquidity measures in the two deciles are identical. The Wilcoxon rank-sum test statistic resulting from a difference-in-difference test of whether the liquidity difference between D1 and D10 is significantly different across high and low VIX innovation regimes is also reported. Panel A reports the results using the standardized percentile ranks of these liquidity measures. Panel B reports the results using the raw liquidity measures. Numbers in parentheses are p-values of the z-statistics.

Panel A: Rank Liquidity Measures				
Net Buying	Price	Turnover	Size	Illiq. Ratio
High VIX Innovation				
Sell (D1, n=34)	0.57	0.70	0.60	0.35
Buy (D10, n=34)	0.63	0.70	0.64	0.32
z-statistic	-4.72	-0.06	-3.20	2.51
	(0.00)	(0.96)	(0.00)	(0.01)
Low VIX Innovation				
Sell (D1, n=34)	0.58	0.70	0.62	0.33
Buy (D10, n=34)	0.61	0.70	0.62	0.34
z-statistic	-3.31	0.07	-0.06	-0.71
	(0.00)	(0.95)	(0.96)	(0.48)
Diff-in-Diff				
z-statistic	-2.40	0.12	-2.31	2.13
	(0.02)	(0.91)	(0.02)	(0.03)

Panel B: Raw Liquidity Measures				
Net Buying	Price ($)	Turnover (%)	Size ($mil)	Illiq. Ratio
High VIX Innovation				
Sell (D1, n=34)	21.56	19.15	1383.95	2.14
Buy (D10, n=34)	24.40	18.99	1363.62	1.50
z-statistic	-3.73	-0.67	-1.54	3.24
	(0.00)	(0.50)	(0.12)	(0.00)
Low VIX Innovation				
Sell (D1, n=34)	23.94	20.02	1765.19	1.67
Buy (D10, n=34)	24.96	19.67	1470.11	1.26
z-statistic	-3.98	-0.18	-0.85	3.23
	(0.00)	(0.86)	(0.40)	(0.00)
Diff-in-Diff				
z-statistic	-2.05	-0.08	-2.16	1.77
	(0.04)	(0.94)	(0.03)	(0.08)

Table VIII

Determinants of Mutual Fund Ownership: Full Sample (1990Q1-2006Q4)

The table reports the results for the 68 cross-sectional regressions of the mutual fund ownership on stock characteristics. See Table II for a description of the independent variables. All variables are expressed in standardized percentile ranks between 0 and 1. The first two columns give the average coefficients and their *t*-statistics. In each cell in the third (fourth) column, the first number reports the number of significantly positive (negative) coefficients, at the 95% confidence level, and the second number gives the number of positive (negative) coefficients. Panel A reports results using price, turnover and size as liquidity proxies, while Panel B reports results using Amihud illiquidity ratio and size as liquidity proxies.

	Average Coefficient	*t*-Stats	Number Positive	Number Negative
Panel A: Price, Turnover, and Size as Liquidity Proxies				
Price	0.238	20.48	67/68	0/0
Turnover	0.211	54.41	68/68	0/0
Size	0.361	23.61	67/68	0/0
Log(B/M)	0.128	23.72	67/68	0/0
Beta	0.083	16.12	64/67	0/1
Specific Risk	-0.067	-10.10	2/8	44/60
Volatility	-0.099	-13.75	0/4	53/64
Yield	-0.201	-26.20	0/0	68/68
Lagged Return	-0.086	-16.03	2/2	63/66
Age	0.033	7.54	38/57	4/11
Constant	0.201	22.94	68/68	0/0
Panel B: Amihud Illiquidity Ratio and Size as Liquidity Proxies				
Illiquidity Ratio	-0.381	-18.78	0/0	67/68
Size	0.259	18.99	64/66	0/2
Log(B/M)	0.116	21.41	67/68	0/0
Beta	0.088	13.55	60/68	0/0
Specific Risk	-0.033	-4.62	9/18	30/50
Volatility	-0.139	-21.51	0/0	65/68
Yield	-0.216	-30.32	0/0	68/68
Lagged Return	-0.033	-5.78	6/18	39/50
Age	0.007	1.42	18/40	22/28
Constant	0.663	34.97	68/68	0/0

Table IX

Dynamic Liquidity Preferences of Mutual Funds

The table reports the results for the cross-sectional regressions of MFO on stock characteristics partitioned by expected market volatility states. See Table II for a description of the independent variables. All variables are expressed in standardized percentile ranks between 0 and 1. The first two columns give the average coefficients and their *t*-statistics (in parentheses) in the high and low VIX quarters using price, turnover, and size as proxies for liquidity. The last two columns report results using the normalized Amihud illiquidity ratio and size as proxies for liquidity. The last three rows report the aggregated liquidity coefficients, the Wilcoxon rank-sum test *z*-statistics and the associated *p*-values. The null hypothesis is that this aggregated liquidity coefficient is not different across the high and low states. In the first two columns, the aggregated liquidity coefficient is the sum of the coefficients of price, turnover, and size. In the last two columns, the aggregated liquidity coefficient is the difference between the coefficients of size and Amihud illiquidity ratio ($\beta_{Size}-\beta_{IlliquidityRatio}$).

	High VIX	Low VIX	High VIX	Low VIX
Price	0.241	0.235		
	(13.52)***	(15.49)***		
Turnover	0.210	0.211		
	(32.32)***	(49.05)***		
Illiquidity Ratio			-0.401	-0.345
			(14.01)***	(12.43)***
Size	0.391	0.331	0.275	0.257
	(17.21)***	(16.98)***	(14.08)***	(13.70)***
Log(B/M)	0.141	0.114	0.128	0.103
	(15.90)***	(21.50)***	(14.42)***	(19.29)***
Beta	0.064	0.103	0.067	0.109
	(10.04)***	(15.36)***	(8.51)***	(12.12)***
Specific Risk	-0.049	-0.085	-0.020	-0.049
	(5.35)***	(9.82)***	(2.10)*	(5.09)***
Volatility	-0.105	-0.094	-0.143	-0.133
	(11.51)***	(8.33)***	(18.75)***	(12.75)***
Yield	-0.213	-0.189	-0.228	-0.205
	(19.63)***	(17.79)***	(22.90)***	(20.57)***
Lagged Return	-0.105	-0.066	-0.049	-0.017
	(15.59)***	(9.56)***	(6.46)***	(2.28)**
Age	0.041	0.026	0.013	0.001
	(5.64)***	(5.24)***	(1.58)	(0.27)
Constant	0.193	0.208	0.675	0.637
	(13.70)***	(19.98)***	(26.08)***	(23.01)***
Observations	137,684	123,168	137,684	123,168
Avg R-squared	0.46	0.43	0.43	0.39
Aggregated Liquidity Coeff.	0.84	0.78	0.68	0.60
z-stats	4.08		3.21	
p-value	(0.00)		(0.00)	

Table X

The Effect of Fund Characteristics on Dynamic Liquidity Preferences of Mutual Funds

The table reports the aggregated liquidity coefficient of size and Amihud illiquidity ratio (i.e., $\beta_{Size} - \beta_{IlliquidityRatio}$) for the stock-level cross-sectional regressions partitioned by expected market volatility states and fund characteristics. I first split funds into a high- and a low-type group based on their characteristics. Then I calculate the fraction of shares held by each type of funds for each stock at each quarter-end. The dependent variable is the ownership by the type of funds specified. The first two columns give the aggregated liquidity coefficients for high VIX and low VIX times separately. The last two columns report the z-statistic (and the associated p-values) of the Wilcoxon rank-sum test that the aggregated coefficients are identical across the high and low states for the fund type considered. The last row in each panel reports the Wilcoxon rank-sum test statistics resulting from difference-in-difference tests of whether the difference between high and low VIX periods is significantly different across fund types.

	High VIX	Low VIX	z-stats	p-values
Panel A: Fund Family Size				
Small Family	0.54	0.43	4.00	(0.00)
Large Family	0.74	0.70	2.09	(0.04)
Diff-in-Diff			2.99	(0.00)
Panel B: Total Load				
Low Load	0.53	0.41	3.10	(0.00)
High Load	0.60	0.56	1.49	(0.14)
Diff-in-Diff			2.28	(0.02)
Panel C: Past Returns				
Loser	0.58	0.55	0.51	(0.61)
Winner	0.54	0.43	2.65	(0.01)
Diff-in-Diff			-1.41	(0.16)
Panel D: Return Volatility				
Low Volatility	0.49	0.48	0.33	(0.74)
High Volatility	0.59	0.44	3.64	(0.00)
Diff-in-Diff			-3.41	(0.00)
Panel E: Investment Style				
Growth	0.59	0.50	3.22	(0.00)
Income	0.66	0.63	1.50	(0.13)
Diff-in-Diff			3.39	(0.00)
Panel F: Fund Turnover				
Low Turnover	0.54	0.41	3.24	(0.00)
High Turnover	0.78	0.70	2.87	(0.00)
Diff-in-Diff			1.89	(0.06)

Table XI

Precautionary Liquidity Holdings and Fund Performance

The table reports the coefficients of the quarterly panel regressions using mutual funds' subsequent abnormal returns as dependent variables. The abnormal returns are obtained using the market model, the CAPM, the Fama-French three-factor model, the Fama-French-Carhart four-factor model, and Ferson and Schadt (1996) conditional model. LiqWt is the fraction of liquid securities (bottom 5% in Amihud illiquidity ratios) in a fund's assets. See Table I for the definition of other variables. All regressions include both fund dummies and time dummies. The associated *t*-statistics using robust standard errors are reported in parentheses. Significance on a ten percent (*), five percent (**), or one percent level (***) is indicated.

	Market Alpha (1)	CAPM Alpha (2)	3-Factor Alpha (3)	4-Factor Alpha (4)	Conditional Alpha (5)
VIX*LiqWt (x100)	0.120	0.118	0.116	0.117	0.118
	(15.56)***	(15.33)***	(15.07)***	(15.25)***	(15.35)***
LiqWt	-0.027	-0.027	-0.026	-0.027	-0.027
	(13.43)***	(13.24)***	(13.07)***	(13.18)***	(13.25)***
Log(TNA)	-0.415	-0.420	-0.402	-0.397	-0.421
	(17.47)***	(17.71)***	(17.00)***	(16.83)***	(17.78)***
Log(FamSize)	0.010	0.010	0.010	0.011	0.010
	(0.73)	(0.73)	(0.74)	(0.81)	(0.76)
Net Flows (x100)	-0.501	-0.403	-0.704	-0.565	-0.542
	(0.13)	(0.11)	(0.19)	(0.15)	(0.14)
Turnover	0.073	0.074	0.075	0.075	0.075
	(1.91)*	(1.91)*	(1.96)*	(1.96)*	(1.94)*
Age	-0.061	-0.060	-0.057	-0.054	-0.062
	(1.86)*	(1.83)*	(1.74)*	(1.66)*	(1.89)*
Expenses	0.829	0.477	-0.065	0.787	2.172
	(0.09)	(0.05)	(0.01)	(0.08)	(0.23)
Total Load	4.004	4.109	4.149	4.127	4.070
	(2.43)**	(2.49)**	(2.53)**	(2.52)**	(2.47)**
Lagged Return	-3.281	-3.267	-3.239	-3.243	-3.239
	(18.09)***	(18.03)***	(17.91)***	(17.96)***	(17.90)***
Return Volatility	-3.830	-3.846	-3.781	-3.614	-3.865
	(2.04)**	(2.05)**	(2.02)**	(1.93)*	(2.06)**
Constant	4.720	4.892	4.699	4.584	4.933
	(6.64)***	(6.90)***	(6.67)***	(6.51)***	(6.97)***
Fund/Time FE	Yes	Yes	Yes	Yes	Yes
Observations	43409	43409	43409	43409	43409
R-squared	0.14	0.13	0.09	0.09	0.13

Table XII

Robustness Tests

The table reports the coefficients of the quarterly panel regressions using mutual funds' liquidity weights (liquid stock holdings as a proportion of TNA) as dependent variables. Liquid stocks are defined as the bottom 5% in Amihud illiquidity ratios. Column (1) reports results controlling for cash holdings. Column (2) reports results using cash holdings as a fraction of total net assets as the dependent variable. Both models are estimated using the post-2000 subsample for which quarterly cash holding information is available. Column (3) reports results excluding fund/quarter observations that are associated with flight-to-liquidity episodes. Column (4) and (5) report sub-period results. For each model, I use the baseline specification in Table V and treat fund-specific effects as fixed. All regressions include fund dummies. I assume that year-specific effects are fully captured by fund-invariant variables, such as the VIX, market weight of liquid stocks, and market illiquidity. The associated *t*-statistics using robust standard errors are reported in parentheses. Significance on a ten percent (*), five percent (**), or one percent level (***) is indicated.

	Cash Holdings		Excl. Flight Episodes	Sub-period	
	Control for Cash	Cash as Dep.		92Q4-00Q1	00Q2-06Q4
	(1)	(2)	(3)	(4)	(5)
VIX	0.139	-0.004	0.089	0.045	0.114
	(10.04)***	(0.47)	(6.12)***	(2.44)**	(8.20)***
Var(Net Flows) (x100)	0.065	0.034	0.076	0.017	0.081
	(0.95)	(1.01)	(1.62)	(0.28)	(1.19)
Net Flows (x100)	-0.833	0.907	-0.455	-0.835	-0.845
	(5.83)***	(11.91)***	(4.07)***	(5.91)***	(5.72)***
Market Weight	0.362	17.481	0.660	0.948	0.449
	(7.08)***	(5.01)***	(35.74)***	(18.44)***	(8.39)***
Market Illiquidity	-32.711		-22.110	5.390	-59.123
	(5.11)***		(4.18)***	(0.74)	(8.90)***
Log(TNA)	3.216	0.365	0.618	0.435	3.234
	(24.16)***	(4.06)***	(6.35)***	(2.32)**	(22.49)***
Log(FamSize)	0.008	-0.043	-0.076	-0.274	-0.052
	(0.09)	(0.78)	(1.32)	(2.54)**	(0.53)
Liquid Stock Beta	0.450		0.827	0.330	0.479
	(4.18)***		(8.19)***	(2.56)**	(4.30)***
Portfolio Concentration	0.758	99.918	20.234	49.910	-18.234
	(0.04)	(2.56)**	(1.50)	(2.25)**	(0.88)
Turnover (x100)	-0.010	0.004	-0.014	-0.197	-0.009
	(2.06)**	(1.36)	(2.63)***	(0.81)	(1.92)*
Age	-0.287	-0.033	0.296	-0.373	-0.512
	(2.31)**	(0.87)	(5.83)***	(2.01)**	(3.81)***
Expenses	-0.360	0.807	-0.976	-1.615	-0.659
	(0.73)	(2.94)***	(2.33)**	(2.49)**	(1.25)
Total Load (x100)	10.125	-14.742	4.423	-9.028	11.959
	(1.38)	(2.89)***	(0.68)	(0.63)	(1.55)
Lagged Return	-1.205	-0.283	-0.468	5.188	-3.214
	(3.14)***	(1.34)	(1.41)	(10.90)***	(7.46)***
Return Volatility	-17.197	2.713	-22.097	-34.108	-26.194
	(3.92)***	(1.00)	(5.38)***	(4.82)***	(5.40)***
Cash	-0.077				
	(5.49)***				
Constant	8.442	-5.347	-6.811	-24.047	16.532
	(1.50)	(2.49)**	(2.44)**	(5.68)***	(2.73)***
Fund/Time FE	Yes	Yes	Yes	Yes	Yes
Observations	26,064	26,064	37662	17,381	24,070
R-squared	0.08	0.04	0.15	0.23	0.08