

Investor Sentiment and the Fragility of Liquidity

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Abstract

This paper identifies investor sentiment as an important driving force in the amplification of liquidity shocks. Using a firm-level vector autoregression (VAR) framework, I find that investors' pessimistic sentiment amplifies the feedback effect between the tightening of funding constraints through mutual fund outflows and the stock market illiquidity. This finding stands up in the face of various controls for other factors that affect liquidity, alternative measures of stock market illiquidity and alternative proxies for investor sentiment. Furthermore, I find economically significant returns for liquidity provision during periods of pessimistic sentiment. Collectively, my findings support a role for investor sentiment in the formation of fragility in liquidity: the property that a small funding shock to the investors' capital can lead to a large jump in stock illiquidity.

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I. Introduction

The liquidity spiral induced by the feedback effect between funding liquidity (i.e., the ease with which investors can obtain funding) and market liquidity (i.e., the ease with which asset is traded) presents a significant challenge for investors. The mutual reinforcement between funding constraint and the price impact of liquidations often leads to the sudden dry-up of liquidity in the stock market. For example, Brunnermeier and Pederson (2009) describe a mechanism in which negative funding shocks force speculators to de-lever their positions, leading to the dry-up of liquidity. In equilibrium, it is possible that a small funding shock to the investors can lead to a sharp reduction in stock liquidity.

In this paper, I propose a behavioral amplification mechanism for the feedback effect between funding liquidity and market liquidity, using capital outflows as a proxy for shocks to funding available to mutual funds. Specifically, I analyze whether investor sentiment influences the funding- market liquidity spirals and explore whether sentiment is a driving force in the amplification of liquidity shocks. Following Brunnermeier and Pederson (2009), I use the term “fragility of liquidity” to refer to the elasticity of stock liquidity with respect to investors’ funding shocks. A stock’s market liquidity is more fragile if the same funding shock triggers a larger reduction in market liquidity. During market turmoil, financial intermediaries such as hedge funds and mutual funds face tighter financing conditions. These include both higher margin requirements (in the case of hedge funds) and an erosion of the capital base through net fund withdrawals from mutual funds. I argue that investors’ pessimistic sentiment plays an important role in

amplifying the market liquidity impact of funding shocks to investors, which I call the “fragility of liquidity”. I focus on the liquidity shocks induced by money outflows from open-ended mutual funds. Notably, my sentiment proxy is measured outside of the financial markets, as I use the of University of Michigan Consumer Sentiment index (orthogonalized with respect to a set of macroeconomic variables).

My focus on the link between investor sentiment and the market liquidity impact of mutual fund outflows is motivated by the fact that investor sentiment, as proposed by DeLong, Shleifer, Summers and Waldman (1990), can be interpreted as capturing the correlated beliefs of uninformed noise traders that are unrelated to fundamentals (changes in the investment opportunity set, “rational” cash flow forecasts, interest rates, etc.), which also refers to excessively optimistic or pessimistic cash flow forecasts (e.g., Baker and Wurgler (2006)). Investor sentiment is generally attributed to individual, retail investors (see, for example, Lee, Shleifer, and Thaler, 1991). Since individual investors hold about 90% of total mutual fund assets (Da, Engelberg and Gao, 2011), mutual fund flows are generally seen as the “dumb money” that is subjected to individual investor’s behavioral bias (Brown et al., 2005; Frazzini and Lamont, 2008.)

Liquidity dry-ups occur because market participants engage in panic selling (a demand effect), or market making sectors withdraw from providing liquidity (a supply effect), or both. The role of investor sentiment can come into play at both the demand and supply of market liquidity. On the demand side, pessimistic sentiment can induce individual investors to pull money out of equity mutual funds simultaneously (Da, Engelberg and Gao, 2011) and create correlated outflows. Open-ended mutual funds,

though not leveraged as hedge funds, are extremely reliant on outside capital to fund its investment opportunities. Because most funds are evaluated against all-equity benchmarks, few maintain significant cash balances (see, for example, Coval and Stafford (2007)). When capital is in immediate demand, mutual funds without significant cash reserves have no choice but to sell holdings quickly, creating a demand for liquidity (e.g., Ben-Rephael, Kandel and Wohl (2011), Coval and Stafford (2007), Edelen and Warther (2001), Lou (2010)). By offering on-demand withdrawals, mutual funds expose themselves to investor actions that are affected by investor sentiments. The demand for liquidity calls for its supply. On the supply side, Kaniel, Saar and Titman (2008) document that contrarian tendency of individuals leads them to act as liquidity providers to institutions that require immediacy. In a sense, individuals act as the irrational market makers as modeled in Baker and Stein (2004). As these market makers are not formally required to continuously provide market-making services, their supply of liquidity could easily be withdrawn when they are pessimistic about the stock market. Furthermore, arbitrageurs know that noise traders are pessimistic today and there will be resale price risk caused by the possibility that noise trader will become even more pessimistic in the future (DeLong, Shleifer, Summers and Waldman, 1990). Hence Arbitrage capital moves slowly to take advantage of the irrational beliefs of sentiment investors. With a limited supply of liquidity in the market during a general crisis of confidence, this sudden reduction in liquidity accelerates the decline in asset prices and induces more withdrawal of capital. By increasing the demand for liquidity and decreasing the supply of liquidity, pessimistic investor sentiment can amplify the dynamic relationship between market liquidity and funding shocks to mutual funds.

To systematically test this prediction, I formulate various firm-level vector autoregressive (VAR) models. I start with the benchmark VAR model to investigate the dynamic interaction between mutual fund outflows and stock market liquidity. I examine mutual fund flows and stock market liquidity for the stocks traded in NYSE/Amex over the period 1991–2009. For each stock, I construct the monthly time-series of stock *OutFlow* to capture the percent of the shares of a given stock owned by mutual funds that is subjected to mutual fund outflows. The idea is that capital flows are from individual investors to mutual funds and then from mutual funds to individual stocks based on funds' portfolio holdings. I use the Amihud (2002) price impact of trade measure to capture stock market liquidity. This measure is the absolute return divided by dollar trading volume. Thus it measures the price impact of trading. The higher is this measure, the higher is the price impact, and the lower the liquidity. This measure is consistent with theoretical research such as Grossman and Miller (1988) which defines liquidity based on price impact as a result of buying and selling pressure. I also consider bid-ask spread as a measure of illiquidity in my robustness checks. My benchmark VAR model includes three endogenous variables: *OutFlow*, illiquidity, and return as the benchmark model. I include return in the VAR system because previous studies identify an important relation of both mutual fund flows and illiquidity with stock returns. I control for any endogenous interaction with returns in all my analyses. I document a positive feedback effect between *OutFlow* and illiquidity.

I then proceed to estimate the VAR model with the presence of the interaction variable pessimistic sentiment. To ensure that my sentiment measure is free of

macroeconomic influences, I conduct my investigation using the residual from the regression of the University of Michigan consumer confidence index on a set of variables that proxy for fundamental economic activities. Furthermore, I construct alternative sentiment measure by controlling for proxies for investor's risk aversion, specifically, by further orthogonalizing the Michigan sentiment proxy to VIX. Finally, in my robustness checks, I also consider the alternative index for investor sentiment constructed by Baker and Wurgler (2006, 2007). I multiply the sentiment indexes by -1 and denote it as pessimistic sentiment. I discover a critical role for investors' pessimistic sentiment in the mutual fund outflow-illiquidity relationship. Given an *OutFlow* corresponding to 1% of a stock's market capitalization, a one-standard-deviation increase in pessimistic sentiment increases the impact of *OutFlow* on Amihud illiquidity by 31% from 19%.

Finally, using a zero-cost contrarian investment strategy as the measure of the return to provide liquidity, I examine whether the return to provide liquidity depends on the state of investor sentiment and whether it is more costly to provide liquidity for stocks which are more fragile in liquidity. The cost of providing liquidity is reflected in the temporary decrease in price accompanying heavy trading and the subsequent increase as prices revert to fundamental values (e.g. Avramov, Chordia and Goyal (2006), Hameed, Kang and Viswanathan(2010).) The zero-cost contrarian investment strategy yields an economically significant return of 2.84% per month when conditioned on pessimistic sentiment states. This return to provide liquidity is much higher than the unconditional return of 1.93%. Furthermore, I condition the return to provide liquidity on state of investor sentiment and the state of market returns, and find that the pessimistic sentiment

combined with down market give rise to a monthly contrarian profit of 3.62%. This number is much higher than the 1.15% when the sentiment is positive in the down market. Finally, I find that the return to provide liquidity comes from the portfolio of stocks that are fragile in liquidity.

This paper contributes to the recent literature on the amplification mechanisms in liquidity crises. Numerous theoretical models point to liquidity shocks as a cause of financial crises. (See, e.g., Adrian and Shin (2008, 2010), Brunnermeier and Pedersen (2009), Diamond and Rajan (2009), Froot (2009), Gromb and Vayanos (2002), and Krishnamurthy (2010)). During periods of financial crisis, a reinforcing mechanism between market liquidity and funding liquidity leads to liquidity spirals and fragility—the property that a small shock can lead to a large jump in illiquidity. Literature has proposed several explanations for the illiquidity amplification mechanism. For example, binding margin constraints (Brunnermeier and Pedersen (2009)) and the risk of experiencing future shocks, due to outflows (Shleifer and Vishny (1997)) can lead investors to liquidate their holdings at the same time. During these episodes it is also hard to find potential liquidity providers. As Duffie (2010), and Duffie and Strulovici (2011) show, the frictions (such as the time to raise capital by intermediaries, the reputation concerns of fund managers and the delays in processing information) preventing buying capital to move quickly to temporary undervalued stocks are most significant during episodes of severe market turmoil. A few empirical works focus on problems at hedge funds, which are thought to drive down stock prices as they respond to margin call with liquidation. Boyson, Stahel, and Stulz (2010) link hedge fund contagion in returns to liquidity shocks.

Sadka (2010) shows that hedge funds with high exposure to liquidity risk underperform during liquidity crises. Aragon and Strahan (2011) argue that the failure of Lehman caused funding problems and losses at hedge funds that used it as a prime broker. All these studies assume investors at play are rational. The role of irrational investors in this illiquidity amplification mechanism, however, has not been a prime subject of inquiry. This paper fills this gap by investigating the role of investor sentiment in the illiquidity amplification mechanism. This paper also complements the empirical work by investigating a different channel for the feedback effect between funding liquidity and market liquidity, using mutual fund outflows as the demand shocks to funding liquidity.

Second, the evidence presented in this paper pertains to the emerging literature on the effect of investor sentiment on stock market outcomes. Baker and Wurgler (2006), Brown and Cliff (2004), Lemmon and Portnaiguina (2006), Qiu and Welch (2004), and other papers have investigated the role of investor sentiment in stock market returns. Antoniou, Doukas and Subrahmanyam (2011) consider the impact of sentiment on the profitability of momentum strategies. Yu and Yuan (2011) show that sentiment has major effects on the mean-variance relationship in the stock market, with the tradeoff between risks and expected returns emerging only in low sentiment periods. Baele, Bekaert, and Inghelbrecht (2010) discuss sentiment and the time-series relationships between government bond and stock market returns. Hwang (2011) provides evidence that a country's popularity among Americans affects U.S. investors' demand for securities from that country and causes security prices to deviate from their fundamental values. This

paper contributes by providing evidence on the amplification effect of sentiment on the interaction between mutual fund outflows and stock market liquidity.

The results in this paper also complement a number of studies on the price impact of mutual fund flows. Previous studies find that aggregate capital flows to mutual funds in a particular sector or in a particular investment style affect both the contemporaneous and subsequent sector returns or style returns. (See, e.g., Warther (1995), Edelen and Warner (2001), Gompers and Metrick (2001), Goetzmann and Massa (2003), Teo and Woo (2004)). Coval and Stafford (2007) examine the price impact of extreme flows on individual stocks. Most of these studies focus on the impact of mutual fund flows on stock return. This paper identifies liquidity as an important channel of the price impact of mutual fund flows.

The paper outline is as follows: Section II describes the sample, data sources, and key variables. The methodology and results on impact of investor sentiment on the interaction of mutual fund flows and market liquidity are presented in Section III. Section IV investigates the cross sectional stock characteristics of fragility of liquidity. Section V examines the return from liquidity provision during different states of investor sentiments for different portfolios of fragile stocks. Section VI concludes.

II. Data and Construction of Variables

A. Investor sentiment index

For the main part of the analysis I measure investor sentiment using the monthly time series of Consumer Sentiment Index constructed by the University of Michigan. The University of Michigan Consumer Sentiment Index ² is measured using survey methodology. The survey is conducted on a sample of at least 500 households and the respondents are asked to answer about 50 core questions, which track consumer attitudes and expectations. The respondents are asked questions about their assessment of the current and future economic conditions.

Consumer confidence generally moves in line with economic variables such as interest rates, inflation and unemployment but sometimes it diverges from them. For example, consumer confidence plunged in August 1991, following Iraq's invasion into Kuwait, beyond anything that could be predicted from economic conditions. In previous research, the University of Michigan Consumer Sentiment Index has been used as a proxy for investor sentiment. For example, Lemmon and Portniaguina (2006) use this measure to explain the cross-section of the 25 Fama_French portfolios. Fisher and Statman (2003) show that consumer confidence goes up and down with the sentiment of individual investors. Qiu and Welch (2004) show that Michigan Consumer Sentiment Index is one of the proxies that best capture the behavior of sentiment investors.

Since the consumer sentiment survey values reflect consumers beliefs about the fundamentals of the economy as well as their over optimism or pessimism (investor sentiment), I remove the effect of fundamentals from the raw survey values. Specifically, I regress the University of Michigan Consumer Sentiment Index on a set of variables that

² Obtained from www.Sca.isr.umich.edu

proxy for fundamental economic activity (Lemmon and Portniaguina, 2006; Hrnjić and Sankaraguruswamy, 2010) as the following specification:

$$CSI = \alpha + \beta_1 \times DIV + \beta_2 \times IP + \beta_3 \times DEF + \beta_4 \times YLD3 + \beta_5 \times GDP + \beta_6 \times CONS + \beta_7 \times URATE + \beta_8 \times CPI + \beta_9 \times CAY \quad (1)$$

CSI is the original University of Michigan Consumer Sentiment Index. *DIV* is the Dividend yields, measured as the total ordinary cash dividend of the CRSP value-weighted index over the last three months deflated by the value of the index at the end of the current month. Industry production growth rate (*IP*) is quarterly change in the natural logarithm of industry production. Default spread (*DEF*) is measured at a monthly frequency, and is the difference between the yield to maturity on Moody's Baa-rated and Aaa-rated bonds, taken from the Federal Reserve Bank of St. Louis. *YLD3* is the monthly yield on the three-month Treasury bill. *GDP* is the GDP growth measured as the quarterly change in the natural logarithm of adjusted GDP. Consumption growth (*CONS*) is measured as the quarterly change in the natural logarithm of personal consumption expenditures. Unemployment rate (*URATE*) is the monthly and seasonally adjusted values as reported by the Bureau of Labor Statistics. The inflation rate (*CPI*) is measured monthly and obtained from CRSP. Consumption-to-wealth ratio (*CAY*) is taken from data provided by Lettau and Ludvigson (2001).

[Insert Figure 1 about here]

I standardize the series to have mean 0 and standard deviation 1. The monthly index is plotted in Figure 1.

B. Mutual Fund Data

The mutual fund sample is constructed by merging the CRSP Survivorship Bias Free Mutual Fund Database with the Thompson Financial CDA/Spectrum holdings database using MFLink provided by WRDS. The CRSP mutual fund database includes information on fund returns, total net assets and other fund characteristics. Monthly total net assets are available for most funds from 1991. Hence the sample period in this study starts from 1991. The CDA/Spectrum mutual funds database includes all registered domestic mutual funds filing with the SEC. The holdings constitute almost all the equity holdings of the funds. Most mutual funds in the database report their holdings on a quarterly basis; I adjust the holdings for stock splits reported in the CRSP stock files.

I require the ratio of equity holdings to total net assets to be between 0.75 and 1. The lower bound is to make sure that the equity portfolio accounts for a significant portion of the total funds' asset while the upper bound is to get rid of some apparent data errors. Summary statistics of more than 5000 mutual fund portfolios over the period 1991 -2009 are presented in Table 1, Panel A. The average fund has Total net assets (TNA) of \$914 million over the sample period.

[Insert Table 1 about here]

C. Firm Level Mutual Fund Flows

One important variable in this study is the firm level outflows, the percent of the shares of a given stock owned by mutual funds that is subjected to fund outflows. I first calculate mutual fund flows using the CRSP Mutual Fund Database. Since we do not

observe flows directly, I infer flows from fund returns and *TNA* as reported by CRSP. Let TNA_t^k be the total net asset of a fund k and let R_t be its return between month $t-1$ and month t . Following the standard practice in the literature (e.g., Zheng (1999), Sapp and Tiwari (2004), Frazzini and Lamont (2008)), I compute flows for fund k in month t , $FundFlow_t^k$ using

$$FundFlow_t^k = TNA_t^k - TNA_{t-1}^k(1 + R_t^k) - MGN_t^k \quad (2)$$

where MGN_t^k is the increase in total net assets due to mergers during month t . I handle mergers by assuming that investors in the merged funds place their money in the surviving fund. I assume that inflows and outflows occur at the end of the month, and that existing investors reinvest dividends and other distributions in the fund. I assign an initial *TNA* value of zero to funds that were newly created, while funds that die have outflows equal to their terminal *TNA*.

Following Frazzini and Lamont (2008), I assume that fund flows pass to stocks according to the holding portfolios of funds. This formulation assumes that all trades were made on the last day of the month. Thus, I have a formula for stock flow by fund k in month t :

$$StockFlow_{i,t}^k = FundFlow_t^k * \text{Proportion of stock in portfolio } k \quad (3)$$

I then aggregate *StockFlow* over all mutual funds that experience outflow to create a total outflow for each stock *i*. For comparability among stocks, I scale the *StockFlow* by the market value ($Mkcap_{i,t}$) of each stock.

$$OutFlow_{i,t} = \frac{\sum_k |StockFlow_{i,t}^k| * D(FundFlow_t^k < 0)}{Mkcap_{i,t}} \quad (4)$$

Where $D(FundFlow_t^k < 0)$ is a dummy variable with the value of one when $FundFlow_t^k < 0$ and zero otherwise.

Combine equation (2) to (4), for stock *i* at month *t*, $OutFlow_{i,t}$ can be expressed as

$$OutFlow_{i,t} = \sum_k \frac{|TNA_t^k - TNA_{t-1}^k(1+R_t^k) - MGN_t^k| * D(FundFlow_t^k < 0)}{TNA_{t-1}^k} * \frac{Holding_{i,t}^k}{Shout_{i,t}} \quad (5)$$

$Holding_{i,t}^k$ is the most recent reported number of shares of stock *i* hold by mutual fund *k* at month *t*. the *Shout* is stock *i* 's number of shares outstanding.

I also construct the firm level *InFlow* in the same way except $D(FundFlow_t^k < 0)$ is replaced with $(FundFlow_t^k > 0)$. Firm level *NetOutFlow* is constructed as

$$NetOutFlow_{i,t} = \sum_k \frac{-[TNA_t^k - TNA_{t-1}^k(1+R_t^k) - MGN_t^k]}{TNA_{t-1}^k} * \frac{Holding_{i,t}^k}{Shout_{i,t}} \quad (6)$$

Figure 2 depicts the monthly firm level mutual fund *OutFlow*, *InFlow* and *NetOutFlow* .

[Insert Figure 2 about here]

D. Other Data and Variables

Shares outstanding, stock returns, share codes, exchange codes, prices, market capitalization and trading volume for all stocks come from the Center for Research on Security Prices (CRSP) daily and monthly files. In the current analysis, I focus on ordinary common shares of firms incorporated in the United States that traded on the NYSE and Amex. Throughout, ADRs, units, REITs, Americus Trust components, closed-end funds and preferred stocks are excluded— that is, stocks that do not have a CRSP share type code of 10 or 11. In addition, to be included in our sample, the stock's price must be within \$3 and \$999. I exclude NASDAQ stocks because their trading protocols are different. The stock should also have at least 60 months of valid observations during the sample period. After applying all the above filters, the final database includes about 4000 stocks over 19 years.

I construct the Amihud (2002) illiquidity measure using the daily return, volume and price. The Amihud proxy is designed to capture the marginal impact of a unit of trading on the stock price. For each stock i for each month t , it is calculated as follows:

$$Illiq_{i,t} = \frac{1}{D} \sum_{d=1}^D \frac{|R_{i,d}|}{DolVolume_{i,d}} \quad (7)$$

Where D is the number of days in month t . $R_{i,d}$ is the daily stock return and $DolVolume_{i,d}$ is the daily dollar trading volume. Following Amihud (2002), I use the logarithmic transformation of illiquidity. Hasbrouck (2009) finds that among various

price impact measures, the Amihud illiquidity measure has the highest correlation to the measures of price impact constructed from high-frequency data.

Summary statistics of stocks over the period 1991 -2009 are presented in Table 1, Panel B. The stocks have average monthly return of 0.85% and average monthly *OutFlow* of 0.08% over the sample period.

III. Empirical Specification and Main Results

A. Benchmark VAR Model

I start by examining the dynamic relationship between mutual fund outflows and the stock market illiquidity. To avoid imposing a priori restrictions on the dynamic interaction of outflows, illiquidity, and returns, I adopt a vector autoregression (VAR) methodology following Vagias and Van Dijk (2011). Vagias and Van Dijk (2011) use the VAR system with international capital flows, market liquidity and market return as endogenous variables to study the impact of international capital flows on local market liquidity.

The general form of an unrestricted VAR model of order p with m endogenous variables and n exogenous factors is as follows:

$$Y_t = A + \sum_{l=1}^p B_l \times Y_{t-l} + C \times X_t + \epsilon_t \quad (8)$$

where $Y_t = (y_{1,t}, y_{2,t}, \dots, y_{m,t})'$ is an $m \times T$ matrix of jointly determined dependent variables assumed to be covariance stationary, $X_t = (x_{1,t}, x_{2,t}, \dots, x_{n,t})'$ is an $n \times T$ vector of exogenous variables, A is an $m \times 1$ vector of intercepts, and B_l ($l = 1, 2, \dots, p$) and C are the $m \times m$ and $m \times n$ coefficient matrices to be estimated. In this paper, Y_t consists of three variables (defined for each stock i): monthly outflows of mutual investors weighted by their percentage holding of the stock ($OutFlow_{i,t}$), monthly stock returns ($R_{i,t}$), and the monthly Amihud illiquidity ($Illiq_{i,t}$). I focus on outflows instead of net outflows because inflows and outflows have asymmetric demand for liquidity. Detail analysis on inflows will be presented in Section III. C.

Suppressing exogenous factors, the stock -specific VAR model can be expressed as follows:

$$\begin{bmatrix} R_{i,t} \\ OutFlow_{i,t} \\ Illiq_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_i^1 \\ \alpha_i^2 \\ \alpha_i^3 \end{bmatrix} + \begin{bmatrix} \beta_{11}^i & \beta_{12}^i & \beta_{13}^i \\ \beta_{21}^i & \beta_{22}^i & \beta_{23}^i \\ \beta_{31}^i & \beta_{32}^i & \beta_{33}^i \end{bmatrix} \begin{bmatrix} R_{i,t-1} \\ OutFlow_{i,t-1} \\ Illiq_{i,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_i^R \\ \epsilon_i^{OutFlow} \\ \epsilon_i^{Illiq} \end{bmatrix} \quad (9)$$

$$\begin{bmatrix} \epsilon_i^R \\ \epsilon_i^{OutFlow} \\ \epsilon_i^{Illiq} \end{bmatrix} \sim N[0, \Sigma_i, \quad \Sigma_i = \begin{bmatrix} (\sigma_i^R)^2 & \sigma_i^{R,Outflow} & \sigma_i^{R,Illiq} \\ \sigma_i^{Outflow,R} & (\sigma_i^{OutFlow})^2 & \sigma_i^{Outflow,Illiq} \\ \sigma_i^{Illiq,R} & \sigma_i^{Illiq,Outflow} & (\sigma_i^{Illiq})^2 \end{bmatrix}$$

Besides the endogenous variables, I take several external factors to control for other sources of inter-temporal variation in liquidity, return and mutual fund outflows. I account for changes in market wide funding liquidity conditions by including the TED

spread (the spread between LIBOR and U.S. Treasury bills). I also include market average returns as exogenous factors in the VAR specifications.

For each stock, I estimate the VAR model using the 5-year window rolled forward every 6 months. To decide upon the optimal lag length p , I use the Hannan-Quinn Information Criterion (HQC) for the firm-specific VARs. I find an optimal lag length equal to one month for the majority of the stocks. Consequently, for the sake of parsimony I use a lag length of one month in all VARs. I require each regression has at least 40 observations.

Table 2 presents the results. Panel A reports the benchmark VAR model with only endogenous variables. Panel B reports the VAR estimation including exogenous variables. In Panel C, I exclude the 2007-2009 crisis period. The estimated coefficients are averaged over time and then across firms.

[Insert Table 2 about here]

The coefficients β_{32}^i of the VAR model are the primary interest of this study. These coefficients describe the market liquidity impact of funding shocks, measured by mutual fund outflows. The coefficients β_{32}^i indicate that fund outflow positively predicts illiquidity for the stock the funds hold. Furthermore, the *OutFlow* coefficients on *Illiq* β_{23}^i indicate the positive feedback effect of market illiquidity on *OutFlow*.

Returns display negative monthly autocorrelation, on average across the stocks after controlling the effect of outflow and illiquidity. The return coefficient on lagged illiquidity is positive and statistically significant. The evidence herein suggests the liquidity premium. The results also resonate with Hameed, Kang and Viswanathan (2010) that decrease in stock returns and market returns increases stock illiquidity. The coefficients on TED spread are positive and significant, indicating that market liquidity is negatively impacted by widening TED spreads, a proxy for market wide funding liquidity.

To ensure that the results are not merely driven by the recent crisis period, I exclude the 2007-2009 time period in Panel C. The evidence in Panel C confirms the feedback effect between outflows and illiquidity.

Denoting the coefficient β_{32}^i from the VAR model as fragility of liquidity, I take the average of fragility of liquidity across stocks and plot the time-series variation of the average fragility in liquidity. Figure 3 shows significant time-series variation in the fragility of liquidity over the sample period 1995 to 2009. Recall that I estimate the VAR model with 5 years rolling windows, so the fragility of liquidity starts from 1995. We observe spikes in fragility associated with periods of liquidity crisis. For example, one of the spikes in the fragility of liquidity coincides with liquidity dry-ups during the subprime crisis (2007-2008) when investor sentiment is also very low. However, liquidity seems to be fragile during 1991-1995 even there were no crisis and we don't see major mutual fund outflows. Interestingly, this period is accompanied by pessimistic sentiments, highlighting the impact of investor sentiment on liquidity.

[Insert Figure 3 about here]

B. Investor Sentiment and the Fragility of Liquidity

To directly examine how investors' pessimistic (negative) sentiment affects the dynamic relationship between outflows and market liquidity, I interact the three endogenous variables with the sentiment index,

$$Y = \alpha + \beta \times Y_{t-1} + \gamma \times NegSent_{t-1} + \mu \times NegSent_{t-1} \times Y_{t-1} \quad (10)$$

Where $Y_t = \{R, OutFlow, Illiq\}$. $NegSent_{t-1}$ is the Sentiment index multiplied by -1.

[Insert Table 3 about here]

Table3 presents the results. The coefficients of negative sentiment interacting with *OutFlow* for the illiquidity equation measure the incremental impact of *OutFlow* on stock market illiquidity when investors' negative sentiment is 1 SD higher than the mean. Given an *OutFlow* corresponding to 1% a stock's market value, a 1 SD increase in negative sentiment leads to an additional 31% SD jump in illiquidity, from the 19% when sentiment is at its average. Pessimistic sentiment also amplifies the feedback effect of illiquidity on mutual fund outflows. The coefficients of negative sentiment interacting with illiquidity for the *OutFlow* equation are positive and significant. Overall, the empirical evidence strongly indicates that investors' pessimistic sentiment amplify the effects of liquidity shocks.

C. Asymmetric Effect of Inflow and Outflow on Liquidity

In my analysis, I aggregate on mutual funds with outflows to construct the firm level outflows instead of netting out mutual funds with inflows because the asymmetric effect of outflows and inflows on liquidity. Brennan, Chordia, Subrahmanyam and Tong (2009) show that the demand for immediacy is stronger for sellers of securities than for buyers since investors are more likely to have a pressing need to raise cash than to exchange cash for securities. That say, mutual funds with outflows are forced to sell immediately, while mutual funds with inflows, though tend to scale up their existing holdings (Coval and Stafford, 2007), are less urgent to do so.

To see how inflows affect the market liquidity for the stocks held by the funds and how investor sentiment affects this relationship, I run the VAR estimation replacing *OutFlow* with *InFlow*.

[Insert Table 4 about here]

Table 4 reports the results. First, consistent with Coval and Stafford (2007), I find that the inflow-driven price pressure can also cause a decline in liquidity funds. When many funds are simultaneously forced to buy the same securities and few others are willing to sell—this upward price pressure increases the demand for liquidity. However, the magnitude of impact is much smaller compared to that of *OutFlow*. An *InFlow* corresponding to 1% a stock's market value leads to a 0.4% SD jump in illiquidity, This finding is in line with Campbell, Ramadorai and Schwartz (2009) that institutions

demand more liquidity when they sell than when they buy. Not surprisingly, pessimistic sentiment attenuates the impact of inflows on market liquidity.

Overall, the results suggest that both mutual outflows and inflows create the demand for liquidity. Nevertheless, investors' pessimistic sentiment amplifies the mutual reinforcing effect of mutual fund outflows and stock market illiquidity, but attenuates the impact of inflows on market illiquidity.

D. Is the Sentiment Index Reflection of Investor Risk Preferences?

One alternative explanation is that the sentiment measure is simply proxies for changes in risk preferences of investors. Although traditional risk-based models do not appear to account for the sentiment effect on liquidity, this effect may still be related to some form of rational expectation if my sentiment measure reflects investor's risk aversion, which determines investor's required rate of return. In this section I construct my sentiment measure by controlling for proxies for investor's risk aversion. Specifically, I replicate the analysis in Table 3 by further orthogonalizing my sentiment index to VIX (the index options-based volatility index).

[Insert Table 5 about here]

Table 5 reports the results. As can be seen, the results remain essentially unchanged even when I orthogonalize the sentiment index with respect to VIX. For example, given an *OutFlow* corresponding to 1% a stock's market value, a 1 SD increase in negative sentiment leads to an additional 23% SD jump in illiquidity. These findings

suggest that the amplification effect of investor sentiment does not arise simply because my sentiment measure captures investors' risk preferences.

E. An Alternative Sentiment Index

In this section, I examine the sensitivity of my results to an alternative index for investor sentiment, which is the measure constructed by Baker and Wurgler (2006, 2007). Baker and Wurgler (2006) form a composite sentiment index that is the first principal component of six measures of investor sentiment. The six measures are the closed-end fund discount, the NYSE share turnover, the number of IPOs, the average first-day return of IPOs, the equity share in new issues, and the dividend premium. To remove business cycle information, they regress each index against growth in industrial production, real growth in durable consumption, non-durable consumption, services consumption, growth in employment, and an NBER recession indicator. Their sentiment index is the first principal component of the residual series from the regressions.

[Insert Table 6 about here]

Table 6 reports the Table 3-equivalent VAR estimation using the Baker and Wurgler sentiment measure in place of the Michigan Sentiment Index. All other variables remain the same as those in Table 3. The evidence in table 6 confirms the amplification effect of investor sentiment on the feedback effect between outflow and illiquidity. Specifically, given an *OutFlow* corresponding to 1% a stock's market value, a 1 SD increase in negative sentiment leads to an additional 48% SD jump in illiquidity. Similar results are obtained for the other coefficients in Table 3. These findings corroborate my previous results.

F. An Alternative Illiquidity Proxy

In this section, I examine the sensitivity of my results using the proportional bid-ask spread (as a proportion of the stock's price) as an alternative measures of liquidity. Table 8 reports the Table 3-equivalent VAR estimation using the proportional bid-ask spread in place of the Amihud Illiquidity measure. All other specifications remain the same as those in Table 3. The evidence in table 7 further confirms the amplification effect of investor sentiment on the feedback effect between outflow and illiquidity.

[Insert Table 7 about here]

IV. Cross Sectional Evidence

Baker and Wurgler (2006, 2007) show that broad waves of sentiment have greater effects on hard to arbitrage and hard to value stocks; these stocks will exhibit high sensitivity to sentiment. Do we expect these hard to arbitrage and hard to value stocks to be more fragile in liquidity? To examine the firm-specific determinants of the fragility of liquidity, I sort varieties of stock characteristics on the fragility of liquidity based on semiannual breakpoints. Table 8 reports the result. Smaller firms are more fragile, which is not surprising given that smaller firms usually have high retail concentration. The same category applies for stocks with low institutional and mutual fund ownership. Highly volatile stocks usually have high speculative appeal and hence relatively hard to value and relatively hard to arbitrage, making them especially prone to fluctuations in

sentiment. The result shows that Volatile stocks are more fragile in liquidity. The number of analysts serves as a proxy for the mass of informed agents as suggested by Brennan and Subrahmanyam (1995). Low analyst coverage stocks are hard to value and they show to be more fragile in liquidity. Earnings surprises serve as the proxy for the extent of estimation uncertainty about fundamental values. However, the result shows that stocks with high negative earnings surprises are more fragile than stocks with positive earnings surprises. A natural interpretation is that negative earnings surprises may indicate distress.

[Insert Table 8 about here]

However, results with respect to book-to-market do not seem to align well with hard to arbitrage and hard to value stocks, at least, at the first glance. Literature shows that growth stocks are usually more subject to sentiment shift. My finding shows that liquidity is more fragile for high book-to-market stocks. One possible explanation is that high book-to-market can also be associated with distress. Overall, for the set of stocks for which sentiment is most likely to operate I find the impact of outflows on market liquidity is the strongest.

V. Contrarian Profit, Investor Sentiment and the Fragility of Liquidity

Kaniel, Saar and Titman (2008) document that contrarian tendency of individuals leads them to act as liquidity providers to institutions that require immediacy. From models of risk-averse liquidity provision such as Grossman and Miller (1988) and Campbell,

Grossman, and Wang (1993) that investors who require immediacy (e.g., institutions) must offer price concessions to induce other risk-averse investors, in this case individuals, to take the other side of their trades. However, these irrational market makers as modeled in Baker and Stein (2004) are not formally required to continuously provide market-making services; their supply of liquidity could easily be withdrawn when they are pessimistic about the stock market. In pessimistic periods, small investors are less inclined to buy losers (Antoniou, Doukas and Subrahmanyam, 2011.) Therefore, the large returns demanded by the uninformed traders enhance price fluctuations, creating more risk in the positions liquidated than in those assets and increasing the premium demanded by other liquidity providers. Therefore, I posit that the expected returns from liquidity provision in equity markets rise during times of pessimistic sentiment. To construct a proxy for the returns from liquidity provision, I examine the extent of price reversals using the contrarian trading strategies that long on the loser securities and short on the winner securities.

I follow the contrarian strategy developed in Avramov, Chordia, and Goyal (2006) and applied by Hameed, Kang and Viswanathan(2010), except that I construct the monthly contrarian profit instead of the weekly ones. I sort the stocks in month t into positive and negative return portfolios. For each month t , returns on stock i ($R_{i,t}$) that are higher (lower) than the median return in the positive (negative) return portfolio are classified as winner (loser) securities. I use stock i 's turnover in month t ($Turn_{i,t}$) to measure the amount of trading. The contrarian portfolio weight of stock i in month $t+1$ within the winner and loser portfolios is given by

$$\omega_{p,it} = (R_{i,t-1}Turn_{i,t-1}) / \sum_{i=1}^{Np} R_{i,t-1}Turn_{i,t-1} \quad (11)$$

where Np denotes the number of securities in the loser or winner portfolios in month t .

The contrarian profits for the loser and winner portfolios for month $t+k$ are:

$$\pi_{p,t+k} = \sum_{i=1}^{Np} \omega_{i,p,t+1} R_{i,t+k} \quad (12)$$

Next I take the difference in profits from the loser and winner portfolios to obtain the zero-investment profits.

I investigate the effect of investor sentiment by conditioning the contrarian profits on the investor sentiment in the month of the portfolio formation month. Specifically, I examine contrarian profits in positive (optimistic) sentiment states and negative (pessimistic) sentiment states.

[Insert Table 9 about here]

Table 9, Panel A reports a significant contrarian profit of 1.93% in month $t+1$ (t -statistic=3.81) for the full sample period. The contrarian profit becomes insignificant as we move to $t+2$. Since the contrarian profits and price reversals appear to last for at most one month, I limit the subsequent analyses to the first month after portfolio formation. Panel B of Table 10 shows that month $t+1$ profits in the negative sentiment month increase noticeably to 2.84% compared to profits of 0.94% in the positive sentiment period.

Hameed, Kang and Viswanathan (2010) show that return to supplying liquidity increases following periods of large drop in market return. The period of pessimistic sentiment might also be the period of down market. To examine whether the high contrarian profit is merely the results of down market, I further condition the contrarian profit on both market return and sentiment. I define down (up) market as the market returns over the previous month less (greater) than its sample mean. Consistent with Hameed, Kang and Viswanathan (2010), contrarian profit is much higher in the down market than the up market, however, the effect of sentiment still exists. Panel C shows that the largest contrarian profit of 3.62% is registered in the period when investor sentiment is pessimistic and in the down market, compared to a profit of 0.94% when sentiment is optimistic in the same down market. In the up market, contrarian profit is 2.07% in the pessimistic sentiment regime and 0.77 in the positive sentiment regime.

As sentiment is an important driving force that amplifies the liquidity shocks. I posit that the return to provide liquidity shall be even higher for stocks which are more fragile in liquidity when sentiment is pessimistic. To test this proposition, I rank the sample stocks into terciles based on the Fragility of Liquidity measured as the β_{32} from the benchmark VAR estimation and construct the contrarian profit for each fragility tercile conditional on the sentiment index. Table 10 shows that the contrarian profit all comes from liquidity provisions to the stocks that are most fragile in liquidity when sentiment is pessimistic. The contrarian profit is statistically and economically significant at 2.85% (t-stat=2.51) for the stocks that are ranked in the highest tercile in the fragility

of liquidity when sentiment is pessimistic, but insignificant for all the other two fragility portfolios and for periods when sentiment is optimistic.

[Insert Table 10 about here]

VI. Conclusion

This paper investigates the impact of investor sentiment on the mutual reinforcement between the tightening of funding constraints through mutual fund outflows and their impact on stock market liquidity. Using a VAR system with *OutFlow*, illiquidity, and return as endogenous variables, I first document the mutual reinforcing effect of mutual fund outflows and stock market liquidity. I then show that when the investor sentiment is pessimistic, liquidity can be fragile, that is a small mutual fund outflow can lead to a large decline in market liquidity of the assets held by the funds. The feedback effect of market illiquidity on mutual fund outflows is also enhanced when sentiment wanes. These empirical evidences confirm that investor sentiment plays a significant role as an amplifying mechanism of liquidity shocks.

Models of risk-averse liquidity provision suggest that investors who require immediacy must offer price concessions to induce other risk-averse investors to take the other side of their trades. I use the idea that short-term stock price reversals following heavy trading reflect compensation for supplying liquidity and examine whether the return from liquidity provision varies with investor sentiment. I find that, indeed, the

return to provide liquidity is higher in periods with pessimistic sentiment. For example, contrarian trading strategies based on return reversals produce economically significant returns (2.84 % per week) during period of pessimistic sentiment. The findings still hold after controlling for stock market return. I confirm Hameed, Kang and Viswanathan (2010), and show that investor sentiment has incremental power to explain contrarian profits after accounting for market returns. Taken together, my results support a supply effect on liquidity of investor sentiment as advocated by Baker and Stein (2004). Finally, I find that the contrarian profits mainly come from portfolio of stocks with fragile liquidity when investor sentiment is pessimistic.

Overall, my paper presents evidence supportive of the role of investor sentiment as an important driving force in the amplification of the liquidity spirals. Pessimistic sentiment not only increases the demand for liquidity by amplifying mutual fund outflows, but also reduces the supply of liquidity by increasing the cost to provide liquidity.

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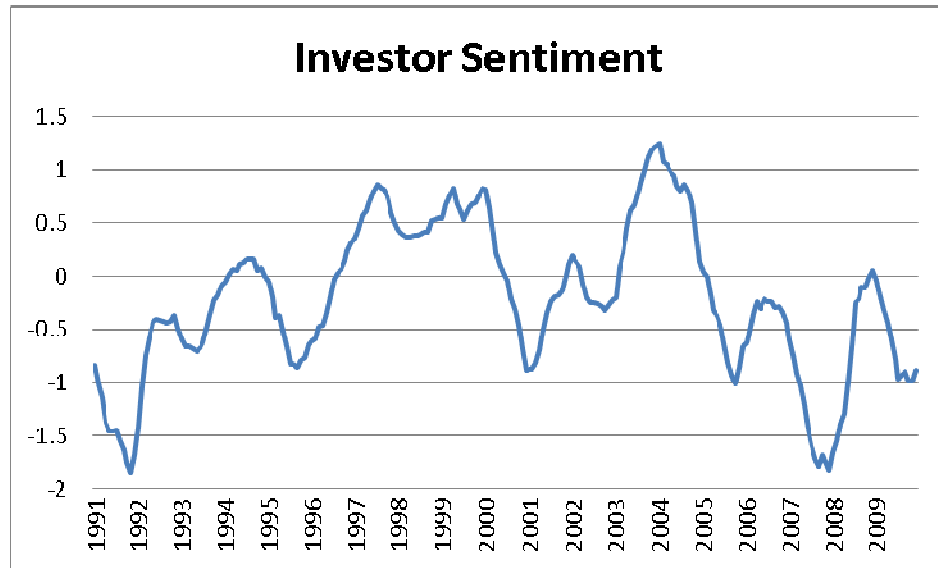


Figure 1 Time Series of Investor Sentiment

The Investor Sentiment Index is the residual from the regression of the University of Michigan Consumer Sentiment Index on a set of macroeconomics variables. The measure is standardized to have mean 0 and standard deviation 1. The sample period is from 1991 -2009.

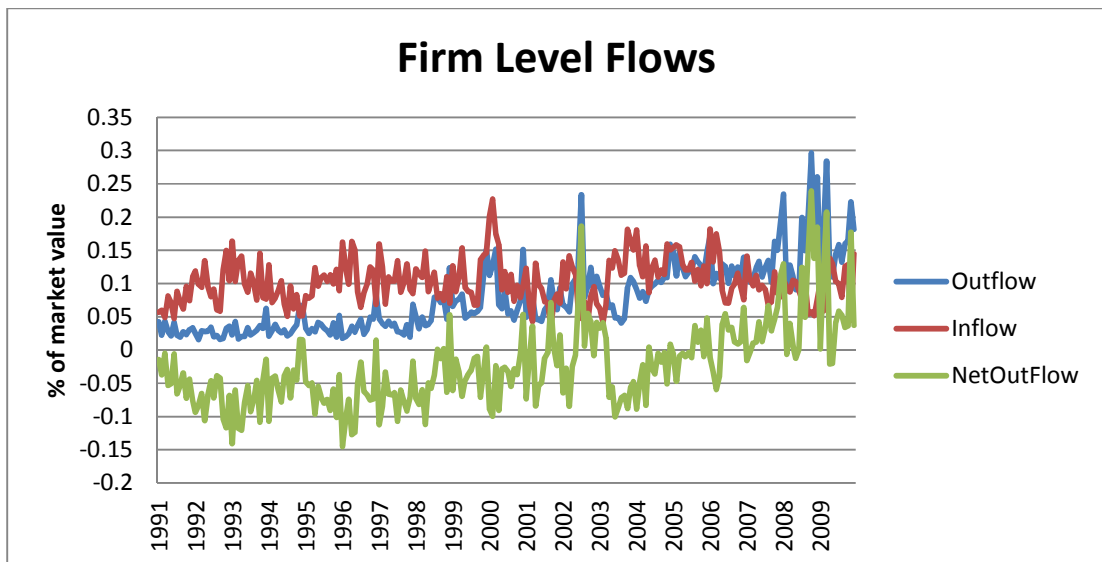


Figure 2 Time Series of Firm Level Mutual Fund Flows

The series are the equal-weighted average of the three variables for all stocks held by mutual funds. *OutFlow*, *InFlow* and *NetOutFlow* are as constructed in section II. C.

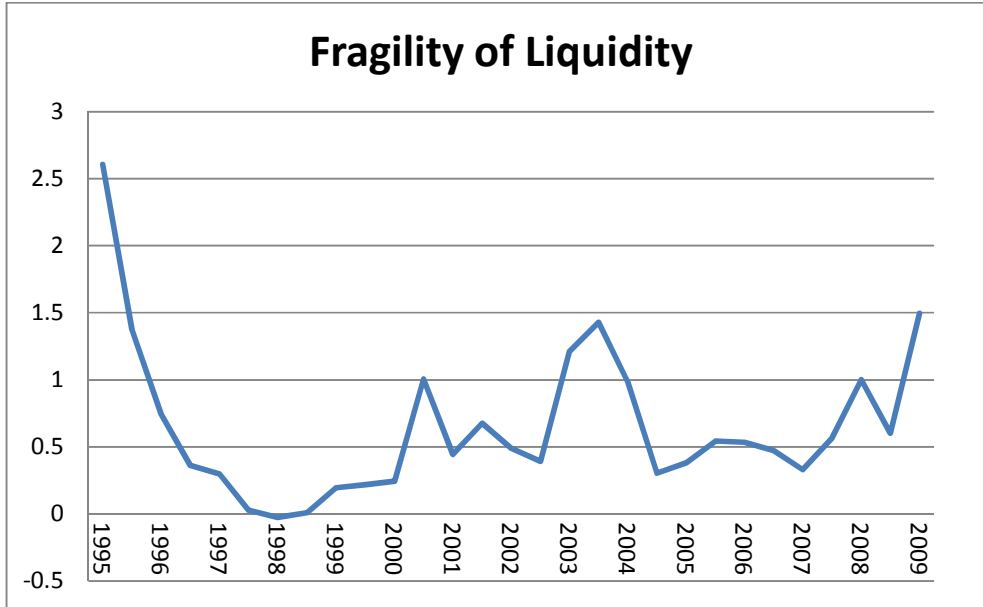


Figure 3 Time Series of Fragility of Liquidity from Baseline VAR model

The fragility of liquidity is the equal-weighted average coefficients β_{32}^i from the benchmark VAR model with exogenous factors.

Table 1: Summary Statistics

This table reports summary statistics for the sample of mutual funds and stocks used in this paper. Panel A reports the summary statistics of Mutual Funds. The number of distinct mutual funds in the sample is 5533. TNA is the total net asset. Net return is the monthly mutual fund return after fund expenses. Panel B reports the summary statistics of the stock sample. The number of stocks is 4429. Return is the monthly stock return, Amihud illiquidity is the log transformation of monthly Amihud illiquidity measure times 10^6 . Bid-Ask spread is the month end Bid-Ask Spread scaled by month end stock price. OutFlow, InFlow and NetOutFlow are as constructed in section II. C. The sample period is from 1991 to 2009.

Variable	Mean	Median	StdDev	P5	P95
Panel A: Funds					
Total Net Assets (\$ millions)	914.26	121.10	4571.64	3.30	3286.23
Net Return (% per month)	0.65	0.92	5.38	-8.23	8.32
Avg. flow/TNA (% per month)	1.67	-0.02	12.65	-5.79	13.82
Panel B: Stocks					
Return (% per month)	0.85	0.35	14.05	-21.31	23.91
OutFlow (%)	0.08	0.04	0.12	0.00	0.33
InFlow (%)	0.12	0.06	0.25	0.00	0.41
NetOutFlow(%)	-0.02	-0.00	0.43	-0.30	0.20
Amihud Illiquidity	0.819	0.040	3.428	0.0003	4.134
Bid-Ask Spread	0.025	0.013	0.042	0.000	0.088

Table 2 Baseline VAR Estimation

The table shows the unrestricted estimates for the first-order VAR model.

$$\begin{bmatrix} R_{i,t} \\ OutFlow_{i,t} \\ Illiq_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_i^1 \\ \alpha_i^2 \\ \alpha_i^3 \end{bmatrix} + \begin{bmatrix} \beta_{11}^i & \beta_{12}^i & \beta_{13}^i \\ \beta_{21}^i & \beta_{22}^i & \beta_{23}^i \\ \beta_{31}^i & \beta_{32}^i & \beta_{33}^i \end{bmatrix} \begin{bmatrix} R_{i,t-1} \\ OutFlow_{i,t-1} \\ Illiq_{i,t} \end{bmatrix} + \begin{bmatrix} \epsilon_i^1 \\ \epsilon_i^2 \\ \epsilon_i^3 \end{bmatrix}$$

I estimate the VAR model using the 5-year window rolled forward every 6 months. $R_{i,t}$ is the monthly stock return, $Illiq_{i,t}$ is the log transformation of monthly Amihud illiquidity measure times 10^6 , $OutFlow_{i,t}$ is constructed as

$$OutFlow_{i,t} = \sum_k \frac{[TNA_t^k - TNA_{t-1}^k(1+R_t^k) - MGN_t^k] * D(FundFlow_t^k < 0)}{TNA_{t-1}^k} * \frac{Holding_{i,t}^k}{Shout_{i,t}}$$

Where TNA_t^k and R_t^k are the total net asset and monthly return of mutual fund k, respectively. MGN_t^k is the increase in total net assets due to mergers. $Holding_{i,t}^k$ is the most recent reported number of shares of stock i hold by mutual fund k and $Shout_{i,t}$ is a stock 's number of shares outstanding. $D(FundFlow_t^k < 0)$ is a dummy variable with the value of one when

$$FundFlow_t^k = TNA_t^k - TNA_{t-1}^k(1 + R_t^k) - MGN_t^k < 0 \text{ and zero otherwise.}$$

The table reports the cross section average (t -statistics) of time series mean. T-statistics (in parentheses) corresponding to the standard error of the mean. In Panel B, the TED spread and market average returns are added as exogenous factors. In Panel C reports the results excluding the time period 2007-2009. The sample period is from 1991 to 2009. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and*, respectively.

Panel A Benchmark VAR model						
	Return	OutFlow	Illiquidity			R ²
Return Equation	-0.036***	-0.044***	3.320***			0.10
(<i>t</i> -statistics)	(-27.30)	(-10.16)	(42.67)			
OutFlow Equation	-0.009***	0.645***	3.311***			0.27
(<i>t</i> -statistics)	(-11.14)	(329.31)	(36.85)			
Illiquidity Equation	-0.093***	1.177***	0.789***			0.46
(<i>t</i> -statistics)	(-27.39)	(41.11)	(676.38)			
Panel B Benchmark VAR model with exogenous factors						
	Return	OutFlow	Illiquidity	TED Spread	Market Return	R ²
Return Equation	-0.048***	-0.020	5.449***	-0.016***	0.976***	0.25
(<i>t</i> -statistics)	(-24.22)	(-1.50)	(19.62)	(-15.81)	(94.11)	
OutFlow Equation	-0.018***	0.389***	3.877***	0.084***	-0.031***	0.30
(<i>t</i> -statistics)	(-9.76)	(113.06)	(13.77)	(63.80)	(-4.14)	
Illiquidity Equation	-0.214***	1.572***	0.649***	0.408***	-0.366***	0.45
(<i>t</i> -statistics)	(-10.46)	(4.21)	(222.19)	(13.19)	(-3.19)	
Panel C Excluding 2007-2009						
	Return	OutFlow	Illiquidity	TED Spread	Market Return	R ²
Return Equation	-0.047***	-0.017**	4.658***	-0.016***	0.910***	0.24
(<i>t</i> -statistics)	(-22.65)	(-2.35)	(20.96)	(-15.05)	(89.33)	
OutFlow Equation	-0.015***	0.384***	2.015***	0.086***	-0.098***	0.28
(<i>t</i> -statistics)	(-9.11)	(107.52)	(15.92)	(61.57)	(-19.14)	
Illiquidity Equation	-0.175***	0.588***	0.642***	0.319***	-0.399***	0.43
(<i>t</i> -statistics)	(-14.71)	(9.99)	(220.14)	(21.13)	(-10.17)	

Table 3 VAR Estimation with Sentiment Index

In this table, I interact the three endogenous variables with the sentiment index.

$$Y = \alpha + \beta \times Y_{t-1} + \gamma \times NegSent_{t-1} + \mu \times NegSent_{t-1} \times Y_{t-1}$$

Where $Y = \{R, OutFlow, Illiq\}$. The TED spread and market average returns are added as exogenous factors. The tables report the cross section average (t -statistics) of time series mean. T-statistics (in parentheses) corresponding to the standard error of the mean.

$NegSent_{t-1}$ is the sentiment index multiplied by -1. The index is standardized to have mean 0 and standard deviation 1. The sample period is from 1991 -2009. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and*, respectively.

	Return	OutFlow	Illiquidity	$NegSent$	Return* $NegSent$	OutFlow * $NegSent$	Illiquidity* $NegSent$	TED Spread	Market Return	R ²
Return Equation	-0.066***	-0.056***	5.518***	-0.003***	0.005*	0.021	-0.053	-0.016***	0.979***	0.34
<i>(t-statistics)</i>	(-30.63)	(-5.71)	(22.46)	(-3.73)	(1.82)	(1.35)	(-0.18)	(-15.31)	(95.98)	
OutFlow Equation	-0.016***	0.376***	3.966***	0.002***	0.008***	-0.009*	5.572***	0.085***	-0.060***	0.38
<i>(t-statistics)</i>	(-8.75)	(100.68)	(21.30)	(3.90)	(3.40)	(-1.75)	(25.36)	(67.31)	(-11.15)	
Illiquidity Equation	-0.126***	0.638***	0.655***	0.038***	-0.063***	1.059***	-0.057***	0.286***	-0.373***	0.52
<i>(t-statistics)</i>	(-11.94)	(10.21)	(207.64)	(11.75)	(-4.69)	(15.23)	(-13.32)	(21.76)	(-10.05)	

Table 4 Inflow, Illiquidity and Sentiment

In this table, I estimate the VAR specifications in table3, replacing $OutFlow_{i,t}$ with $InFlow_{i,t}$. $InFlow_{i,t}$ is constructed as

$$InFlow_{i,t} = \sum_k \frac{|TNA_t^k - TNA_{t-1}^k(1+R_t^k) - MGN_t^k| * D(>0)}{TNA_{t-1}^k} * \frac{Holding_{i,t}^k}{Shout_{i,t}}$$

Where TNA_t^k and R_t^k are the total net asset and monthly return of mutual fund k, respectively. MGN_t^k is the increase in total net assets due to mergers. $Holding_{i,t}^k$ is the most recent reported number of shares of stock i hold by mutual fund k and $Shout_{i,t}$ is a stock's number of shares outstanding. $D(FundFlow_t^k > 0)$ is a dummy variable with the value of one when $FundFlow_t^k = TNA_t^k - TNA_{t-1}^k(1 + R_t^k) - MGN_t^k > 0$ and zero otherwise.

The sentiment index is multiplied by -1 and standardized to have mean 0 and standard deviation 1. The sample period is from 1991 - 2009. T statistics (in parentheses) corresponding to the standard error of the mean. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and*, respectively.

Equation	Return	InFlow	Illiquidity	<i>NegSent</i>	Return* <i>NegSent</i>	InFlow * <i>NegSent</i>	Illiquidity* <i>NegSent</i>	TED Spread	Market Return	R ²
Return	-0.040***	0.024***	1.752***	0.002***	-0.013***	-0.010***	-0.196***	-0.014***	0.960***	0.34
(t-statistics)	(-19.91)	(11.41)	(23.24)	(5.08)	(-6.29)	(-3.34)	(-3.26)	(-19.71)	(98.58)	
InFlow	0.052***	0.626***	2.208***	-0.003***	-0.005***	0.028***	-0.719***	0.051***	0.450***	0.39
(t-statistics)	(26.75)	(172.05)	(21.29)	(-5.11)	(-2.61)	(7.84)	(-11.13)	(54.18)	(62.36)	
Illiquidity	-0.112***	0.014***	0.739***	0.022***	-0.024***	-0.051***	-0.081***	0.108***	-0.134***	0.52
(t-statistics)	(-16.81)	(2.89)	(205.14)	(12.68)	(-5.73)	(-7.39)	(-18.75)	(21.67)	(-9.49)	

Table 5, Sentiment Orthogonal to Macroeconomic Conditions, and VIX

In this table, I estimate the VAR specifications in table3 with the sentiment orthogonalized to VIX. I regress the University of Michigan Consumer Sentiment index on VIX and a set of macroeconomics variables described in section II. A. I use the residuals from this regression as the sentiment proxy.

The sentiment index is multiplied by -1 and standardized to have mean 0 and standard deviation 1. The sample period is from 1991 - 2009. T statistics (in parentheses) corresponding to the standard error of the mean. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and*, respectively.

	Return	OutFlow	Illiquidity	<i>NegSent</i>	Return* <i>NegSent</i>	OutFlow * <i>NegSent</i>	Illiquidity* <i>NegSent</i>	TED Spread	Market Return	R ²
Return Equation	-0.062***	-0.022**	5.020***	0.000	-0.020***	0.038***	0.102	-0.016***	0.965***	0.34
<i>(t-statistics)</i>	(-30.43)	(-2.44)	(21.70)	(0.37)	(-8.62)	(3.01)	(0.40)	(-15.97)	(95.84)	
OutFlow Equation	-0.012***	0.360***	4.691***	-0.002***	0.005**	-0.028***	0.352**	0.085***	-0.054***	0.38
<i>(t-statistics)</i>	(-7.31)	(104.16)	(22.03)	(-5.45)	(2.43)	(-7.11)	(2.24)	(68.54)	(-9.80)	
Illiquidity Equation	-0.158***	0.595***	0.656***	0.023***	-0.029**	0.777***	-0.038***	0.295***	-0.306***	0.52
<i>(t-statistics)</i>	(-13.90)	(9.63)	(210.66)	(8.38)	(-2.51)	(14.55)	(-10.74)	(21.59)	(-8.58)	

Table 6 Alternative Investor Sentiment Index

In this table, I estimate the VAR specifications in table3 with the monthly sentiment index constructed by Baker and Wurgler (2007), using trading volume (measured as total NYSE turnover), dividend premium, closed-end fund discount, number and first day returns in IPO's, and the equity share in new issues. Because these variables are partly related to economic fundamentals, Baker and Wurgler regress each proxy against growth in industrial production, real growth in durable, non-durable, and services consumption, growth in employment, and an NBER recession indicator, and use the residuals from this regression as the sentiment proxies. The overall sentiment index is the first principal component of the six sentiment proxies. The sentiment index is standardized to have mean 0 and standard deviation 1 and multiplied by -1.

	Return	OutFlow	Illiquidity	<i>NegSent</i>	Return* <i>NegSent</i>	OutFlow * <i>NegSent</i>	Illiquidity* <i>NegSent</i>	TED	Market Return	R ²
Return Equation <i>(t-statistics)</i>	-0.063*** (-23.04)	-0.037*** (-2.68)	5.101*** (18.12)	-0.000 (-0.11)	0.023*** (5.07)	-0.070*** (-2.62)	-2.315*** (-5.97)	-0.020*** (-16.41)	0.932*** (90.77)	0.33
OutFlow Equation <i>(t-statistics)</i>	-0.009*** (-4.32)	0.385*** (84.54)	3.785*** (19.96)	0.011*** (14.89)	0.001 (0.26)	-0.041*** (-5.33)	5.662*** (23.57)	0.082*** (58.06)	-0.103*** (-19.84)	0.36
Illiquidity Equation <i>(t-statistics)</i>	-0.118*** (-8.85)	0.795*** (9.91)	0.658*** (148.68)	0.088*** (12.42)	-0.050** (-2.18)	1.649*** (16.01)	-0.119*** (-15.32)	0.216*** (19.24)	-0.300*** (-7.90)	0.52

Table 7 Alternative Illiquidity Proxy

In this table, I estimate the VAR specifications in table3 using the proportional bid-ask spread (as a proportion of the stock's price) as the measures of liquidity.

NegSent is the University of Michigan Sentiment Index (orthogonal to macroeconomic conditions) multiplied by -1. The index is standardized to have mean 0 and standard deviation 1. The sample period is from 1991 -2009. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and*, respectively.

Equation	Return	OutFlow	Illiquidity	<i>NegSent</i>	Return* <i>NegSent</i>	OutFlow * <i>NegSent</i>	Illiquidity* <i>NegSent</i>	TED Spread	Market Return	R ²
Return	-0.060***	-0.041***	0.117***	-0.003***	0.001	0.057***	-0.042***	-0.010***	1.043***	0.35
<i>(t-statistics)</i>	(-24.71)	(-4.71)	(16.77)	(-3.81)	(0.44)	(4.54)	(-4.56)	(-7.91)	(94.18)	
OutFlow	-0.011***	0.405***	0.183***	0.004***	0.009***	-0.019***	0.056***	0.099***	-0.025***	0.39
<i>(t-statistics)</i>	(-4.60)	(91.14)	(19.61)	(5.88)	(3.35)	(-3.63)	(8.61)	(59.79)	(-3.82)	
Illiquidity	-0.004*	0.148***	0.467***	0.006***	0.004	0.083***	-0.017***	0.101***	-0.078***	0.34
<i>(t-statistics)</i>	(-1.82)	(15.02)	(107.70)	(6.61)	(1.11)	(8.02)	(-3.34)	(46.81)	(-11.49)	

Table 8 Characteristics of Stocks with Fragile Liquidity

This table shows the characteristics of stocks for fragility-sorted portfolios. The fragility of liquidity is the coefficients β_{32}^i from the benchmark VAR model. Number of Analyst is the number of analysts making a forecast for the firm's earnings, obtained from the I/B/E/S Summary File. Earning Surprise is the difference between realized quarterly EPS and the median forecast of quarterly EPS from I/B/E/S Summary File, divided by the stock price at the end of the final month of the fiscal quarter for which earnings is being forecast.

Stocks are sorted into portfolios based on June or December fragility. T-statistics (in parentheses) corresponding to the standard error of the mean. The sample period is from 1991 to 2009. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and*, respectively.

	Fragility Quintile:					
	Low	2nd Quintile	Middle	4th Quintile	High	High - Low
Fragility	-0.0471 (-4.16)	0.0047 (5.96)	0.0267 (5.23)	0.1686 (5.37)	5.4336 (10.41)	5.4807*** (10.4)
Book-to-market	0.4794 (66.64)	0.5109 (47.8)	0.5691 (48.94)	0.6164 (38.88)	0.7547 (30.94)	0.2753*** (13.2)
Volatility	0.0265 (34.06)	0.0257 (29.16)	0.0284 (32.69)	0.0311 (36.26)	0.0331 (40.49)	0.0067*** (21.94)
Institutional Ownership	0.6118 (31.94)	0.6383 (34.2)	0.5761 (28.62)	0.4803 (30.43)	0.3313 (48.29)	-0.2805*** (-18.91)
Number of institutions	180.5079 (42.7)	142.7291 (35.42)	90.5702 (21.65)	57.2474 (20.34)	28.7812 (25.27)	-151.7267*** (-35.61)
Mutual Fund ownership	0.1255 (16.56)	0.1266 (15.25)	0.1113 (14.1)	0.0892 (18.22)	0.0669 (27.68)	-0.0586*** (-9.44)
Size (\$ bill)	4.2738 (19.72)	2.2036 (29.91)	0.8937 (27.58)	0.4387 (30.14)	0.1913 (28.7)	-4.0825*** (-18.84)
Number of Analyst	6.2977 (62.17)	5.1797 (90.64)	3.6179 (44.5)	2.6030 (39.72)	1.8036 (63.89)	-4.4941*** (-38)
Earning Surprise	0.0003 (4.32)	0.0003 (4.68)	0.0000 (0.14)	-0.0002 (-1.62)	-0.0008 (-6.04)	-0.0011*** (-11.56)

Table 9 Contrarian Profits and Investor Sentiment

Monthly stock returns are sorted into winner (loser) portfolios if the returns are above (below) the median of all positive (negative) returns in month t . Contrarian portfolio weight for stock i in month t is given by:

$$\omega_{p,it} = (R_{i,t-1}Turn_{i,t-1}) / \sum_{i=1}^{Np} R_{i,t-1}Turn_{i,t-1}$$

where $R_{i,t}$ and $Turn_{i,t}$ are stock i 's return and turnover in month t .

The contrarian profits for the loser and winner portfolios for month $t+k$ are:

$$\pi_{p,t+k} = \sum_{i=1}^{Np} \omega_{i,p,t+1} R_{i,t+k}$$

Panel A reports the unconditional contrarian profits for month $t+k$, for $k=1$ and 2. Panel B reports the contrarian profits conditional on investor sentiment. Pessimistic (Optimistic) refers to sentiment index of the portfolio formation month being below (above) zero. Panel C reports the contrarian profits for month $t+1$ conditional on investor sentiment and the market return. Down (Up) market is defined as the market returns over the previous month less (greater) than its sample mean. Newey-West autocorrelation-corrected t -statistics are given in parentheses. Sample period is 1991-2009. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Panel A Unconditional Contrarian Profits				
Portfolio	Month			
	t+1		t+2	
Loser	1.19%		0.23%	
Winner	-0.75%		0.13%	
Loser minus Winner	1.93%***		0.10%	
(<i>t</i> -statistics)	(3.81)		(0.22)	
Panel B Contrarian Profits Conditional on Investor Sentiment				
Portfolio	Pessimistic		Optimistic	
Loser	2.92%		-0.73%	
Winner	0.07%		-1.67%	
Loser minus Winner	2.84%***		0.94%	
(<i>t</i> -statistics)	(3.87)		(1.35)	
Panel C Contrarian Profits Conditional on Investor Sentiment and Market Returns				
Portfolio	Pessimistic	Optimistic	Pessimistic	Optimistic
	Down market		Up market	
Loser	3.66%	-1.20%	2.18%	-0.35%
Winner	0.04%	-2.35%	0.11%	-1.11%
Loser minus Winner	3.62%***	1.15%	2.07%**	0.77%
(<i>t</i> -statistics)	(3.67)	(0.98)	(1.90)	(0.93)

Table 10 Contrarian Profits based on Fragility of Liquidity and Investor Sentiment

Sample stocks are independently ranked into terciles based on Fragility of Liquidity measured as β_{32} from benchmark VAR estimation. Monthly stock returns are sorted into winner (loser) portfolios if the returns are above (below) the median of all positive (negative) returns for each tercile portfolio of fragility of liquidity in month t .

Contrarian portfolio weight for stock i in month t is given by:

$$\omega_{p,it} = (R_{i,t-1}Turn_{i,t-1}) / \sum_{i=1}^{Np} R_{i,t-1}Turn_{i,t-1}$$

where $R_{i,t}$ and $Turn_{i,t}$ are stock i 's return and turnover in month t .

The contrarian profits for the loser and winner portfolios for month $t+k$ are:

$$\pi_{p,t+k} = \sum_{i=1}^{Np} \omega_{i,p,t+1} R_{i,t+k}$$

The table shows the contrarian profits conditional on investor sentiment for each fragility tercile. Pessimistic (Optimistic) refers to sentiment index of the portfolio formation month being below (above) zero. Newey-West autocorrelation-corrected t -statistics are given in parentheses. Sample period 1991-2009. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Sentiment	Fragility Terciles		
	Terciles 1	Terciles 2	Terciles 3
Pessimistic	0.02%	1.90%	2.85%**
(<i>t</i> -statistics)	(0.02)	(1.22)	(2.51)
Optimistic	-0.99%	0.16%	0.30%
(<i>t</i> -statistics)	(-0.84)	(0.21)	(0.32)