The asymmetric sentiment effect on equity liquidity and investor trading behavior in the subprime crisis period: Evidence from the ETF Market

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ABSTRACT

Using index and financial exchange-traded funds (ETFs), this study explores whether the asymmetric sentiment effect on equity liquidity and investor trading behavior exists during the subprime crisis period. Our results show that in the bearish sentiment period, sentiment has a more significant impact on proportional quoted spread, market depth, asymmetric depth and net buying pressure. We also find that funding constraint problem play an important role in the asymmetric sentiment effect on equity liquidity and investor trading behavior. Our study provides a better overall understand of the demand side liquidity effect during the subprime crisis period.

Keywords: Asymmetric sentiment; Equity liquidity; Net buying pressure; Subprime crisis; Funding constraint

JEL Classification: G10; G11; G14

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1. Introduction

This paper examines the demand side liquidity (sentiment) effect on equity liquidity in subprime crisis period, because noise traders play an important role in liquidity, particularly for riskier assets (Black, 1986; Trueman, 1988). From the theoretical perspective, De Long, Shleifer, Summers, and Waldmann (1990) (DSSW, hereafter) argue that investor sentiment measure serves as a proxy signal for expectations of future market movements and leads to noise traders' trading decisions that are not fully justified by fundamental news and deviates price from fundamental value. Baker and Stein (2004) find that when the investor sentiment is bearish, the short-sale constraint plays an important role to keep noise traders out of the market, leading to a decrease in equity liquidity. At a subsequent date, informed traders and arbitrageurs will submit buy order to provide liquidity into market. Thus, bearish (bullish) sentiment leads to decrease (increase) equity liquidity.

However, if informed traders and arbitrageurs exhibit funding constraint problem in the bearish sentiment period, they could fails to correct mispricing and submit buy order to provide liquidity into market. They become liquidity demanders to liquidate their holding positions and thereby further decreasing equity liquidity. We thus expect that in the bearish sentiment period, investor sentiment could decrease equity liquidity more significantly when investors face funding constraint problem. Prior sentiment related literature does not incorporate funding constraint problem in the analysis. Our study thus provides a better overall understanding of the demand side liquidity effect during the subprime crisis period.

The funding constraint problem on liquidity suppliers gets more attention within the recent literature. Kyle and Xiong (2001), Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) all argue from a theoretical model that when arbitrageurs faced funding constraints, they could change from liquidity supplier to

demanders and liquidate the positions in risky assets to establish funding inflows. Therefore, the price wedge further widens and equity liquidity decreases. Using negative market return to proxy investor funding constraint problem, Hameed, Kang, and Viswanathan (2010) explore the effect of funding constraint on equity liquidity. Their empirical results show that a large negative market return is related to the tightness of funding liquidity and lead to a reduction in the level of liquidity provision and thereby decreasing equity liquidity. Karolyi, Lee and Dijk (2012) examine how commonality in liquidity varies in ways related to supply determinants (funding liquidity) and demand determinants (correlated trading and investor sentiment). Their results show that demand-side explanations for commonality are more reliable.

This study examines how investor sentiment affects equity liquidity and investor trading behavior in subprime crisis period using index and financial exchange-traded funds (ETFs). The extreme variations in sentiment and equity liquidity that are evident during the subprime crisis period provide a valuable opportunity to examine the ways in which investor sentiment affect equity liquidity. We further explore whether bearish and bullish sentiment affects equity liquidity and trading behavior equally. In addition, we follow Hameed, Kang, and Viswanathan (2010) using negative market return to proxy investor funding constraint problem, we then explore whether funding constraint problem could affect the relation between investor sentiment and equity liquidity.

Our study seeks to answer the following research question. First, we examine whether bearish sentiment could increase net selling pressure and illiquidity problem in subprime crisis period. Hameed, Kang, and Viswanathan (2010) argue that panic selling by investor sentiment affects equity illiquidity. However, Hameed et al. (2010) only explore the relation between investor funding constraint and equity liquidity. There are only few empirical studies focusing on whether the bearish sentiment leads to a decrease in equity liquidity and an increase in net selling pressure and on whether

bullish and bearish sentiment have a negative or positive effect on liquidity, especially for the subprime crisis period.

Second, we explore whether there is an asymmetric sentiment effect on equity liquidity and investor trading behavior in the subprime crisis period. Kaplanski and Levy (2010), Chen (2011) and Akhtar et al. (2011) all find that bearish sentiment has more sensitive than bullish sentiment on stock market return. We are interesting in whether bearish sentiment leads to increase equity illiquidity and net selling pressure more significantly than bullish sentiment. In addition, we include funding constraint problem in our analysis and examine whether bearish sentiment increase illiquidity and net selling problem more significantly when investors face funding constraint problem in the subprime crisis period.

Third, prior studies have explored the impact of sentiment measures on various securities such as ADRs (Grossmann et al., 2007), closed-end funds (Bodurtha et al., 1995; Brown, 1999), index futures (Kurov, 2008), U.S. individual stocks (Brown and Cliff, 2004; Lee et al., 2002; Baker and Wurgler, 2006) and 18 industrialized countries individual stocks (Schmeling, 2009). We contribute to this literature by exploring the sentiment effect on equity liquidity and investor trading behavior in the more liquid Index ETF markets. In addition, ETFs allow investors to replicate the equity market index. They are more suitable for our direct sentiment measure, which is an aggregative expectation of future market movements.

Fourth, following Lee, Mccklow, and Ready (1993), we measure equity liquidity including price (the spread) and quantity dimensions (the market depth). We also measure investor trading behavior using net buying volume and asymmetric depth. We could capture how sentiment affects investor trading direction not only from the volume dimension but also from the limit order dimension. In this way, our research is more complete than previous empirical studies. In addition, most previous studies have

used lower frequency data. The use of lower frequency data may not permit detection of how investor sentiment affects liquidity and trading behavior if it occurs for relatively short time periods and is masked by the aggregate nature of the data. The higher frequency intra-day data used in our study allows us to draw more precise inferences.

Our main empirical findings are summarized as follows. First, we find that bullish (bearish) investor sentiment leads to a decrease (increase) in proportional quoted spread and increase (decrease) in market depth, thereby improving (decreasing) equity liquidity. These results provide support the theoretical models of Baker and Stein (2004). Second, we also find that, in general, a higher bullish sentiment increases net buying pressure and asymmetric depth, indicating that a higher bullish sentiment leads to increase limit buy orders and buyer trading volume. Third, we also find the asymmetric sentiment effect on equity liquidity and investor trading behavior, indicating that bearish sentiment has a more significant impact on proportional quoted spread, market depth, asymmetric depth and net buying pressure relative to bullish sentiment.

Finally, we examine whether funding constraint problem plays a role on how bullish and bearish sentiment and equity liquidity. Our results suggest that when most investors expect future returns to be more bearish than bullish in market decline periods, investor sentiment affects bid-ask spread, market depth, asymmetric depth, and net buying pressure more significantly. These results also imply that in the bearish sentiment period, short-sale constraint causes noise traders out of market and decrease equity liquidity. When arbitrageurs could face funding constraint problem in the market decline period, they could become liquidity demander to sell off their holding positions and thereby further widening the price wedge and decreasing equity liquidity. In addition, most of financial ETFs yield more sensitivity than index ETFs, since

financial industry has a more direct impact relative to other industry in the subprime crisis period.

The remainder of this paper is organized as follows. Section 2 develops our research hypothesis. Section 3 describes the sample selection procedure and research method. Section 4 reports and analyzes the empirical results. Finally, the conclusions of this study are presented in Section 5.

2. Hypothesis development

DSSW (1990) argue from the theoretical perspective that noise traders acting in concert on non-fundamental signals, that is so called sentiment, can create a systematic risk. Since noise trading causes deviations in price from fundamental value created by investor sentiment, arbitrage is facing risky and rational traders choose not to fully restore prices to their fundamentals-based levels. Thus, potential loss and risk aversion may reduce arbitrageurs' holding positions. Consequently, arbitrage fails to eliminate mispricing in the short run, and investor sentiment affects security prices in equilibrium as well as causing risk.

Baker and Stein (2004) further propose a theoretical model that links investor sentiment and market liquidity. They argue that when the noise traders, who are irrational investors, receive signals about future cash flows, the short-sales constraint could lead them to be active in the market during a period of positive sentiment (bullish sentiment), and the market thus becomes overvalued. However, when the noise traders have a negative sentiment (bearish sentiment), the short-sales constraint keeps them out of the market altogether. There is a positive relationship between investor sentiment and equity liquidity.

Hypothesis 1: *Bearish (Bullish) sentiment leads to decrease (increase) equity*

liquidity and net buying trading behavior.

Prior psychology studies have explored the psychological bias of negativity (Kanouse and Hanson, 1971; Peeters, 1971, Beach and Strom, 1989). The negative effect can be defined as a situation in which there is a greater impact of negative versus positive stimuli on a subject (Peeters and Czapiński, 1990). In addition, Akhtar et al. (2011) also argue two possible phenomena to explain the asymmetric sentiment effect. First, investors could give more weight to potential costs than to potential gains in trading decisions, from the standpoint of prospect theory (Kahneman and Tversky, 1979). Second, negative information is weighted more heavily than positive information in the formation of the overall evaluation.

We extend theory of DSSW (1990) and Baker et al. (2004) and argue that when there is higher bullish sentiment in a market, noise traders could overestimate the relative precision of their own signals over the trading behavior of others and buy more positions in their portfolio. Arbitrageurs could sell part of their position to meet a profit, thereby increasing equity liquidity and net buying volume. However, when bearish sentiment dominates market expectations, noise traders tend to buy fewer stocks or close out their existing long positions. The psychological bias of negativity and short-sale constraint could both lead noise traders out of market altogether. In addition, potential loss and the risk aversion could cause arbitrageurs to withdraw from buying positions to correct mispricing and providing liquidity in the extreme variation crisis period. Bearish sentiment thus leads to significantly decrease equity liquidity and net buying volume.

Hypothesis 2: *Bearish sentiment affects equity liquidity and investor trading behavior more significantly relative to bullish sentiment.*

The prior results assume that stock market conditions do not affect investor sentiment. We relax this assumption and argue for the following hypothesis. When bearish sentiment dominates the market, short-sale constraint and limit to arbitrage could cause arbitrageurs to withdraw from buying positions to correct mispricing and provide liquidity. If securities prices decline below their fundamental values during a market decline period, position huge loss and the risk aversion could cause arbitrageurs to face funding constraint (Kyle and Xiong, 2001). This induces arbitrageurs to become liquidity demanders as they liquidate their position in risky assets to obtain funding inflows, further widening the price wedge, and decreasing equity liquidity and net buying volume significantly. We thus expect that bearish sentiment affects equity liquidity and investor trading behavior more significantly in market declines period.

Hypothesis 3: *when the most investors expect future returns to be more bearish than bullish during market decline periods, investor sentiment affects equity liquidity and investor trading behavior more significantly*.

3. Data source and research methodology

3.1 Data source and sample selection

In this study uses index and financial ETFs to explore how the investor sentiment affects equity liquidity and investor trading behavior in the subprime crisis period. For our empirical examination of index ETFs, we select those funds tracking the S&P 500 Index (SPY) and those funds tracking the NASDAQ 100 Index (QQQQ). We also examine 10 financial ETFs, the average daily trading volume of which must be higher than 14,000 units from January 1, 2007 to December 31, 2008, and then divide them

into four groups.[1] In the broad U.S. financial sector group, we include the financial select sector SPDR (XLF) and iShares Dow Jones US financial sector (IYF). Their underlying index includes broad financial business in the United States, such as commercial and investment banking, capital markets, diversified financial services, insurance, and real estate. In the banking group, we consider the KBW bank ETF (KBE) and KBW regional banking ETF (KRE). Thus, the underlying index includes national money center banks and regional banking institutions listed on the U.S. stock markets.

In the brokerage and asset management group, we consider iShares Dow Jones U.S. broker-dealers (IAI) and KBW capital markets ETF. The underlying index includes securities brokers and dealers, online brokers, asset managers, and securities or commodities exchanges. Finally, for the insurance group, the underlying index consists of personal and commercial lines, property/casualty, life insurance, reinsurance, brokerage, and financial guarantees.

In this study, we employ intra-day data on ETFs taken from the TAQ and use daily abstract trading and quotes data from 9:30 am to 4:00 pm. We follow the previous literature on controlling for different trading mechanisms and include all the data in the AMEX, NYSE, NASDAQ and NYSE Arca (Archipelago) exchanges in our samples. The period under examination is the post-decimalization period which runs from 1 January 2007 to 31 December 2008; this period contains the dotcom bubble industry cycle as well as the sub-prime mortgage crisis period.

Finally, following Chung and Zhao (2003) and Chung (2006), we eliminate all quotes falling under the following three criteria: (i) where either the bid or the ask price is equal to or less than zero, (ii) where either the bid or the ask depth is equal to

[1] We divide the financial ETFs into four groups (broad financial sector, banking, brokerage and asset management, and insurance). The details on our research samples are provided in the Appendix.

or less than zero, and (iii) where either the price or volume is equal to or less than zero. Furthermore, we follow Huang and Stoll (1996) who delete quoting and trading data with the following characteristics: (i) all quotes with a negative bid-ask spread or a bid-ask spread of greater than US$5, (ii) all trades and quotes which are either before-the-open or after-the-close, (iii) all trade prices, P_t, where: $|(P_t - P_{t-1}) / P_{t-1}|>0.1$, (iv) all ask quotes, a_t, where: $|(a_t - a_{t-1}) / a_{t-1}|>0.1$, and (v) all bid quotes, b_t, where: $|(b_t - b_{t-1}) / b_{t-1}|>0.1$.

3.2 Measures of investor sentiment

Using direct measures of investor sentiment, II and AAII, are proxy for the noise trader presence.[2] Following Brown and Cliff (2004), we collect direct measures of bearish and bullish sentiment from the Investor Intelligence (II) and American Association of Individual Investors (AAII). The II is collected by categorizing approximately 150 market newsletters each week. Following the reading of the newsletters, the market is classified as bullish, bearish, or neutral based on the expectations of future market movements. The AAII is released by the American Association, a non-profit organization, which asks each individual investor where they expect the stock market will be in six months, and the results are classified as bullish, bearish, or neutral.

In the present study, we follow Wang et al. (2006) to adopt the ratio of the bearish percentage to the bullish percentage as our measures of investor sentiment; when they are higher (lower), market investors demonstrate more bearish (bullish) sentiment. Since the AAII and II sentiment indicators are all weekly-based, in order to resolve this data frequency problem, we adopt the method whereby each trading day of a week has

[2] Examples in the literature on the II and AAII sentiment index include Solt and Statman (1988), Clarke and Statman (1998), Shefrin (1999), Fisher and Statman (2000), Brown and Cliff (2004, 2005), and Ho and Hung (2008).

the same value as the beginning of the week.

3.3 Measure of equity liquidity

3.3.1 Proportional quoted spread

We use the proportional quoted spread as the illiquidity proxy. The formula for the proportional quoted spread is (Ask_t - Bid_t) / [(Ask_t + Bid_t) / 2], where Ask_t and Bid_t are the respective intraday ask and bid prices at time *t*. We then calculate the average of all the proportional quoted spreads in one day as the liquidity variable. We then examine how the investor sentiment affects the proportional quoted spread. In order to control for the factors that might be important in determining the spread, following Copleand and Galai (1983) and Stoll (2000), we investigate the following regression model: [3]

$$Spread_{it} = \alpha + \beta_1 Ret_{it} + \beta_2 Vol_{it} + \beta_3 LogV_{it} + \beta_4 Spread_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t + \beta_7 Bullish_t + \varepsilon_{it} \quad (1)$$

where $Spread_{it}$ is the daily proportional quoted spread for ETF *i* on day t, Ret_t is the daily return for ETF *i* on day t, VOL_t is the daily Parkinson volatility for ETF *i* on day t, *V* is the daily trading volume for ETF *i* on day *t*; D_{short} is a dummy variable that equals 1 from September 17, 2008 to October 17, 2008, a period when the U.S. Securities and Exchange Commission prohibited short sales of financial company stocks, and zero otherwise; *Bearish* is a dichotomous variable taking a Sentiment index, II and AAII, for the day equal to or greater than 1; and *Bullish* is a dichotomous variable taking a sentiment index, II and AAII, for the day of less than 1. We argue that a higher bullish sentiment leads to a narrower proportional quote spread, indicating improving equity liquidity. We thus expect the negative sign for β_6 and β_7 in equation (1).

In addition, when most investors feel more a higher bullish future expectation in

[3] We do not include the trading volume to be a regressor, since Baker and Stein (2004) propose that trading volume increases as dumb investors become more optimistic.

the market, noise traders purchase more stocks for their portfolios. Arbitrageurs could sell part of their position to meet a profit, thereby decreasing the proportional quoted spread. However, when bearish sentiment is the major sentiment in the market, noise traders could choice to sell off their holding position. Since limit to arbitrage, increasing trading costs and short-sale constraint could lead arbitrageurs to withdraw from buying positions to correct mispricing and provide liquidity, the proportional quoted spread increase. In addition, potential loss and the risk aversion could cause arbitrageurs to sell their holding positions. We therefore expect that in the bearish sentiment period, investor sentiment thus leads to have more significantly impact on proportional quote spread.

3.3.2 Market depth

In this section, we consider how bearish and bullish sentiment affects market depth, since equity liquidity has both a price dimension (the spread) and a quantity dimension (the depth). Lee et al. (1993) argue that liquidity providers are sensitive to change in information asymmetry risk and use both spread and depth to actively manage this risk. Thus, whether investor sentiment affects market depth is an important factor in determining the relationship between sentiment and liquidity. We therefore define depth as the number of shares at the best bid and ask price and average each depth on day *t* as our depth variable. Finally, we then divide the market depth by 100 to narrow the size of the variable. The daily average market depth is thus the market depth variable used in our analysis.

By following Ahn, Bae, and Chan (2001), in order to control for factors that may be of importance in determining market depth, we then examine the relationship between the investor sentiment and market depth in the following regression model:

$$Depth_{it} = \alpha + \beta_1 Vol_{it} + \beta_2 LogV_{it} + \beta_3 Depth_{it-1} + \beta_4 D_{short} + \beta_5 Bearish_t + \beta_6 Bullish_t + \varepsilon_{it} \quad (2)$$

where $Depth_t$ is the daily average market depth for ETF i on day t.[4] We argue that a higher bullish sentiment leads to an increasing market depth, indicating improving equity liquidity. We thus expect the negative sign for β_5 and β_6 in equation (2).

We hypothesize that during the bullish sentiment market period, noise traders could be trading underlying assets more aggressively and arbitrageurs could also participate by buying fewer stocks or by selling their existing long positions, thereby increasing market depth. During bearish sentiment periods, noise traders tend to trade less than bullish sentiment periods (Baker and Stein, 2004). In addition, the short-sales constraint keeps noise traders out of the market altogether, and increasing trading costs could lead arbitrageurs to withdraw from buying positions to correct mispricing. Based on the previous argument, we suggest that in the bearish sentiment period, investor sentiment causes market depth to decrease more significant and vice versa.

3.4 Measure of Investor Trading Behavior

3.4.1 Asymmetric depth

In this section, we use asymmetric depth as an alternative measure to capture investor trading behavior from limit order book. Huang and Stoll (1994) examined how the asymmetric depth affects quotes returns and price returns. Chung (2006) also uses asymmetric depth to measure adverse selection costs and analyze the effect of investor protection on asymmetric depth. Following Brockman and Chung (1999), we define dollar depth as the number of shares at the best bid and ask price multiplied by their respective prices and cumulate each depth on date *t*. We use the cumulative dollar depth in the calculation of asymmetric depth (*AsyDepth*), which is defined as the dollar depth

[4] The remaining control variables are the same as those in Equation (1).

at the best bid price divided by the dollar depth at the best ask price.

We furthermore use daily asymmetric depth to measure investor limit order submission behavior and explore how investor sentiment affects asymmetric depth in the following regression model:

$$AsyDepth_{it} = \alpha + \beta_1 RET_{it-1} + \beta_2 VOL_{it} + \beta_3 LogV_{it} + \beta_4 AsyDepth_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t + \beta_7 Bullish_t + \varepsilon_t \quad (3)$$

where $AsyDepth_{it}$ is the percentage asymmetric depth for ETF *i* on day *t*, which is the daily dollar depth at the best bid price divided by the dollar depth at the best ask price and then multiplied by 100.[5] We argue that a higher bullish sentiment leads to an increasing asymmetric depth, indicating increasing relative higher limit buy order. We thus expect the negative sign for β_6 and β_7 in equation (3).

We also hypothesize that during higher bullish sentiment in the market, noise traders tend to place more limit buy orders and arbitrageurs could place limit sell orders to sell part of their position to meet a profit. When bearish sentiment dominates the market, noise traders will place more limit sell orders in the market. In addition, potential loss and risk aversion may cause arbitrageurs to use more limit sell orders to sell off their holding positions. We thus argue that in the bearish sentiment period, investor sentiment leads to have a more significantly impact on asymmetric depth than bullish sentiment period.

3.4.2 Net buying pressure

The research design aims to tackle the question of whether in the bearish sentiment period could lead to serious net selling pressure or panic selling more significantly than in the bullish sentiment period during subprime crisis period. As for the net buying pressure variable, we use the algorithm proposed by Lee and Ready (1991) to

[5] The remaining control variables are the same as those in Equation (1).

distinguish whether the transactions are buyer or seller initiated. The algorithm classifies a trade as a buyer (seller) initiated trade if the traded price is higher (lower) than the mid-point of the bid and ask price. We assign a value of +1 (–1), which represents whether each transaction is a buyer (seller) initiated trade, multiply the assigned value by trading volume, and sum up all the multiplying results that occur each day. Finally, the net buying pressure variable is the ratio of buyer initiated volume divided by seller initiated volume.

Following Brown, Walsh and Yuen (1997) and Chordia, Roll and Subrahmanyam (2002), we control for the factors that may be of importance in determining net buying volume and examine the relationship between investor sentiment and net buying volume, using the following regression model:

$$NetBuying_{it} = \alpha + \beta_1 RET_{it-1} + \beta_2 VOL_{it} + \beta_3 LogV_{it} + \beta_4 NetBuying_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t + \beta_7 Bullish_t + \varepsilon_t \quad (4)$$

where $NetBuying_t$ is the ratio of buyer initiated volume divided by seller initiated volume for ETF i on day t.[6] We argue that a higher bullish sentiment leads to an increasing net buying pressure, indicating increasing relative higher buying trading volume. We thus expect the negative sign for β_6 and β_7 in equation (4).

When there is a higher bullish sentiment in the market, noise traders could overestimate the relative precision of their own signals and buy more positions for their portfolios, indicating increasing net buying volume. However, during bearish sentiment periods, limit to arbitrage, increasing trading costs and short-sale constraints could cause arbitrageurs to withdraw from buying positions to correct mispricing, leading to decrease in net buying volume. According to the 'prospect' theories (Kahneman and Tversky, 1979) and the 'disposition effect', investors that can invest will tend to hold their positions or reduce their trading activity when they are

[6] The remaining control variables are the same as those in Equation (1).

experiencing losses. We thus hypothesize that in the bearish sentiment period, investor sentiment leads to have a more significantly impact on net buying pressure than bullish sentiment period.

For all the model specifications (i.e., Equations (1) to (4)), we use a panel data regression framework to investigate the effects of bearish and bullish on equity liquidity and investor trading behavior. We perform the Hausman test on all of our empirical models. We find no misspecification from the use of the random effects model; this model is therefore selected for the estimation of all of our empirical models. We also follow the method of Wansbeek and Kapteyn (1989),[7] which we use to handle both balanced and unbalanced data.

4. Empirical results

4.1 Basic statistics

Table 1 provides the summary statistics for our empirical sample. For the Index ETFs group, we could find the lowest average *Spread* of 0.0214 and the highest average *Depth* of 264.37, indicating that they are the most liquid ETFs group. In addition, they have the highest average *LogV* of 18.93 and the lowest average *VOL* of 0.0128 in our sample period. Comparing with the four type financial ETFs, the financial sector is the most liquid group, with the lowest average *Spread* of 0.0617 and the highest average *Depth* of 106.76.37 and *LogV* of 15.67. We also find the negative average *Ret* among all group, indicating that our empirical samples in the market decline period. For the sentiment index variables, the average of *AAII* is 1.225 and the median of *AAII* is 1.068. They are both higher than *II* and higher than 1, indicating that the bearish sentiment is higher than bullish sentiment and individual investor sentiment is more

[7] See the SAS PANEL procedure.

bearish in the subprime crisis period.

Figure 1 shows the average level of weekly sentiment variables (*II* and *AAII*) from 1 January, 2007 to 31 December, 2008. Unsurprisingly, the figure shows our sentiment indexes move together. The *AAII* sentiment index tends to be more volatile and pessimistic than the *II* index. In addition, when the *II* or *AAII* index exceeds 1, these indicate that the bearish sentiment is higher than bullish sentiment. We find that an *II* or *AAII* greater than 1 captures the Bear Stearns event on the March 2008, the Fannie Mace and Freddie Mac events on the July to August 2008, the Lehman Brothers, Merill Lynch and AIG events on the September to October 2008 in the subprime crisis period.

<Table 1 is inserted about here>

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4.2. Effect of bearish and bullish sentiment on equity liquidity

4.2.1. Effect of bearish and bullish sentiment on proportional quoted spread

We begin by providing an empirical analysis to examine how bullish and bearish sentiment affects proportional quoted spread. We use *II* and *AAII* to measure investor sentiment and it is already well documented that important stock characteristics such as return, volatility, and short-sales constraint dummies may have an effect on proportional quoted spread. We include trading volume among the control variables, since Baker and Stein (2004) propose that a higher trading volume could reflect high investor sentiment and lead to low expected returns.[8] In addition, the spreads have narrowed with the growth in trading volume in recent years.

[8] We also do not include trading volume as our regression control variable and the regression results are similar to those found in Table 2. Those results are not reported here in order to save space; however, they are available upon request.

As shown in Table 2, the lagged proportional quoted spread variables have a significant impact on the proportional quoted spread for all empirical results. An increase in *VOL* has a significantly positive impact on *Spread* from 0.130 to 2.781. These results are similar to previous research which finds that volatility has a positive impact on the bid-ask spread (Copeland and Galai, 1983; Amihud and Mendelson, 1987). Most of our results show a positive relationship between *Ret* and *Spread* in our research samples. In addition, we also find the most of coefficients on *LogV* are statistically significant from -0.004 to -0.010, suggesting a positive relation between equity liquidity and trading volume. For the short-sales constraint dummy variable, we find the significantly positive relation between D_{short} and *Spread* from 0.002 to 0.396. Investor could not short sell financial stocks during this period and the results suggest that the most of investor is unwilling to submit buy order and provide liquidity into the market. Thus, the bid-ask spread is relative higher in the short-selling constraint period.

For the bearish and bullish sentiment variables, the results in panel A of Table 2 show that an increase in *Bearish* leads to a significant increase in *Spread* for all group from 0.001 to 0.083. However, we also find the positive relation between *Bullish* and *Spread*, only significantly for financial sector, brokerage and insurance groups. In the panel B, we find the *Bearish* variable from AAII index also has a significantly positive impact on *Spread* from 0.01 to 0.036. In addition, we also find the coefficient on *Bullish* are positive significant for financial sector and insurance groups. These results suggest our hypothesis 1 that after controlling for lagged spread, return, volume, volatility and the short-sale constraint dummy, bearish sentiment tends to result in higher proportional quoted spreads and bullish sentiment leads to decrease proportional quoted spread. We also find that institutional sentiment has a more significantly impact relative to individual sentiment.

In addition, *Bearish* sentiment has a higher significantly impact on proportional quoted spread relative to *Bullish* sentiment. These results support our hypothesis 2 and indicate that when most investors feel more bullish about the market, noise trader also chase to purchase more stocks for their portfolios. Arbitrageurs could sell part of their position to meet a profit and provide liquidity for the market. However, when bearish investor sentiment is strong, noise traders sell more holding positions and arbitrageurs withdraw from buying positions to correct mispricing and provide liquidity in the bearish sentiment period, since limit to arbitrage and short-sale constraint. In addition, potential loss and the risk aversion could cause arbitrageurs to sell their holding positions. Thus, arbitrage could not provide enough liquidity into market and investor sentiment could affect bid-ask spread more significantly in the bearish sentiment period.

<Table 2 is inserted about here>

4.2.2. Effect of bearish and bullish sentiment on market depth

In this section, we examine how bearish and bullish sentiment affects market depth. We also use *II* and *AAII* to measure investor sentiment and, following Ahn, Bae, and Chan (2001) and Brockman and Chung (2003), to control important characteristics such as lagged depth, volatility, trading volume and short-sale dummy, factors that may have an effect on market depth.[9] We then examine how investor sentiment affects market depth using Equation (2). As Table 3 shows, the coefficient on $Depth_{t-1}$ has a positive significantly impact on *Depth* from 0.51 to 0.86. We also find that an increase in *VOL* could have a negative impact on *Depth* from -41.12 to -105.12. These findings may

[9] We also do not include trading volume as our regression control variable; the regression results are similar to the results of Table 3. These results are not reported here in order to save space, but are available upon request.

be due to limit order traders using fewer limit orders to avoid taking market risk. These results are support to Goldstein and Kavajecz (2004). For the *LogV* variable, we both find the positive and negative relation between *LogV* and *Depth* and these results are similar with Ahn, Bae and Chan (2001). Since the theoretical model suggest different results on the relation between reading volume and depth, Lee et al. (1993) argue that transaction could consume liquidity and lead to negative relation and Chung, Van Ness and Van Ness (1999) argue that higher trading volume could cause higher probability of execution and leads to place more limit order to increase market depth.

As shown from Table 3, we also show that there is a significantly negative relation between *Bearish* sentiment (*II* and *AAII*) and *Depth* for all groups from -1.95 to -3.47 for *II* and -1.04 to -4.92 for *AAII*. For the *Bullish* sentiment variable in panel A, we find the negative relation between *Bullish* and *Depth*, only insignificantly for financial sector and insurance groups. For the *Bullish* sentiment variable in panel B, we also find the negative relation between *Bullish* and *Depth*, only significantly for index, financial sector and insurance groups.

These results imply that stronger bearish investor sentiment tends to result in lower market depth after controlling for lagged market depth, volatility, trading volume and short-sale constraint dummy. In sum, as Tables 2 and 3 shows, stronger bearish sentiment appears to cause increasing proportional quoted spread and decreasing market depth, indicating that higher sentiment could improve equity liquidity. Our results provide support for our hypotheses 1 and are consistent with the theory of Baker and Stein (2004).

In addition, *Bearish* sentiment has a higher significantly impact on market depth than *Bullish* sentiment. In sum of Tables 2 and 3 results, we could find that in the bearish sentiment period, investor sentiment affects proportional quote spread and market depth more significantly. These results support our hypothesis 2. When most

investors feel more bearish about the market, noise trader also chases to sell off their holding positions from their portfolios. Since short-sales constraint and limit to arbitrage could lead to arbitrageurs withdraw from buying positions to correct mispricing and provide liquidity, funding constraint problem and the risk aversion could cause arbitrageurs to sell their holding positions and becomes liquidity demander. Thus, investor sentiment could affect bid-ask spread and market depth more significantly in the bearish sentiment period.

<Table 3 is inserted about here>

4.3. Effect of bearish and bullish sentiment on investor trading behavior

4.3.1. Effect of bearish and bullish sentiment on asymmetric depth

We next examine the relationship between investor sentiment and investor trading behavior. Investor trading behavior can be measured using the volume and limit order dimensions. In this section, we measure investor trading behavior using from the limit order book. Asymmetric depth is thus defined as the dollar depth at the best bid price divided by the dollar depth at the best ask price. This measures investor limit order submission direction. As shown in Table 4, our results show that an increase in volatility could increase asymmetric depth. There is a significant and negative relationship between Ret_{t-1} and *AsyDepth*, indicating that a past negative return could lead to higher limit buy order in the next trading day.

Table 4 also shows that there is a significantly negative relation between *Bearish* sentiment and *AsyDepth* for all groups from -0.03 to -0.08 for *II* and -0.02 to -0.15 for *AAII*. We only find that *Bullish* variable in panel A has a negative significantly impact on *AsyDepth* for full sample column and index group. These results indicate that in the bearish sentiment period, investor sentiment has a significantly impact on investor

order submission decision. In the bearish sentiment period, investor could place more limit buy order than sell order when the bullish sentiment increase and use more limit sell order when the bearish sentiment increase. These results are supporting our hypothesis 2 that in the bullish sentiment period, higher sentiment causes noise trader to place more limit buy order and arbitrageurs could place limit sell order to meet profit. However, in the bearish sentiment period, arbitrageurs place more sell limit orders to take profits from their holding positions, to avoid potential loss and for risk aversion. In addition, noise traders tend to place more sell limit orders. Given that a higher bearish sentiment induces a higher limit sell orders than limit buy orders, indicating decreasing asymmetric depth.

<Table 4 is inserted about here>

4.3.2. Effect of bearish and bullish sentiment on net buying pressure

We next examine how bearish and bullish sentiment affects net buying pressure using Equation (4). Table 5 shows that the lagged one period net buying pressure, $NetBuying_{t-1}$ has a significant and positive impact on *NetBuying* from 0.02 to 0.77. In addition, prior return has a positive impact on *NetBuying*, only significantly for brokerage group. These results are consistent with previous findings that prior market moves and net buying volume affect investor trading strategy (Chordia et al., 2002; Huang and Chou, 2007). In addition, we also find the significantly positive relation between *LogV* and *NetBuying* from 0.11 to 0.89, suggesting that higher trading volume is associated with higher net buying pressure.

As shown in Table 5, our results show that the coefficients on *Bearish* are negative significant for all groups from -0.22 to -2.41. In addition, the *Bullish* variable has a negative significantly impact on *NetBuying*, only for financial sector and

brokerage groups in panel A. These results suggest our hypothesis 1 that that a higher degree of bearish sentiment leads to a decrease in net buying pressure after controlling for lagged net buying pressure, lagged return, volatility, trading volume and short-sale constraint dummy. We also find that in the *Bearish* sentiment period, investor sentiment has a more significantly impact on net buying pressure.

As we observe from Table 4 and 5, most of our results show that institutional sentiment index (II) has a more significant impact on asymmetric depth and net buying pressure relative to the individual sentiment index (AAII). This could be due to that institutional investor bullish and bearish expectations release on the newsletters could have a higher impact on the market participators. In addition, most of financial ETFs yield more sensitivity than index ETFs, since financial industry has a more direct impact relative to other industry in the subprime crisis period. We also find that investor sentiment affects investor trading behavior, indicating that higher bullish (bearish) sentiment leads to relative higher limit buy (sell) order and increasing (decreasing) net buying pressure. In the bearish sentiment period, investor sentiment has a more significantly impact on asymmetric depth and net buying pressure relative to in the bullish sentiment period. These results also support our hypotheses 2 and suggest that in the bearish sentiment period, noise traders tend to place more sell limit orders and net selling volume. Arbitrageurs could also place more sell limit orders and net selling volume to take profits from their holding positions, to avoid potential loss and for risk aversion. Thus, investor sentiment affects asymmetric depth and net buying pressure more significantly in the bearish sentiment period.

<Table 5 is inserted about here>

4.4. The Impact of Stock Market Condition

The foregoing analysis provides empirical evidence that bearish sentiment affects

equity liquidity and investor trading behavior more sensitive and significantly than bullish sentiment. These results may occur because when expectations are bearish, noise trader sell off their holding positions, short-sale constraint and limit to arbitrage could cause arbitrageurs to withdraw from buying positions to correct mispricing and provide liquidity. If securities prices decline below their fundamental values during a market decline period, position huge loss and the risk aversion could cause arbitrageurs to face funding constraint (Kyle and Xiong, 2001). This induces arbitrageurs to become liquidity demanders as they liquidate their position in risky assets to obtain funding inflows, further widening the price wedge, and decreasing equity liquidity and net buying volume significantly. Thus, our results imply that investor funding constraint plays an important role in the asymmetric sentiment effect.

In this section, we further explore whether investor funding constraint is an important factor in the asymmetric sentiment effect. Hameed, Kang, and Viswanathan (2010) explore how a market decline affects liquidity dry-up as the indication of capital constraints in the marketplace. Their results show that a reduction in market liquidity following market decline is related to the tightness in funding liquidity, since a large negative return could reduce the investor capital that is tied to marketable securities. Thus, funding problems from negative returns could reduce investor willingness to provide liquidity to the market, leading to an increase in market illiquidity. Following Hameed et al. (2010), we thus use the lagged period negative market return to proxy investor funding problems and explore how investor sentiment and negative returns interact with equity liquidity and investor trading behavior, using the following regression model:

$$\begin{aligned} Spread_{it} = {} & \alpha + \beta_1 Ret_{it} + \beta_2 Vol_{it} + \beta_3 LogV_{it} + \beta_4 Spread_{it-1} + \beta_5 D_{short} + \\ & \beta_6 Bearish_t Negative_{t-1} + \beta_7 Bearish_t Postive_{t-1} + \\ & \beta_8 Bullish_t Negative_{t-1} + \beta_9 Bullish_t Postive_{t-1} + \varepsilon_{it} \end{aligned} \tag{5a}$$

$$Depth_{it} = \alpha + \beta_1 Vol_{it} + \beta_2 LogV_{it} + \beta_3 Depth_{it-1} + \beta_4 D_{short} + \beta_5 Bearish_t Negative_{t-1} + \beta_6 Bearish_t Postive_{t-1} + \beta_7 Bullish_t Negative_{t-1} + \beta_8 Bullish_t Postive_{t-1} + \varepsilon_{it} \quad (5b)$$

$$AsyDepth_{it} = \alpha + \beta_1 RET_{it-1} + \beta_2 VOL_{it} + \beta_3 LogV_{it} + \beta_4 AsyDepth_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t Negative_{t-1} + \beta_7 Bearish_t Postive_{t-1} + \beta_8 Bullish_t Negative_{t-1} + \beta_9 Bullish_t Postive_{t-1} + \varepsilon_t \quad (5c)$$

$$NetBuying_{it} = \alpha + \beta_1 RET_{it-1} + \beta_2 VOL_{it} + \beta_3 LogV_{it} + \beta_4 NetBuying_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t Negative_{t-1} + \beta_7 Bearish_t Postive_{t-1} + \beta_8 Bullish_t Negative_{t-1} + \beta_9 Bullish_t Postive_{t-1} + \varepsilon_t \quad (5d)$$

where *Bearish* is a dichotomous variable taking a *Sentiment* index, *II* and *AAII*, for the day equal to or greater than 1. The *Bullish* is a dichotomous variable taking a *Sentiment* index, *II* and *AAII*, for the day of less than 1. *Positive* (*Negative*) takes the value of unity if the lagged one week market return is higher than zero (equal to or less than zero), and zero otherwise.[10] Therefore, *BearishNegative* indicates that most investors are more bearish than bullish about expected future returns when the past weekly ETFs return is equal to or less than zero.

<Table 6 is inserted about here>

As shown in Panel A of Table 6, *BearishII_Negative* and *BearishAAII_Negative* both have the most significantly positive impact on *Spread* for all groups from 0.002 to 0.093 for *BearishII_Negative* and 0.001 to 0.030 for *BearishAAII_Negative*. In Panel B of Table 6, we also show the interaction relationship between investor sentiments and funding constraint effect on market depth. The results also show that *BearishII_Negative* and *BearishAAII_Negative* affect *Depth* more significantly for all groups. The coefficients on *BearishII_Negative* are statistically significant from -2.00 to -3.98 and on *BearishAAII_Negative* are statistically significant from -0.46 to -6.15.

[10] The remaining control variables are the same as those in Equation (1) to (4).

We also explore how the interaction relationships between investor sentiment and funding constraint affect investor trading behavior. As shown in Panel C of Table 6, we find the significantly negative relation between *BearishII_Negative* and *AsyDepth* from -0.03 to -0.10 and the significantly negative relation between *BearishAAII_Negative* and *AsyDepth* from -0.02 to -0.15. In panel D of Table 6, the coefficients on *BearishII_Negative* have a negative significantly impact on *NetBuying* for all group from -0.47 to -2.31. The coefficients on *BearishAAII_Negative* have a significant and negative impact on *NetBuying* for all groups from -0.28 to -2.90. In addition, the coefficients on *BullishAAII_Negative* and *BullishAAII_Positive* both have insignificantly impact on *AsyDepth* and *NetBuying* for all groups.

In sum, our results show that *Bearish* sentiment has a more significant impact on equity liquidity and investor trading behavior when the index ETFs last week's return is negative. These results suggest our hypothesis 3 and that investor funding constraint is an important factor in the asymmetric sentiment effect. In addition, financial ETFs have more sensitivity than index ETF group.

4.5. Robustness Check

We do not divide sentiment into bullish and bearish sentiment period and directly examine how investor sentiment affects proportional quoted spread, market depth, asymmetric depth, and net buying pressure. The empirical results show that both *II* and *AAII* sentiment index affect equity liquidity and investor trading behavior. We also find that the coefficients on sentiment have a significantly positive impact on proportional quote spread and a significantly negative impact on market depth for all groups. In addition, the coefficients on sentiment have a significantly negative impact on asymmetric depth and net buying pressure for all groups. These empirical results suggest that higher bullish (bearish) sentiment leads to narrow (wide) proportional

quoted spread, increasing (decreasing) market depth, decrease (increase) asymmetric depth and net buying pressure.

We also use different method to measure market condition. We defined that if the weekly ETF return minus risk-free rate (3-month Treasury bill) is positive (negative), then the market condition is up (decline). We use this definition setting market condition dummy variable and then create regression model like equation (5). Our empirical results are similar Table 6, indicating that when the most investors expect future returns to be more bearish than bullish during market decline periods, investor sentiment affects bid-ask spread, market depth, asymmetric depth and net buying pressure all more significantly.[11]

5. Conclusions

This study examines how bearish and bullish sentiment affects equity liquidity and investor trading behavior during subprime crisis period. Our study uses intraday data to measure equity liquidity and investor trading behavior on the 2-index ETfs and 8 financial ETFs (which are divided into financial sector, banking, brokerage, and insurance groups). We use the proportional quoted spread and market depth measure of equity liquidity. In addition, we also measure investor trading behavior using net buying volume (volume dimension) and asymmetric depth (limit order dimension). We use direct measures of investor sentiment, Investors' Intelligence (II) and American Association of Individual investors (AAII), as a proxy for the noise trader presence.

Our results show that a higher degree of bullish sentiment leads to a decrease in the proportional quoted spread, an increase in market depth, asymmetric depth and net buying pressure. These results indicate that stronger bullish sentiment improves equity liquidity, supporting the theory of Baker and Stein (2004). Further, we explore how

[11] These results are not reported here in order to save space, but are available upon request.

bearish and bullish sentiment impacts equity liquidity and net buying volume equally. Our results show that in the bearish sentiment period, investor sentiment has a more significantly impact on proportional quoted spread, market depth, asymmetric depth and net buying pressure relative to bullish sentiment period. Finally, we relax the assumption that market conditions do not affect investor sentiment and explore whether funding constraint problem could increase limit to arbitrage and lead to asymmetric sentiment effect. Our results show that hen the most investors expect future returns to be more bearish than bullish during market decline periods, investor sentiment affects bid-ask spread, market depth, asymmetric depth and net buying pressure all more significantly. These results also imply that investor funding constraints play an important role in the asymmetric sentiment effect on equity liquidity and investor trading behavior.

Our results also show that *II* has more significant impacts than the *AAII* sentiment index. This could be due to that institutional investor bullish and bearish expectations release on the newsletters could have a higher impact on the market participators. In addition, most of financial ETFs yield more sensitivity than index ETFs, since financial industry has a more direct impact relative to other industry in the subprime crisis period.

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Appendix: Details of the Exchange-Traded Fund Data

Ticker	Full Title of ETFs	Exchange	Observations	Definition
1. Index ETFs				
SPY	SPDR S&P 500	NYSEArca	504	The index exchange-traded funds which track the S&P 500 Index.
QQQQ	PowerShares QQQ	NasdaqGM	504	The index exchange-traded funds which track the Nasdaq 100 Index.
2. Broad US Financial Sector				
XLF	Financial Select Sector SPDR	Amex	504	The underlying index includes commercial and investment banking and capital markets, diversified financial services, insurance and real estate.
IYF	iShares Dow Jones US Financial Sector	NYSEArca	504	The underlying index includes companies in the Banking, Non-life insurance, Life insurance, Real estate and General finance industry groups.
3. Banking				
KBE	KBW Bank ETF	Amex	504	The underlying index includes national money center banks and regional banking institutions listed on the US stock markets.
KRE	KBW Regional Banking ETF	Amex	504	An equal weighted index of geographically diverse companies representing regional banking institutions listed on the US stock markets.
4. Brokerage and Asset Management				
IAI	iShares Dow Jones U.S. Broker-Dealers	NYSEArca	504	Companies providing a range of specialized financial services, such as securities brokers and dealers, online brokers and securities or commodities exchanges.
KCE	KBW Capital Markets ETF	Amex	504	Situated in the US capital market industry and includes broker dealers, asset managers, trust and custody banks and a stock exchange.
5. Insurance				
KIE	KBW Insurance ETF	Amex	504	Situated in the insurance and publicly traded in the US, including personal and commercial lines, property/casualty, life insurance, reinsurance, brokerage and financial guarantees.
IAK	iShares Dow Jones US Insurance	NYSEArca	502	The underlying index includes companies in the following Full line insurance, insurance brokers, property and casualty insurance reinsurance and life insurance industry groups.

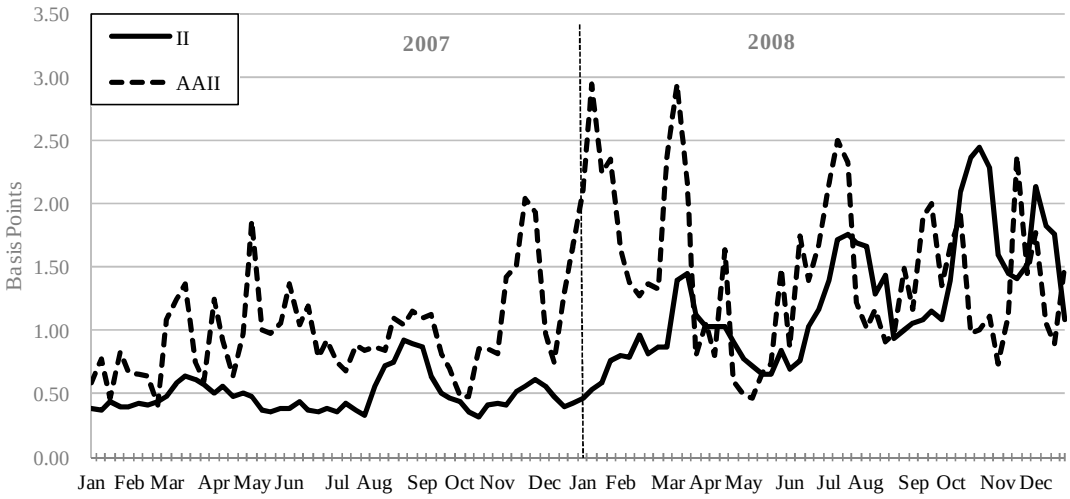

Figure 1. Sentiment Index. This figure plots the time-series daily values of *II* and *AAII* during the period from 1 January 2007 to 31 December 2008. *II* is Investor Intelligence indicator and is collected by categorizing approximately 150 market newsletters each week. *AAII* is American Association of Individual Investors indicator and is released by the American Association, which asks each individual investor where they expect the stock market will be in six months.

Table 1 Descriptive statistics

Variables	Mean	Median	S.D.	Min.	Max.
Panel A: Sentiment Index					
II	0.854	0.673	0.514	0.311	2.450
AAII	1.225	1.068	0.563	0.407	2.950
Panel B: Dependent and Control Variables					
Index ETFs					
SP	0.0214	0.0227	0.0088	0.0095	0.1003
Depth	364.37	270.76	332.68	24.25	1803.20
AsyDepth	1.0066	1.0010	0.0976	0.6923	1.7817
NetBuying	1.1089	1.0340	0.4229	0.0045	3.8040
Ret	-0.0014	-0.0003	0.0275	-0.1823	0.1459
LogV	18.93	18.93	0.55	16.86	20.59
VOL	0.0128	0.0097	0.0105	0.0016	0.0717
Financial Sector					
SP	0.0617	0.0473	0.0379	0.0267	0.3690
Depth	106.76	73.23	101.20	1.46	521.67
AsyDepth	1.0245	1.0005	0.2583	0.3590	2.4826
NetBuying	5.8249	1.0653	148.2394	0.0114	4691.1900
Ret	-0.0020	-0.0015	0.0319	-0.1823	0.1459
LogV	15.67	16.11	2.92	9.01	20.56
VOL	0.0197	0.0151	0.0173	0.0012	0.1400
Banking					
SP	0.1232	0.0993	0.0747	0.0404	0.7572
Depth	17.75	15.82	11.71	1.66	88.76
AsyDepth	1.1184	0.9687	0.7067	0.0987	11.1185
NetBuying	1.5611	1.1245	1.9372	0.0118	30.8889
Ret	-0.0015	-0.0017	0.0323	-0.1791	0.1584
LogV	14.23	14.52	1.49	6.68	17.31
VOL	0.0218	0.0175	0.0187	0.0011	0.1386
Brokerage					
SP	0.1411	0.1115	0.0966	0.0546	1.6748
Depth	28.14	22.32	21.27	1.91	118.19
AsyDepth	1.2482	1.0236	1.0357	0.0644	15.0743
NetBuying	1.3715	1.0959	1.4605	0.0353	25.2308
Ret	-0.0019	-0.0006	0.0325	-0.1856	0.1409
LogV	13.15	13.27	1.22	9.68	16.33
VOL	0.0212	0.0164	0.0171	0.0027	0.1248
Insurance					
SP	0.3413	0.1947	0.4521	0.0677	4.5378
Depth	30.45	22.34	27.26	1.47	198.95
AsyDepth	1.0035	0.9901	0.3112	0.1791	4.5341
NetBuying	4.2704	1.3528	17.7576	0.0049	302.0000
Ret	-0.0015	-0.0002	0.0283	-0.1522	0.1875
LogV	10.49	10.50	1.81	5.30	14.78
VOL	0.0154	0.0100	0.0173	0.0002	0.1452

Notes: Panel A provides the descriptive statistics for the investor sentiment variables, and Panel B provides the dependent and control variables, with the data covering the period from January 1, 2007 to December 31, 2008. In Panel A, *Sentiment* is measured by *II* and *AAII*. *II* is Investor Intelligence indicator and is collected by categorizing approximately 150 market newsletters each week. *AAII* is American Association of Individual Investors indicator and is released by the American Association, which asks each individual investor where they expect the stock market will be in six months. In Panel B, *Spread* is the average daily percentage spread for ETF *i* on day *t*; *Depth* is the daily average of the market depth for ETF *i* on day *t*; *AsyDepth* is the daily asymmetry depth for ETF *i* on day *t*; *NetBuying* is the daily percentage net buying pressure for ETF *i* on day *t*; *Ret* is the daily return for ETF *i* on day *t*; *V* is the daily trading volume for ETF *i* on day *t*; and *Vol* is the daily Parkinson volatility for ETF *i* on day *t*. The full sample represents the descriptive statistics results for 10 ETFs composed of two indices and 8 financial ETFs; the index ETFs represent the descriptive statistics results for SPY and QQQQ index ETFs; the financial sector represents the regression results for the broad U.S. financial sector group; the banking represents the regression results for the banking group; the brokerage represents the regression results for the brokerage and asset management group; and the insurance represents the regression results for the insurance group.

Table 2 Effect of Bearish and Bullish Sentiment on Proportional Quoted Spread

	Full Sample		Index ETF		Financial Sector		Banking		Brokerage		Insurance	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: II												
Bearish	0.023	3.33***	0.001	2.46**	0.011	2.72***	0.016	2.33**	0.039	5.00***	0.094	3.43***
Bullish	0.023	1.54	0.001	0.38	0.009	1.73*	0.012	1.62	0.032	3.01***	0.083	1.97**
Ret	0.223	2.75***	0.002	0.40	-0.008	-0.46	0.059	1.24	0.122	2.12**	1.057	3.76***
Vol	1.974	9.13***	0.130	3.03***	0.393	6.22***	0.762	5.29***	1.159	6.73***	1.436	1.99**
LogV	-0.010	-4.34***	0.001	-0.32	-0.005	-7.88***	-0.007	-5.52***	-0.008	-5.30***	0.287	0.43
$Spread_{t-1}$	0.563	61.22***	0.546	20.31***	0.593	19.31***	0.496	18.05***	0.409	14.25***	0.603	24.20***
D_{short}	0.077	5.58***	0.002	2.64***	0.002	0.37	0.029	3.27***	0.047	4.00***	0.377	7.63***
C	0.179	4.29***	0.016	2.19**	-0.008	-1.37	0.126	5.43***	0.131	6.42***	0.020	0.30
Adj. R^2	0.40		0.52		0.63		0.46		0.53		0.66	
Panel B: AAII												
Bearish	0.016	2.60***	0.001	2.28**	0.017	2.66***	0.007	1.75*	0.016	2.63***	0.036	1.96**
Bullish	0.014	1.04	0.001	1.29	0.011	1.91*	0.005	0.63	0.006	2.20**	0.063	1.56
Ret	0.248	3.05***	0.002	0.5	-0.049	-0.96	0.061	1.25	0.230	3.49***	1.052	3.73***
Vol	1.755	9.84***	0.161	9.31***	0.276	2.70***	0.592	5.41***	1.834	11.54***	2.781	5.17***
LogV	-0.006	-2.86***	-0.001	-0.07	-0.006	-8.27***	-0.005	-4.16***	-0.004	-2.34**	-0.103	-0.23
$Spread_{t-1}$	0.562	60.54***	0.490	17.65***	0.589	22.83***	0.515	18.69***	0.301	9.86***	0.609	24.45***
D_{short}	0.101	7.84***	0.002	3.24***	0.031	3.40***	0.039	4.47***	0.102	8.73***	0.396	8.58***
C	0.129	3.05***	0.007	1.83*	0.100	8.21***	0.099	4.55***	0.092	3.31***	0.007	0.10
Adj. R^2	0.40		0.55		0.60		0.45		0.51		0.66	

Notes: This table provides details of the effects of bearish and bullish sentiment on the bid–ask spread during the subprime crisis period. The regression model is

$$Spread_{it} = \alpha + \beta_1 Ret_{it} + \beta_2 Vol_{it} + \beta_3 LogV_{it} + \beta_4 Spread_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t + \beta_7 Bullish_t + \varepsilon_{it}$$

where the dependent variable is the daily percentage spread for ETF_i on day *t*, which is regressed on lagged percentage spread, *Ret*, *LogV*, *Vol*, the short-sales constraint dummy, bearish and bullish sentiment variables on day *t*. The *Sentiment* variable is the *II* on trading day *t* (Panel A), and the *AAII* on trading day *t* (Panel B). *Ret* is the daily return for ETF *i* on day *t*; *Vol* is the daily Parkinson volatility for ETF *i* on day *t; V* is the daily trading volume for ETF *i* on day *t*; D_{short} is a dummy variable that equals 1 from September 17, 2008 to October 17, 2008, a period when the U.S. Securities and Exchange Commission prohibited short sales of financial company stocks, and zero otherwise; *Bearish* is a dichotomous variable taking a Sentiment index, II and AAII, for the day equal to or greater than 1; and *Bullish* is a dichotomous variable taking a sentiment index, II and AAII, for the day of less than 1. The full sample represents the regression results for 10 ETFs comprising of two indices and 8 financial ETFs; the index ETFs represent the regression results for SPY and QQQQ index ETFs; the financial sector represents the regression results for the broad U.S. financial sector group; the banking represents the regression results for the banking group; the brokerage represents the regression results for the brokerage and asset management group; and the insurance represents the regression results for the insurance group. We use a panel data regression framework and perform the Hausman test on all of our empirical models. We find no misspecification from the use of the random effects model; this model is therefore selected for the estimation of all of our empirical models. The *t*-values examine whether the regression coefficient is significantly different from zero. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3 Effect of Bearish and Bullish Sentiment on Market Depth

	Full Sample		Index ETF		Financial Sector		Banking		Brokerage		Insurance	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: II												
Bearish	-2.39	-4.35***	-2.06	-3.61***	-3.47	-3.18***	-2.73	-3.04***	-2.88	-3.42***	-2.99	-3.06***
Bullish	-2.15	-2.44**	-1.95	-1.92*	-2.56	-1.26	-2.42	-2.17**	-3.43	-2.17**	-2.41	-1.22
Vol	-41.12	-2.93***	-1.10	-0.04	-33.83	-1.14	-54.13	-2.49**	-47.39	-2.06***	-43.67	-1.18
LogV	-0.43	-3.12***	1.42	2.96***	-3.55	-9.56***	-0.44	-2.78***	0.39	1.47	28.40	1.32
$Depth_{t-1}$	0.82	123.78***	0.73	33.68***	0.54	24.80***	0.82	65.81***	0.86	54.66***	0.83	48.05***
D_{short}	-0.26	-0.30	-1.00	-1.03	-0.98	-0.55	-0.18	-0.18	0.86	0.61	-0.58	-0.24
C	14.31	4.78***	-21.33	-2.28**	52.90	9.94***	14.11	6.07***	2.81	0.85	7.82	5.56***
Adj. R^2	0.74		0.58		0.62		0.81		0.85		0.77	
Panel B: AAII												
Bearish	-1.30	-2.63***	-1.79	-2.61***	-4.92	-2.85***	-1.06	-2.22**	-1.64	-2.66***	-5.68	-2.59***
Bullish	-1.04	-1.55	-1.12	-1.95*	-1.89	-2.33**	-0.81	-0.79	-1.58	-1.18	-3.69	-1.83*
Vol	-72.42	-5.80***	-59.43	-2.37**	-105.12	-3.82***	-102.94	-7.37***	-97.49	-5.31***	-98.25	-2.51**
LogV	-0.36	-2.28**	1.71	3.67***	-2.84	-9.60***	-0.40	-2.47**	12.31	2.42**	0.23	0.42
$Depth_{t-1}$	0.83	128.28***	0.73	33.56***	0.51	23.34***	0.82	65.49***	0.84	51.15***	0.84	61.68***
D_{short}	-0.45	-0.51	-0.86	-0.89	0.14	0.08	-0.22	-0.22	0.02	0.02	-3.31	-1.08
C	12.91	4.36***	-25.43	-2.86***	51.08	9.89***	13.88	5.93***	8.51	3.97***	18.11	1.68*
Adj. R^2	0.74		0.58		0.62		0.81		0.85		0.76	

Notes: This table provides details of the effects of bearish and bullish sentiment on market depth during the subprime crisis period. The regression model is

$$Depth_{it} = \alpha + \beta_1 Vol_{it} + \beta_2 LogV_{it} + \beta_3 Depth_{it-1} + \beta_4 D_{short} + \beta_5 Bearish_t + \beta_6 Bullish_t + \varepsilon_{it}$$

where the dependent variable is the daily market depth for ETF_i on day *t*, which is regressed on lagged market depth, *Vol*, *LogV*, the short-sales constraint dummy, bearish and bullish sentiment variables on day *t*. The *Sentiment* variable is the *II* on trading day *t* (Panel A), and the *AAII* on trading day *t* (Panel B). *Vol* is the daily Parkinson volatility for ETF *i* on day *t; V* is the daily trading volume for ETF *i* on day *t*; D_{short} is a dummy variable that equals 1 from September 17, 2008 to October 17, 2008, a period when the U.S. Securities and Exchange Commission prohibited short sales of financial company stocks, and zero otherwise; *Bearish* is a dichotomous variable taking a Sentiment index, II and AAII, for the day equal to or greater than 1; and *Bullish* is a dichotomous variable taking a sentiment index, II and AAII, for the day of less than 1. The full sample represents the regression results for 10 ETFs comprising of two indices and 8 financial ETFs; the index ETFs represent the regression results for SPY and QQQQ index ETFs; the financial sector represents the regression results for the broad U.S. financial sector group; the banking represents the regression results for the banking group; the brokerage represents the regression results for the brokerage and asset management group; and the insurance represents the regression results for the insurance group. We use a panel data regression framework and perform the Hausman test on all of our empirical models. We find no misspecification from the use of the random effects model; this model is therefore selected for the estimation of all of our empirical models. The *t*-values examine whether the regression coefficient is significantly different from zero. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Effect of Bearish and Bullish Sentiment on Asymmetric Depth

	Full Sample		Index ETF		Financial Sector		Banking		Brokerage		Insurance	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: II												
Bearish	-0.05	-2.41**	-0.03	-3.50***	-0.08	-2.58***	-0.06	-2.28**	-0.08	-2.45**	-0.06	-2.44**
Bullish	-0.03	-1.75*	-0.03	-1.74*	-0.07	-1.47	-0.04	-0.83	-0.08	-1.33	-0.06	-1.18
Ret_{t-1}	-0.05	-0.31	0.14	1.26	0.42	1.60	0.06	0.26	0.17	0.56	0.09	0.31
Vol	0.02	0.04	2.72	5.38***	2.25	2.65***	2.29	3.02***	-0.37	-0.46	1.29	1.71*
LogV	-0.01	-3.80***	-0.06	-7.45***	-0.02	-4.77***	-0.02	-3.49***	-0.02	-3.35***	-0.03	-4.17***
$AsyDepth_{t-1}$	0.04	4.73***	0.03	2.10**	0.03	1.31	0.05	3.07***	0.02	1.05	0.03	3.43***
D_{short}	-0.03	-0.98	-0.04	-2.30**	0.06	1.58	0.04	0.94	0.01	0.18	0.09	1.52
C	1.20	23.98***	2.16	14.05***	1.27	23.19***	1.28	12.59***	1.33	18.84***	1.31	16.22***
Adj. R^2	0.02		0.10		0.03		0.03		0.02		0.03	
Panel B: AAII												
Bearish	-0.04	-2.26**	-0.02	-1.81*	-0.03	-2.46**	-0.10	-2.09**	-0.22	-1.89*	-0.04	-2.23**
Bullish	-0.03	-0.78	-0.01	-0.53	-0.01	-0.33	-0.08	-1.32	-0.15	-1.30	-0.04	-1.17
Ret_{t-1}	-1.18	-4.66***	-0.44	-2.93***	-0.35	-1.87*	-2.22	-4.26***	-2.32	-2.26**	-0.08	-0.38
Vol	1.14	1.89*	-0.38	-1.05	0.71	1.56	1.64	1.45	4.84	2.40**	-0.21	-0.49
LogV	-0.01	-0.78	-0.01	-2.84***	-0.02	-2.78***	-0.01	-0.40	0.02	0.83	-0.01	-1.78*
$AsyDepth_{t-1}$	0.03	4.46***	0.03	2.09**	0.03	1.89*	0.08	3.04***	-0.10	-1.38	0.04	5.03***
D_{short}	-0.21	-5.26***	-0.04	-1.53	-0.08	-2.56***	-0.32	-3.97***	-0.50	-3.01***	-0.04	-1.18
C	1.16	10.08***	0.94	21.62***	1.20	10.70***	1.14	5.42***	1.13	2.65***	1.12	19.82***
Adj. R^2	0.02		0.07		0.03		0.03		0.02		0.03	

Note: This table provides details of the effects of bearish and bullish sentiment on asymmetry depth during the subprime crisis period. The regression model is:

$$AsyDepth_{it} = \alpha + \beta_1 RET_{it-1} + \beta_2 VOL_{it} + \beta_3 LogV_{it} + \beta_4 AsyDepth_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t + \beta_7 Bullish_t + \varepsilon_t$$

The dependent variable is the daily asymmetry depth at day *t*, which is regressed on lagged asymmetry depth, lagged *RET*, *VOL*, *LogV*, the short-sales constraint dummy, bearish and bullish sentiment variables on day *t*. The *Sentiment* variable is the *II* on trading day *t* (Panel A), and the *AAII* on trading day *t* (Panel B). *Ret* is the daily return for ETF *i* on day *t*; *Vol* is the daily Parkinson volatility for ETF *i* on day *t*; *V* is the daily trading volume for ETF *i* on day *t*; D_{short} is a dummy variable that equals 1 from September 17, 2008 to October 17, 2008, a period when the U.S. Securities and Exchange Commission prohibited short sales of financial company stocks, and zero otherwise; *Bearish* is a dichotomous variable taking a Sentiment index, II and AAII, for the day equal to or greater than 1; and *Bullish* is a dichotomous variable taking a sentiment index, II and AAII, for the day of less than 1. The full sample represents the regression results for 10 ETFs comprising of two indices and 8 financial ETFs; the index ETFs represent the regression results for SPY and QQQQ index ETFs; the financial sector represents the regression results for the broad U.S. financial sector group; the banking represents the regression results for the banking group; the brokerage represents the regression results for the brokerage and asset management group; and the insurance represents the regression results for the insurance group. We use a panel data regression framework and perform the Hausman test on all of our empirical models. We find no misspecification from the use of the random effects model; this model is therefore selected for the estimation of all of our empirical models. The *t*-values examine whether the regression coefficient is significantly different from zero. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Effect of Bearish and Bullish Sentiment on Net Buying Pressure

	Full Sample		Index ETF		Financial Sector		Banking		Brokerage		Insurance	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: II												
Bearish	-0.67	-2.84***	-0.38	-1.83*	-1.41	-2.78***	-0.56	-2.24**	-0.75	-3.03***	-2.13	-1.90*
Bullish	-0.56	-1.75*	-0.54	-1.27	-0.96	-2.52**	-0.50	-1.00	-0.59	-1.92*	-3.24	-1.43
Ret_{t-1}	3.21	1.55	2.32	0.89	0.59	0.21	3.88	1.38	2.65	1.30	0.50	0.04
Vol	-6.08	-1.13	-0.38	-0.02	-14.19	-1.48	-13.35	-1.95*	-5.37	-0.92	-33.17	-0.97
LogV	0.11	2.04**	0.66	5.01***	0.20	2.30**	0.30	0.75	0.13	2.18**	0.10	0.34
$OIBNUM_{t-1}$	0.02	1.79*	0.15	3.50***	0.26	1.83*	0.01	1.09	0.00	0.21	0.76	2.52**
D_{short}	0.33	0.95	0.13	0.35	0.13	0.30	0.39	0.86	0.16	0.46	1.33	0.63
C	3.73	5.74***	-9.94	-3.46***	0.60	0.57	2.45	5.29***	3.99	5.22***	4.32	1.37
Adj. R^2	0.02		0.04		0.04		0.02		0.03		0.02	
Panel B: AAII												
Bearish	-0.34	-2.22**	-0.27	-1.69*	-0.56	-2.55**	-0.42	-2.09**	-0.22	-1.96**	-2.41	-1.82*
Bullish	-0.24	-0.71	-0.52	-1.48	-0.72	-1.54	-0.30	-0.69	-0.29	-1.19	-2.76	-0.94
Ret_{t-1}	3.11	1.51	1.78	0.73	1.30	0.46	3.58	1.28	4.31	2.94***	-0.76	-0.04
Vol	-19.57	-4.66***	-22.66	-3.48***	-30.29	-4.47***	-21.70	-3.94***	-7.27	-2.44**	-67.82	-1.94*
LogV	-0.04	-0.73	0.89	6.06***	0.22	2.45**	0.21	0.58	-0.06	-1.36	0.22	0.67
$OIBNUM_{t-1}$	0.02	1.79*	0.06	1.43	0.26	1.86*	0.01	0.99	0.00	-0.25	0.77	1.98**
D_{short}	0.32	0.98	0.06	0.16	0.27	0.59	0.23	0.53	0.13	0.53	1.33	0.46
C	3.13	4.53***	-13.71	-5.11***	0.53	0.51	2.77	5.55***	2.66	4.52***	5.41	1.41
Adj. R^2	0.02		0.04		0.04		0.02		0.02		0.02	

Note: This table provides details of the effects of bearish and bullish sentiment on percentage standardized net buying volume during the subprime crisis period. The regression model is:

$$NetBuying_{it} = \alpha + \beta_1 RET_{it-1} + \beta_2 VOL_{it} + \beta_3 LogV_{it} + \beta_4 NetBuying_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t + \beta_7 Bullish_t + \varepsilon_t$$

The dependent variable is the daily percentage net buying pressure at day *t*, which is regressed on lagged percentage net buying pressure, lagged *RET*, *VOL*, *LogV*, the short-sales constraint dummy, bearish and bullish sentiment variables on day *t*. The *Sentiment* variable is the *II* on trading day *t* (Panel A), and the *AAII* on trading day *t* (Panel B). *Ret* is the daily return for ETF *i* on day *t*; *Vol* is the daily Parkinson volatility for ETF *i* on day *t; V* is the daily trading volume for ETF *i* on day *t*; D_{short} is a dummy variable that equals 1 from September 17, 2008 to October 17, 2008, a period when the U.S. Securities and Exchange Commission prohibited short sales of financial company stocks, and zero otherwise; *Bearish* is a dichotomous variable taking a Sentiment index, II and AAII, for the day equal to or greater than 1; and *Bullish* is a dichotomous variable taking a sentiment index, II and AAII, for the day of less than 1. The full sample represents the regression results for 10 ETFs comprising of two indices and 8 financial ETFs; the index ETFs represent the regression results for SPY and QQQQ index ETFs; the financial sector represents the regression results for the broad U.S. financial sector group; the banking represents the regression results for the banking group; the brokerage represents the regression results for the brokerage and asset management group; and the insurance represents the regression results for the insurance group. We use a panel data regression framework and perform the Hausman test on all of our empirical models. We find no misspecification from the use of the random effects model; this model is therefore selected for the estimation of all of our empirical models. The *t*-values examine whether the regression coefficient is significantly different from zero. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Effect of Bearish and Bullish Sentiment on liquidity and trading behavior conditioned by positive/negative return

	Full Sample		Index ETF		Financial Sector		Banking		Brokerage		Insurance	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: Quote Spread												
BearishII_Negative	0.029	3.92***	0.002	2.79***	0.011	2.80***	0.019	2.61***	0.042	5.10***	0.093	2.77***
BearishII_Positive	0.017	2.30**	0.001	2.16**	0.011	2.40**	0.012	1.74*	0.034	4.05***	0.074	2.27**
BullishII_Negative	0.026	1.69*	0.001	1.21	0.008	1.70*	0.009	1.88*	0.028	3.14***	0.092	1.38
BullishII_Positive	0.021	1.35	0.001	0.28	0.009	1.71*	0.014	1.09	0.036	2.40**	0.083	1.20
Adj-R^2	0.40		0.57		0.63		0.46		0.52		0.66	
BearishAAII_Negative	0.018	2.71***	0.001	2.48**	0.008	2.82***	0.008	2.05**	0.030	3.99***	0.023	1.98**
BearishAAII_Positive	0.013	1.88*	0.001	0.69	0.005	2.44**	0.002	0.43	0.003	0.73	0.014	1.08
BullishAAII_Negative	0.016	1.28	0.001	1.08	0.006	1.34	0.001	0.14	0.004	0.51	0.011	0.38
BullishAAII_Positive	0.006	0.42	0.001	0.66	0.006	1.84*	0.007	0.72	0.008	2.82***	0.007	0.26
Adj-R^2	0.40		0.55		0.56		0.45		0.52		0.66	
Panel B: Market Depth												
BearishII_Negative	-2.92	-4.48***	-2.54	-3.56***	-3.98	-3.37***	-3.51	-3.06***	-2.99	-3.39***	-4.01	-3.06***
BearishII_Positive	-1.92	-3.67***	-2.00	-3.33***	-3.16	-2.78***	-2.22	-2.67***	-2.84	-3.12***	-2.86	-2.56***
BullishII_Negative	-2.37	-2.88***	-2.00	-2.20**	-2.99	-1.38	-2.50	-2.71***	-4.41	-2.69***	-1.41	-0.67
BullishII_Positive	-1.66	-1.57	-1.66	-1.47	-2.52	-1.18	-1.38	-1.01	-2.00	-1.18	-3.28	-1.78*
Adj-R^2	0.74		0.58		0.61		0.81		0.85		0.77	
BearishAAII_Negative	-1.55	-2.64***	0.46	-2.62***	-6.15	-3.36***	-1.13	-2.34**	-1.78	-2.60***	-6.17	-2.61***
BearishAAII_Positive	-0.80	-1.79*	0.45	-2.36**	-2.07	-2.17**	-0.53	-0.97	-1.08	-1.44	-5.00	-2.18**
BullishAAII_Negative	-1.05	-1.77*	0.87	-2.58***	-1.98	-2.41**	-1.00	-0.93	-1.61	-1.26	-3.78	-1.84*
BullishAAII_Positive	-0.54	-0.58	1.00	-0.88	-3.43	-1.76*	0.19	0.17	-0.38	-0.25	-3.49	-1.50
Adj-R^2	0.74		0.58		0.62		0.81		0.85		0.76	

Table 6 (Continue) Effect of Bearish and Bullish Sentiment on liquidity and trading behavior conditioned by positive/negative return

	Full Sample		Index ETF		Financial Sector		Banking		Brokerage		Insurance	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel C:Asymmetric Depth												
BearishII_Negative	-0.05	-2.29**	-0.04	-3.51***	-0.08	-2.61***	-0.07	-2.37**	-0.14	-2.68***	-0.10	-2.39**
BearishII_Positive	-0.03	-1.81*	-0.03	-2.58***	-0.07	-2.25**	-0.06	-2.22**	-0.06	-1.60	-0.05	-1.79*
BullishII_Negative	-0.04	-1.31	-0.02	-0.85	-0.06	-1.08	-0.04	-0.87	-0.07	-0.88	-0.05	-0.81
BullishII_Positive	-0.03	-1.73*	-0.03	-2.10**	-0.08	-1.51	-0.05	-0.98	-0.10	-1.74*	-0.07	-1.59
Adj-R^2	0.02		0.10		0.03		0.03		0.02		0.03	
BearishAAII_Negative	-0.06	-3.04***	-0.02	-1.86*	-0.03	-2.48**	-0.10	-2.42**	-0.28	-1.78*	-0.04	-2.52**
BearishAAII_Positive	-0.04	-2.38**	-0.02	-1.55	-0.03	-2.07**	-0.03	-0.90	-0.15	-1.75*	-0.03	-2.13**
BullishAAII_Negative	0.01	-0.04	0.01	0.31	0.01	0.03	-0.04	-0.55	-0.15	-0.89	-0.04	-1.23
BullishAAII_Positive	-0.07	-1.56	-0.04	-1.51	-0.02	-0.77	-0.11	-1.23	-0.16	-1.51	-0.03	-0.91
Adj-R^2	0.02		0.07		0.03		0.04		0.02		0.03	
Panel D: Net Buying Pressure												
BearishII_Negative	-0.73	-2.67***	-0.74	-2.05**	-1.56	-2.82***	-0.56	-2.10**	-0.91	-3.12***	-3.58	-1.89*
BearishII_Positive	-0.60	-2.66***	-0.35	-1.60	-0.92	-2.50**	-0.56	-2.08**	-0.57	-3.00***	-3.33	-1.80*
BullishII_Negative	-0.55	-1.82*	-0.47	-1.60	-1.01	-2.65***	-0.54	-1.07	-0.62	-2.24**	-2.29	-1.36
BullishII_Positive	-0.57	-1.44	-0.43	-0.98	-1.27	-2.17**	-0.39	-0.70	-0.73	-1.77*	-2.31	-1.43
Adj-R^2	0.02		0.04		0.04		0.02		0.03		0.02	
BearishAAII_Negative	-0.33	-2.14**	-0.39	-2.22**	-0.62	-2.71***	-0.45	-2.05**	-0.28	-2.34**	-2.90	-1.93*
BearishAAII_Positive	-0.35	-2.00**	-0.20	-1.22	-0.48	-2.04**	-0.42	-2.01**	-0.16	-1.37	-2.29	-1.70*
BullishAAII_Negative	-0.30	-0.87	-0.56	-1.54	-0.73	-1.49	-0.41	-0.90	-0.33	-1.24	-4.47	-1.40
BullishAAII_Positive	-0.13	-0.35	-0.56	-1.43	-0.71	-1.41	-0.19	-0.37	-0.29	-1.12	-1.66	-0.53
Adj-R^2	0.02		0.05		0.04		0.02		0.03		0.02	

Note: This table provides details of the effects of bearish and bullish sentiment conditioned by positive and negative return on proportional quoted spread, market depth, asymmetric depth, and percentage standardized net buying volume. The regression model is:

$$Spread_{it} = \alpha + \beta_1 Ret_{it} + \beta_2 Vol_{it} + \beta_3 LogV_{it} + \beta_4 Spread_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t Negative_{t-1} + \beta_7 Bearish_t Postive_{t-1} + \beta_8 Bullish_t Negative_{t-1} + \beta_9 Bullish_t Postive_{t-1} + \varepsilon_{it}$$

$$Depth_{it} = \alpha + \beta_1 Vol_{it} + \beta_2 LogV_{it} + \beta_3 Depth_{it-1} + \beta_4 D_{short} + \beta_5 Bearish_t Negative_{t-1} + \beta_6 Bearish_t Postive_{t-1} + \beta_7 Bullish_t Negative_{t-1} + \beta_8 Bullish_t Postive_{t-1} + \varepsilon_{it}$$

$$AsyDepth_{it} = \alpha + \beta_1 RET_{it-1} + \beta_2 VOL_{it} + \beta_3 LogV_{it} + \beta_4 AsyDepth_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t Negative_{t-1} + \beta_7 Bearish_t Postive_{t-1} + \beta_8 Bullish_t Negative_{t-1} + \beta_9 Bullish_t Postive_{t-1} + \varepsilon_t$$

$$NetBuying_{it} = \alpha + \beta_1 RET_{it-1} + \beta_2 VOL_{it} + \beta_3 LogV_{it} + \beta_4 NetBuying_{it-1} + \beta_5 D_{short} + \beta_6 Bearish_t Negative_{t-1} + \beta_7 Bearish_t Postive_{t-1} + \beta_8 Bullish_t Negative_{t-1} + \beta_9 Bullish_t Postive_{t-1} + \varepsilon_t$$

In Panel A, the dependent variable is the daily percentage spread at day *t*, which is regressed on lagged percentage spread, *Ret*, *LogV*, *Vol*, the short-sales constraint dummy, BearishNegative, BearishPositive, BullishNegative and BullishPositive sentiment variables on day *t*. In Panel B, the dependent variable is the daily market depth at day *t*, which is regressed on lagged market depth, *Vol*, *LogV*, the short-sales constraint dummy, BearishNegative, BearishPositive, BullishNegative and BullishPositive sentiment variables on day *t*. In Panel C, the dependent variable is the daily asymmetric depth at day *t*, which is regressed on lagged asymmetry depth, lagged *RET*, *VOL*, *LogV*, the short-sales constraint dummy, BearishNegative, BearishPositive, BullishNegative and BullishPositive sentiment variables on day *t*. In Panel D, the dependent variable is the daily percentage net buying pressure at day *t*, which is regressed on lagged percentage net buying pressure, lagged *RET*, *VOL*, *LogV*, the short-sales constraint dummy, BearishNegative, BearishPositive, BullishNegative and BullishPositive sentiment variables on day *t*. *Bearish* is a dichotomous variable taking a *Sentiment* index, *II* and *AAII*, for the day equal to or greater than 1. *Bullish* is a dichotomous variable taking a *Sentiment* index, *II* and *AAII*, for the day of less than 1. *Positive* (*Negative*) takes the value of unity if lagged one weekly ETF return is higher than zero (equal to or smaller than zero), and zero otherwise. The full sample represents the regression results for 10 ETFs comprising of two indices and 8 financial ETFs; the index ETFs represent the regression results for SPY and QQQQ index ETFs; the financial sector represents the regression results for the broad U.S. financial sector group; the banking represents the regression results for the banking group; the brokerage represents the regression results for the brokerage and asset management group; and the insurance represents the regression results for the insurance group. We use a panel data regression framework and perform the Hausman test on all of our empirical models. We find no misspecification from the use of the random effects model; this model is therefore selected for the estimation of all of our empirical models. The *t*-values examine whether the regression coefficient is significantly different from zero. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.