Retail Investor Attention and Herding Behavior

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ABSTRACT

In this paper, we argue that the internet is one of the resources for investors who lack the information required to make investment decisions. When individual investors are able to obtain information from public resources such as Google search, the degree of investor attention related to a particular company can cause similar emotions among investors, leading to herding behavior for retail investors. Empirical results confirm that Google Search Volume Index can be a proxy for the investor attention of uninformed individual investors, and the measure of abnormal search volume index (*ASVI*, hereafter) shows that individual investors become more attentive to the information and exhibit more herding behavior. Empirical evidence also shows that reaching the price limit generates an information-grabbing effect, which further enhances the impact of investor attention on individual herding behavior. Further, in general, small cap firms generate more intensive herding by individual investors. In addition, we explore the asymmetric impact of *ASVI* on herding behavior for bull and bear markets, and confirm that the individual investor buy herding phenomenon is stronger in bull markets, especially for small capitalization firms. However, in bear markets, with greater price deterioration for large cap firms, we detect herding behavior on the sell side.

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1. Introduction

Research finds that before investors make a decision to invest in a stock, they face a challenging stock picking problem, and whenever investors have a limited ability to search for a target stock among many shares, they tend to choose the kind of stocks which attract their attention in the near future (Odean (1999), Barber and Odean (2008)). One strand of research proposes several variables which may serve as representations of the results of investors information attention[2]. Da, Engelberg, and Gao (2011) propose using Google search volume index (*SVI*, hereafter) as a more direct investor attention proxy, as the rationale of *SVI* implies a more proactive approach from investors to surf online for the relevant information of a particular company. Yet, Da et al. (2011, 2015) also argue that institutional investors may obtain more sophisticated and complex information than retail investors, who can only obtain financial information through online searches. They find that retail investors use public Google search engines to obtain a variety of information such as the company's financial condition, product launches, and market related statistics and use this information to analyze the state of capital markets and ultimately make investment decisions. Recent research on the investor attention effect highlights the association between *SVI* and stock market performance and generates the conclusion that higher *SVI* is aligned with higher liquidity (Bank, Larch and Peter (2011), Latoeiro, Ramos and Veiga (2013), Fink and Johann (2014), Ding and Hou (2015)), higher volatility (Latoeiro et al. (2013), Dimpfl and Jank (2016)) and higher short term abnormal returns (Da et al. (2011), Bank et al. (2011)).

[2] including excess returns (Barber and Odean (2008)), excess trading volume (Hou, Xiong, and Peng (2009), Gervais, Kaniel and Mingelgrin (2001), Barber and Odean (2008)), Media coverage (Barber and Odean (2008), Fang and Peress (2009), Yuan (2015)), Limit-hit events (Seasholes and Wu (2007)) and advertising expenditure (Chemmanur and Yan (2009), Grullon, Kanatas and Weston (2004), and Lou (2014)).

Although research has inferred that *SVI* is a pertinent proxy for individual investor attention, none have directly observed the influence of *SVI* on investor trading behavior. Our study represents a pioneering investigation into the linkage between *SVI* and individual investor herding behavior, to explore how investor attention affects the investor decision-making.

Herding occurs when a group of investors with the same inclinations follows the trading behavior of a leader. Research provides theoretical grounds for the association between herding behaviors and information (Shleifer and Summers (1990), Nofsinger and Sias (1999), Sias (2004)). Theoretical arguments contend that investor herding has information-driven and behavior-driven motives. Information-driven herding specifies that institutional investors may make similar investment decisions when they face correlated information environments (Hirshleifer, Subrahmanyam, and Titman, 1994). Using the information-based herding argument, investors may herd if they have access to similar information, have similar educational and career path backgrounds, and execute similar trading strategies. For instance, Zhuo and Lai (2009) use data from the Hong Kong market to verify the theory of information cascades in herding. They find that more herding behavior is generated where there is a higher proportion of informed based trading as measured by the probability of informed trading (PIN, hereafter), especially for sell side herding. They further confirm the information cascades argument by observation of the association between institutional herding and informed trading. However, they did not investigate individual herding behavior.

Behavior-driven herding takes place when investors mimic the trading behavior of other investors, causing groups of investors with no common ties to revise their decisions (Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992), Sias (2004), Chiao, Hung, and Lee (2011)). Researchers usually attribute individual herding behavior to psychological bias (representativeness heuristic and disposition effect) and attention grabbing effect (Barber, Odean, and Zhu (2009), Merli and Roger (2013), Li, Rhee, and Wang (2017)). Nevertheless, the literature has focused on the phenomenon of individual herding as exhibited in stock performance and trading volume, and neglected consideration of possible sources of information which could induce individual herding. Moreover, Bikhchandani et al. (1992), Sgroi (2002), and Kultti and Miettinen (2006) argue that when the cost of information search is low, investors obtain free information and herd. Inspired by the aforementioned literature, we argue that when individual investors are able to obtain information from public resources such as Google search, the nature of the news (good news or bad) about a particular company can cause similar emotions among investors, leading to herding behavior, particularly for retail investors. Overall, we find that Google *SVI* serves as a pertinent proxy of individual investor attention where higher abnormal *SVI* would lead to more significant individual herding behavior.

Barber, Lee, Liu, and Odean (2008) and Degryse, Jong, Ravenswaaij, and Wuyts (2005) both indicate that investors' investment intention may be observed from their order aggressiveness. Hence in the current paper, we compute a herding measure based on both intraday submitted-orders and completed-trades statistics, and posit that investor buy and sell orders will exhibit more significant herding behavior.[3] Our study further proposes that the impact of *ASVI* on herding behavior may be enhanced when stock prices hit the upper and lower bounds of the daily limit. Another stream of studies documents this "attention-grabbing effect": the higher the price limit-hit frequency, the higher the information attention it attracts (Greenwald and Stein (1988),

[3] Submitted-order refers to investors' buy and sell order submissions only, which reflects investor intention to buy or sell the underlying assets. Completed-trade refers to completed deals.

(1991), Seasholes and Wu (2007), Lin, Ko, Lin, and Yang (2017)). We find when the market price is close to the upper (lower) limit, individual traders demonstrate significant buy (sell) order herding behavior when *ASVI* is high. Finally, some studies also reveal that small capitalization stocks exhibit more intensive herding behavior (Lakonishok, Shleifer, and Vishny, 1992; Choi and Sias, 2009; Venezia, Nashikkar, and Shapira, 2011). Therefore, we shed light on the herding behavior of individual investors by further classifying the underlying stocks into above/below median capitalization stocks and show that in general individual investors exhibit more significant buy order herding behavior in firms with small capitalization. Moreover, we further find *ASVI* has an asymmetric impact on individual herding behavior in bullish and bearish markets, and find that individual buy herding is stronger in bullish markets, especially for small capitalization firms. Conversely, in bear markets, with price deterioration greater in large cap firms, we find herding behavior on the sell side is stronger for large capitalization firms.

This study makes five major contributions. First, we embrace the opportunity to take retail-investor dominated[4] and high internet usage Taiwan market[5] as an experiment to examine the relation between information attention and herding behaviors. Overall, studies investigating individual investor herding behavior are scarce. We confirm that the *ASVI* can serve as a useful information attention proxy for predicting individual investor herding behavior. Second, we compare the intensity of herding behavior of retail and institutional traders who use Google to search for information about stocks and confirm that *ASVI* has a more significant impact on

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[4] The proportion of trading volume for retail investors was 77.61%, 74.45%, 69.02%, 68.34%, and 68.94% in 2009, 2010, 2011, 2012, and 2013, respectively.

[5] According to Oxford Internet Institute, the online population of Taiwan exceeded 80% in 2013. Please see https://i0.wp.com/geonet.oii.ox.ac.uk/wp-content/uploads/sites/46/2015/07/OII-Internet_population_cartogram.png.

individual herding. Third, we confirm the information-grabbing hypothesis, which posits that there is more significant individual herding when the price reaches the upper or lower price limit boundary. Fourth, we show that *ASVI* has a more significant impact on order-submitting herding behavior. Finally, we also examine the role of the underlying stock capitalization on the association between *ASVI* and herding behavior.

The remainder of this study is organized as follows. Section 2 reviews the past literature and develops the hypotheses. Section 3 offers the data and methodology. Section 4 presents the results and analysis. The final section consists of the discussion and conclusion.

2. Literature Review

The majority of the herding literature explores institutional herding,[6] and few studies have focused on individual herding behavior. Barber et al. (2009) investigate the herding behavior of individual investors using data from 665,533 households between 1997 and 1999 in the U.S. and confirm that reasons explaining herding behavior among institutional investors, including the principle-agent view, information cascades, and responses to shared information are not useful in explaining individual herding behavior. They find that individual herding could be systematic and especially, that buying behavior could be driven by past performance and abnormal trading volume observed from individual stocks. Therefore, the authors conclude that individual herding is likely to be caused by psychological bias

[6] For instance, Zhou and Lai (2009) used data from the Hong Kong market to verify the theory of information cascades in herding. They find that more herding is generated where there is a higher proportion of informed based trading as measured by PIN, especially sell side herding. Zhuo and Lai (2009) confirm the information cascades argument by observing the association between herding and informed trading, but individual herding behavior is not investigated in their study. See also Lakonishok et al. (1992), Grinblatt, Titman, Wermers (1995), Sias (2004).

(representativeness heuristic and disposition effect) and attention grabbing effects. Barber et al. (2009) documented systemic trading among noise traders.

Our study is motivated by Barber et al. (2009), who noted that individual herding is also an important phenomenon since it creates a “systematic noise”. In Taiwanese market where stock trading is dominated by individual investors, there is an urgent need to understand individual herding in depth. This would also be a substantial contribution to the literature. Barber et al. (2009) proposed past returns and abnormal trading volume as the leading proxies of individual herding. Thus, our study suggests that these two factors carry more “ex-post” features. Since the past returns and trading volume implies certain investors are already engaged in the trading of the underlying stocks, it is difficult to determine a clear point of herding initiation. This is why we contend that *ASVI* is a more ex-ante proxy of investors searching for information and committing to herding behavior.

Furthermore, Vayanos and Wang (2007) develop a search cost model that posits a clientele effect in explaining the relationship between search cost and trading volume. They contend that investors preferring short search times will search for more liquid and higher trading volume assets, whereas more patient investors have lower-switching-rate and higher search time. Lin, Tsai and Sun (2012) investigated Taiwanese investors’ trading behavior from the limit order books. Using Vayanos and Wang’s (2007) search cost model, they find that individual investors prefer to trade small cap stocks at the market opening and institutional investors like to trade large cap stocks at the market close due to the relatively low search cost for different types of investors. Merli and Roger (2013) trace individual herding persistence by applying trading records of over 80,000 French individual investors between 1999 and 2006. They find poor past performance induces significant herding in next quarter, and persistent herding at individual investor level occurs among less sophisticated investors.

Li et al. (2017) use a trading-volume based measure to observe herding behavior of institutional and individual investors in the Chinese market by applying data from SSE 180 index shares between 2002 and 2004. They find that institutional investors are more informed and individual investors rely more on the public information. Like Barber et al. (2009), they argue that individual herding is more likely to be driven by "*psychological biases, market sentiment and attention–grabbing events*". The authors find both institutional and individual herding are positively related to trading volume, and that their herding Grangers cause each other. Although Li et al. (2017) investigate the herding behavior of institutional and individual investors, for their empirical examination the authors still use the ex-post proxy of past stock returns and trading volume to observe investor herding.

Based on the information grabbing hypothesis, our study proposes using a more "ex-ante" proxy. We suggest that for individual investors with limited sources of information and easy access to the internet, the Google *SVI* can serve as an investor attention proxy, as it represents active searching by individual investors to obtain information on stocks. A higher abnormal *SVI* suggests a higher degree of attention, and induces more significant herding behavior, particularly for the individual investors who attempt to gain information from the open access.

In another strand of literature, De Long, Shleifer, Summers, and Waldmann (1990) suggest that noisy traders who overreact or underreact to information cause stock prices to temporarily deviate from their basic value. There are two types of investor sentiment indicators, direct emotional indicators, and indirect emotional indicators. The former is constructed based on survey of bullish/bearish views of investors for the future market. For instance, Shiller, Kon-Ya, and Tsutsui (1996) conduct a semi-annual survey of institutional investors' perspectives on the US and Japanese stock markets to obtain market sentiment indicators. The latter is calculated from market observation, and includes excess abnormal return (Barber and Odean, 2008), volume (Barber and Odean, 2008; Gervais et al. 2001) and advertising costs (Chemmanur and Yan, 2009). It is relatively difficult to directly measure investor sentiment and literature on it is scarce. Da et al. (2011) proposed a new direct sentiment indicator to detect investor attention, the Google search volume index. By applying data on Russell 3000 index stocks between 2004 and 2008, they find that *SVI* effectively captures the attention of retail investors, and is able to predict stock prices. The higher *SVI* is, the greater the stock price will be in the following two weeks, and the larger the degree of reversal within a year. Da et al. (2015) also examine whether investors can predict a company's earnings and revenues by using Google search engine to search for the company's products. They demonstrate that the higher the *SVI*, the more accurate the prediction for the positive revenue surprise, standardized unexpected earnings, and abnormal earnings during the earnings announcement period. Bank et al. (2011) also indicate that there is a positive relationship between online search and trading activities, which implies that search engines can reduce information asymmetry and improve the retail investors' willingness to invest.

Vlastakis and Markellos (2012) suggest that *SVI* is a proxy variable of information demand and has a significant positive relation with the past volatility and turnover of stocks. In addition, investors' demand for information rises significantly in a period of positive stock returns. Similarly, Gwilym, Wang, Hasan and Xie (2016) show that market returns and the Chinese stock index increase with *SVI*. The aforementioned studies have generally confirmed that *SVI* can serve as an information attention and market sentiment proxy and has predictive power for financial commodity returns, market volatility, liquidity, and volume (Dimpfl and Jank, 2016; Ding and Hou, 2015; Fink and Johann, 2014; Goddard, Kita and Wang, 2015). The literature focuses on the impact of information contained in past stock performance and trading volume on individual herding, but neglects sources of information which may induce herding. Thus, our study contributes to the literature by using abnormal *SVI* as an investor attention proxy to observe individual herding behavior. We further posit that the information grabbing effect brought by the abnormal *SVI* could lead to more buy orders, and more significant individual herding occurs in buying behavior than selling behavior, and more in order behavior than in trade.

Few studies explore herding in relation to investor attention. Shleifer and Summers (1990) propose that individual investors may exhibit herding behavior when they receive similar messages, such as analysts' recommendations, or the speech of influential business owners or government officials. Froot, Scharftstein and Stein (1992) and Hirshleifer et al. (1994) note that overconfidence and herding behavior occur because investors consider themselves to have better information than other investors, but in fact the information they obtain is not superior. Nofsinger and Sias (1999) show that herding behavior occurs when a group of investors accesses similar information at the same time to trade securities synchronically. Sias (2004) argues that one of the factors driving herding behavior is investors obtaining similar information. Hong, Kubik and Stein (2005) also suggest that since investors transmit information by word of mouth, fund managers in the same city trade the same stock.

From the aforementioned literature, when investors have shown a certain degree of attention to the same stock, they may easily make similar trading decisions. Yet, thus far no study has shed light on the relationship between the Google search volume index (we treat the index as an investor attention proxy) and individual herding behavior. We first propose that when a group of individual investors pays attention to the same stock, the abnormal search volume index involving a specific stock will be higher. This will be reflected in the trading decisions of the retail investors. Under these circumstances, it is very likely that individual investors searching for information through Google search will exhibit herding behavior. The first hypothesis is thus:

Hypothesis 1: The Google search volume index (information attention index) is positively related to herding behavior.

Further, Kelly and Ó Gráda (2000) state that: "*social interactions between individuals affect their decisions on equity participation and other financial decisions.*" Hsieh (2013) suggests that herding of individual investors is probably driven by behaviors and emotions. Da et al. (2011) find that using the Google search engine is the most convenient method for retail investors to obtain a variety of information. Da et al. (2011, 2015) further conclude that institutional traders have more sophisticated and complex information sources than retail investors. Most retail investors can only use public information resources such as Google search engine to obtain financial information. Therefore, we predict that the higher the abnormal Google search volume index, the higher the degree of individual investor herding behavior induced, unlike institutional investor herding. Our hypothesis 2 is thus:

Hypothesis 2: The degree of positive relationship between the Google search volume index (investor attention index) and herding is larger for retail investors than institutional investors.

Furthermore, Barber et al. (2008) and Degryse et al. (2005) both indicate that investors' investment intention may be observed from their order aggressiveness.

Barber et al. (2009), Foucault, Moinas and Theissen (2007) and Lin et al. (2012) also mention that individual investors limited orders may contain information correlated with trading. In the current study, we propose that to some extent the order book exhibits more significant individual herding than the done-deal trade book. Individual investors reflect the attention effect of a particular stock through placing either a buy order or a sell order on the underlying stock. Therefore, in this study, we posit that the impact of abnormal search volume index on individual herding is more pronounced in the order book than in the trade book.

Hypothesis 3: The degree of positive relationship between the Google search volume index (investor attention index) and herding is more significant when observing individual herding behavior with order book data than with trade data.

Further, Fama (1989) and Subrahmanyam (1994) suggest that when the market price of a stock is closer to the stock price limit, investors more aggressively submit orders, leading to increasing trading volume and volatility before the stock price reaches its upper/lower limit and accelerating the speed at which it reaches the limit. A few studies demonstrate that the higher the price limit-hit frequency, the higher the investor attention (Greenwald and Stein, 1988, 1991; Seasholes and Wu, 2007; Lin et al. 2017). Seasholes and Wu (2007) show that when a price limit event occurs, it attracts greater investor attention. They contend that the higher attention may drive investors to purchase stocks they have not invested in before. Lin et al. (2017) also find a positive relation between limit-hit frequency and investor attention. Greenwald and Stein (1988, 1991) indicate that investors can obtain more information during the price-limit hit.

In this paper, we postulate that when the underlying stock price movement hits the price limit, the investor attention index signals a more significant herding effect.

Further, investor attention is higher when the market is in a more bullish or bearish state, leading to more aggressive herding. We thus construct the following hypothesis:

Hypothesis 4: When the market price is close to the upper (lower) limit, the investor attention proxy (ASVI) has a more significant association with herding behavior.

Lakonishok et al. (1992), Wermers (1999, 2006), Choi and Sias (2009), and Venezia et al. (2011) all suggest that small capitalization firms generate more intense herding. Hung, Lu, and Lee (2010) investigate mutual fund herding in Taiwan and find that fund managers herd to buy small capitalization stocks, along with stocks which are undervalued with lower returns. However, Kremer and Nautz (2013) only find a significant size effect for non-active institutional investors. Palomino (1996), Sias (2004), and Blasco, Corredor, and Ferreruela (2012) all propose that large firms with better information quality may have cheaper search costs, leading to a higher propensity to herd.

We follow Lakonishok et al. (1992), Wermers (1999, 2006), Choi and Sias (2009), and Venezia et al. (2011) and suggest that the *ASVI* is a free source of information for retail investors. With lower search costs using Google and lower transaction costs for trading, the *ASVI* generates a more significant impact on small cap firms than large cap firms, in particular for retail investor herding behavior. Hypothesis 5 is thus:

Hypothesis 5: The investor attention proxy (ASVI) in general has a more significant association with buy (sell) order individual herding behavior when the underlying stocks have below median capitalization.

Finally, Kim, Yagüe, and Yang (2008) argue that there may be an asymmetric relation between the upper and lower price limits in which investors are more enthusiastic in providing liquidity when the upper limit is reached, while there will be a wider spread when the lower price limit is struck. Cho, Russell, Tiao, and Tsay (2003) find that in Taiwan, the price reaches the upper limit more rapidly than the lower limit. Lin (2009) finds that since price continuation may be higher for high risk stocks, small cap firms may exhibit higher volatility spillover and price continuation. This asymmetric relation may be explained by the differing degrees of investor confidence during bullish and bear markets. Both Daniel, Hirshleifer, and Subrahmanyam (2001) and Gervais and Odean (2001) present models in which the degree of overconfidence can vary over time and investors attitudes may be endogenous to market conditions. For instance, Gervais and Odean (2001) find that in bull markets, investors may become more overconfident. We thus postulate that in bull markets, investors exhibit herding behavior in buy orders due to overconfidence, especially for small capitalization stocks which are considered to have high risk and high potential returns. Investors who already own stocks have different sell points since owners have their own required rate of return. Therefore, we may not observe sell herding behavior in bullish markets. In bear markets, as prices deteriorate investors may start chasing undervalued stocks, which may bring higher potential capital gains. This causes more buy orders to be submitted for large cap stocks which suffer from greater declines in stock prices. The degree of overconfidence would also fall in a bear market, which could induce the original stockowners to engage in sell herding in large cap stocks, due to the greater capital loss than small cap firms. Therefore, we may observe herding behavior on both the buy and sell sides for large capitalization firms in a bear market.

Hypothesis 6: The investor attention proxy (ASVI) exhibits asymmetric effects under different market conditions. In a bullish market the ASVI has a more significant association with individual buy order herding behavior in small capitalization firms.

In a bearish market, the ASVI has a more significant association with both individual buy and sell order herding behavior in large capitalization firms.

3. Data and Methodology

Our dataset comprises all intraday transactions and orders of individual common stocks, including investor category[7], transaction/order date and time, transaction/order price and volume, and purchase/sell order specification. The data are obtained from the Taiwan Stock Exchange Corporation (TWSE, hereafter), with the sample period running from 2009 to 2013, covering a total of 831[8] different common stocks. Next, following Da et al. (2011) we download each listed company's weekly historical search volume index by selecting the area filter "Taiwan" and category filter "Finance" from Google Trends based on its abbreviated name as given by TWSE[9] from the year 2009 to 2013.

We first follow Lakonishok et al. (1992) and Zhou and Lai (2009)'s herding measure to estimate individual and institutional investors' weekly trade/order herding index by each stock based on the intraday frequency data[10]. The trade/order herding index is as follows:

$$Herd_{i,j,t} = (\mid P_{i,j,t} - E[P_{i,j,t}] \mid - E\mid P_{i,j,t} - E[P_{i,j,t}] \mid) \times 100. \quad (1)$$

where $P_{i,j,t}$ is the ratio of the number of purchase (sell) trades/orders to total number of trades/orders of stock i for type j of investor in a given week t. j includes retail and institutional investors. The greater the value of $Herd_{i,j,t}$, the higher the intensity of herding. Furthermore, if $P_{i,j,t}$ is larger (less) than $E[P_{i,j,t}]$, the herding measure is classified as buy-side (sell-side).

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7 There are a total of four types of investors operating in Taiwan: individuals, securities investment trust funds (SITF), qualified foreign institutional investors (QFIIs), and other companies.

8 We excluded delisted stocks (4), newly listed stocks (15), and low search volume stocks (24).

9 Please see http://www.twse.com.tw/en/.

10 Zhou and Lai (2009) modify the model of Lakonishok et al. (1992) by considering the number of trades instead of changes in stockholding. The measure thus considers the number of trades/orders rather than trading volume.

$E[P_{i,j,t}]$ is the average $P_{i,j,t}$ for all stocks for type j of investor in a given week t.

$E|\, P_{i,j,t} - E[P_{i,j,t}]\, |$ is the adjusted factor for the herding measure which adjusts the scale difference in different number of trades/orders[11].

We then follow the model of Da et al. (2011) to compute the *SVI* index. Based on their suggestion, we adjust *SVI* to control for time trends and other low-frequency seasonal issues. The definition of abnormal *SVI* (*ASVI*) is the log of *SVI* during the week minus the log of median *SVI* during the previous eight weeks.

$$ASVI_{i,t} = \log(SVI_{i,t}) - \log[\ \mathrm{Med}(SVI_{i,t-1},\ldots\ldots, SVI_{i,t-8})\ ]. \qquad (2)$$

Where log ($SVI_{i,t}$) is the logarithm of *SVI* for stock i during week t, and log[Med($SVI_{i,t-1},\ldots\ldots, SVI_{i,t-8}$)] is the logarithm of the median value of *SVI* for stock i during the previous eight weeks.

After estimating both the *ASVI* and the herding proxy, we can examine the relationship between investors' degree of attention for stocks and their herding behavior. Following Zhou and Lai (2009), we also control for the other determinants of the herding behavior in the pooled OLS and panel regression models as follows[12]:

$$Herd_{i,j,t} = a_0 + a_1 \times ASVI_{i,t} + a_2 \times Herd_{i,-j,t} + a_3 \times CAP_{i,t} + a_4 \times RET_{i,t-1} + a_5 \times EP_{i,t} + a_6 \times VOL_{i,t} + a_7 \times STD_{i,t} + a_8 \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,t} \qquad (3)$$

where $Herd_{i,j,t}$ is the individual (institutional) herding measure for stock i in a given week t. $ASVI_{i,t}$ is abnormal *SVI* for stock i in a given week t. $CAP_{i,t}$ is market capitalization of stock i in a given week t. $RET_{i,t-1}$ is past returns of stock i during the previous 1 week. $EP_{i,t}$ is the inverse of the P/E ratio for stock i in a given week t. $VOL_{i,t}$ is the trading volume of stock i in a given week t. $STD_{i,t}$ is the standard deviation of daily returns for stock i during the prior 3 months. $VIX_{i,t}$ is the mean value

[11] Please refer to Lakonishok et al. (1992) for details on how to compute the adjustment factor.
[12] We also include *VIX* to control for investor sentiment. In addition, we consider overall, buy-side, and sell-side order and trade herding measures for retail and institutional traders.

of daily *VIX* during the week *t*. $\varepsilon_{i,t}$ is disturbance term. We also control for the correlated herding between individual and institutional investors, when the dependent variable ($Herd_{i,j,t}$) is the individual (institutional) herding measure, the independent variable ($Herd_{i,-j,t}$) is the institutional (individual) herding measure.

To confirm hypothesis 1, we expect there is a positive significant coefficient generated by the a_1. To confirm hypothesis 2, we prediction that a_1 for the individual herding equation is more significant and has a higher magnitude compare with the a_1 for the institutional herding equation.

Furthermore, we include upper price limit reached and lower price limit reached events in equation (4) and (5), and examine the effects of individual investors' attention to stocks and their herding behavior during event and non-event periods. The pooled OLS and panel regression models are as follows:[13]

$$Herd_{i,j,t} = b_0 + b_1 \times Up_{i,t} + b_2 \times ASVI_{i,t} + b_3 \times Up_{i,t} \times ASVI_{i,t} + b_4 \times Herd_{i,-j,t} + b_5 \times CAP_{i,t} + b_6 \times RET_{i,t-1} + b_7 \times EP_{i,t} + b_8 \times VOL_{i,t} + b_9 \times STD_{i,t} + b_{10} \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,j,t}. \tag{4}$$

$$Herd_{i,j,t} = c_0 + c_1 \times Lo_{i,t} + c_2 \times ASVI_{i,t} + c_3 \times Lo_{i,t} \times ASVI_{i,t} + c_4 \times Herd_{i,-j,t} + c_5 \times CAP_{i,t} + c_6 \times RET_{i,t-1} + c_7 \times EP_{i,t} + c_8 \times VOL_{i,t} + c_9 \times STD_{i,t} + c_{10} \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,j,t}. \tag{5}$$

where the upper price limit ($Up_{i,t}$) is defined as 1 when stock *i* reaches the upper price limit in a given week, otherwise it is 0. The lower price limit ($Lo_{i,t}$) is defined as 1 when stock *i* reaches the lower price limit in a given week; otherwise it is 0. The definitions of the other variables are the same as in equation (3).

[13] We also apply the absolute number of days during a week in which the upper and lower limit is reached instead of the upper and lower price limit dummy variables in Table 3 and obtain consistent results. The above robustness results are available from the authors upon request.

To confirm hypothesis 3, we compare the regression results using buy (sell) orders and buy (sell) trade data as the main dependent variables in each table. We expect the magnitude of order herding to be more significant than that of herding measured with trading data. To confirm hypothesis 4, we predict that b_3 (c_3) and the coefficient of ($b_2 + b_3$) (($c_2 + c_3$)) will be significantly positive. This will be especially strong during buy order herding behavior when the price hits the upper limit and under sell order herding behavior when the price reaches the lower limit.

To enhance the robustness of the empirical analysis, we conduct further analyses of upper (lower) price limit for several days in a given week which may increase the degree of relationship between Google search volume index and herding behavior. Thus, we replicate the regression specification by replacing the upper (lower) price limit dummy variable with two dummy variables, *Uu1* (*Ll1*) and *Uu2* (*Ll2*). *Uu1* (*Ll1*) equals 1 if the upper (lower) price limit occurs for one or two days in a given week, and 0 otherwise. Similarly, *Uu2* (*Ll2*) equals 1 if the upper (lower) price limit is reached three, four, or five days in a given week, and 0 otherwise. To confirm hypothesis 4, we predict that the coefficient of ($d_3 + d_4$) (($e_3 + e_4$)) and the coefficient of ($d_3 + d_5$) (($e_3 + e_5$)) will be significantly positive. We also expect *Uu2* and *Ll2* will generate more significant results, as it represents frequency of more bullish/bearish market thus may lead to more pronounced herding. Therefore, we present equation (6) and (7) as follows:

$$Herd_{i,j,t} = d_0 + d_1 \times Uu1_{i,t} + d_2 \times Uu2_{i,t} + d_3 \times ASVI_{i,t} + d_4 \times Uu1_{i,t} \times ASVI_{i,t} + d_5 \times Uu2_{i,t} \times ASVI_{i,t} + d_6 \times Herd_{i,-j,t} + d_7 \times CAP_{i,t} + d_8 \times RET_{i,t-1} + d_9 \times EP_{i,t} + d_{10} \times VOL_{i,t} + d_{11} \times STD_{i,t} + d_{12} \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,j,t}. \quad (6)$$

$$Herd_{i,j,t} = e_0 + e_1 \times Ll1_{i,t} + e_2 \times Ll2_{i,t} + e_3 \times ASVI_{i,t} + e_4 \times Ll1_{i,t} \times ASVI_{i,t} + e_5 \times Ll2_{i,t} \times ASVI_{i,t} + e_6 \times Herd_{i,-j,t} + e_7 \times CAP_{i,t} + e_8 \times RET_{i,t-1} + e_9 \times EP_{i,t} + e_{10} \times VOL_{i,t} + e_{11} \times STD_{i,t} + e_{12} \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,j,t}. \quad (7)$$

To confirm hypothesis 5, we divide the total sample into two subsample sets, the Above Median Market Capitalization and Below Median Market Capitalization groups. We then re-run the baseline regression in equation (3) for the two subsample groups and expect that the coefficient of $ASVI_{i,t}$ will be more significant in the Below Median Market Capitalization than the Above Median Market Capitalization group.

To further assess whether the impact of *ASVI* on herding behavior exhibits asymmetry effects with market capitalization stocks of different scale, we replicate the regression by including a market capitalization dummy variable *MC*, which equals 1 if market capitalization is below the median and 0 otherwise, and an interaction terms between market capitalization, upper (lower) limited reached dummy, and the *ASVI* proxy. To confirm hypothesis 6, we expect (f_4 +f_6) and (f_4 + f_5 +f_6 + f_7) in equation (8) to be significantly positive for all and buy order herding in a bullish market. Further, in a bullish market the magnitude of buy order herding in small capitalization stocks (f_4 + f_5 +f_6 + f_7) will be larger than herding for large capitalization stocks (f_4 +f_6). We also predict that (g_4 +g_6) and (g_4 + g_5 +g_6 + g_7) in equation (9) will be significantly positive for sell order herding in a bearish market. Further, in a downside market, the magnitude of sell order herding in large capitalization stocks (g_4 +g_6) will be larger and more significant than for small capitalization stock (g_4 + g_5 +g_6 + g_7) herding. We present equations (8) and (9) as follows:

$$Herd_{i,j,t} = f_0 + f_1 \times MC_{i,t} + f_2 \times Up_{i,t} + f_3 \times MC_{i,t} \times Up_{i,t} + f_4 \times ASVI_{i,t} + f_5 \times MC_{i,t} \times ASVI_{i,t} + f_6 \times Up_{i,t} \times ASVI_{i,t} + f_7 \times MC_{i,t} \times Up_{i,t} \times ASVI_{i,t} + f_8 \times Herd_{i,-j,t} + f_9 \times CAP_{i,t} + f_{10}$$

$\times RET_{i,t-1} + f_{11} \times EP_{i,t} + f_{12} \times VOL_{i,t} + f_{13} \times STF_{i,t} + f_{14} \times VIX_{i,t}$ + Industry dummy $+\varepsilon_{i,j,t}$. (8)

$Herd_{i,j,t} = g_0 + g_1 \times MC_{i,t} + g_2 \times Lo_{i,t} + g_3 \times MC_{i,t} \times Lo_{i,t} + g_4 \times ASVI_{i,t} + g_5 \times MC_{i,t} \times ASVI_{i,t} + g_6 \times Lo_{i,t} \times ASVI_{i,t} + g_7 \times MC_{i,t} \times Lo_{i,t} \times ASVI_{i,t} + g_8 \times Herd_{i,-j,t} + g_9 \times CAP_{i,t} + g_{10} \times RET_{i,t-1} + g_{11} \times EP_{i,t} + g_{12} \times VOL_{i,t} + g_{13} \times STD_{i,t} + g_{14} \times VIX_{i,t}$ + Industry dummy $+\varepsilon_{i,j,t}$. (9)

We conduct robustness tests to replace the individual/institutional Herding measures by computing Abnormal individual/institutional Herding statistics ($AHerd_{i,j,t}/AHerd_{i,-j,t}$) which is equal to original Herding measures minus the median Herding measures during the previous eight weeks in equations (3), (4), (5), (8) and (9), revised as equations (10), (11), (12), (13) and (14). To confirm hypothesis 1, we predict that h_1 for the individual order herding equation will be significantly positive. In addition, we predict that k_3 (l_3) and the coefficient of (k_2 + k_3) ((l_2 + l_3)) in equations (11) and (12) will be significantly positive, supporting hypothesis 4, which contends that buy(sell) order herding behavior will be especially strong when the price hits the upper(lower) limit. To confirm hypothesis 6, we further expect that (m_4 +m_6) and (m_4 + m_5 +m_6 + m_7) in equation (13) will be significantly positive for all and buy order herding in a bullish market. Further, in a bullish market the magnitude of buy order herding in small capitalization stocks (m_4 + m_5 +m_6 + m_7) will be larger than for large capitalization stock (m_4 +m_6) herding. We also predict that (n_4 +n_6) and (n_4 + n_5 +n_6 + n_7) in equation (14) will be significantly positive for sell order herding in a bearish market. Further, in a downside market, the magnitude of sell order herding in large capitalization stocks (n_4 +n_6) will be larger and more significant than small capitalization stock (n_4 + n_5 +n_6 + n_7) herding.

$AHerd_{i,j,t} = h_0 + h_1 \times ASVI_{i,t} + h_2 \times AHerd_{i,-j,t} + h_3 \times CAP_{i,t} + h_4 \times RET_{i,t-1} + h_5 \times EP_{i,t} + h_6 \times VOL_{i,t}$

$$+ h_7 \times STD_{i,t} + h_8 \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,t}. \tag{10}$$

$$AHerd_{i,j,t} = k_0 + k_1 \times Up_{i,t} + k_2 \times ASVI_{i,t} + k_3 \times Up_{i,t} \times ASVI_{i,t} + k_4 \times AHerd_{i,-j,t} + k_5 \times CAP_{i,t} + k_6 \times RET_{i,t-1} + k_7 \times EP_{i,t} + k_8 \times VOL_{i,t} + k_9 \times STD_{i,t} + k_{10} \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,j,t}. \tag{11}$$

$$AHerd_{i,j,t} = l_0 + l_1 \times Lo_{i,t} + l_2 \times ASVI_{i,t} + l_3 \times Lo_{i,t} \times ASVI_{i,t} + l_4 \times AHerd_{i,-j,t} + l_5 \times CAP_{i,t} + l_6 \times RET_{i,t-1} + l_7 \times EP_{i,t} + l_8 \times VOL_{i,t} + l_9 \times STD_{i,t} + l_{10} \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,j,t}. \tag{12}$$

$$AHerd_{i,j,t} = m_0 + m_1 \times MC_{i,t} + m_2 \times Up_{i,t} + m_3 \times MC_{i,t} \times Up_{i,t} + m_4 \times ASVI_{i,t} + m_5 \times MC_{i,t} \times ASVI_{i,t} + m_6 \times Up_{i,t} \times ASVI_{i,t} + m_7 \times MC_{i,t} \times Up_{i,t} \times ASVI_{i,t} + m_8 \times AHerd_{i,-j,t} + m_9 \times CAP_{i,t} + m_{10} \times RET_{i,t-1} + m_{11} \times EP_{i,t} + m_{12} \times VOL_{i,t} + m_{13} \times STF_{i,t} + m_{14} \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,j,t}. \tag{13}$$

$$AHerd_{i,j,t} = n_0 + n_1 \times MC_{i,t} + n_2 \times Lo_{i,t} + n_3 \times MC_{i,t} \times Lo_{i,t} + n_4 \times ASVI_{i,t} + n_5 \times MC_{i,t} \times ASVI_{i,t} + n_6 \times Lo_{i,t} \times ASVI_{i,t} + n_7 \times MC_{i,t} \times Lo_{i,t} \times ASVI_{i,t} + n_8 \times AHerd_{i,-j,t} + n_9 \times CAP_{i,t} + n_{10} \times RET_{i,t-1} + n_{11} \times EP_{i,t} + n_{12} \times VOL_{i,t} + n_{13} \times STD_{i,t} + n_{14} \times VIX_{i,t} + \text{Industry dummy} + \varepsilon_{i,j,t}. \tag{14}$$

4. Empirical Results

4.1 Descriptive Statistics

Table 1 depicts descriptive statistics of *ASVI*, herding proxy and other control variables. We can see that based on the herding measure of Lakonishok et al. (1992), individual herding is more significant for the order book than for the record of actual trades, as are the investors buy orders. The mean values of Order *Herd* (*Herd_B*) are 4.471 (4.386) greater than those of Trade *Herd* (*Herd_B*) (4.463 (4.357)). In addition, individual total and buy order herding behavior occurs more often (Order *Herd*=5.179, Order *Herd_B*=6.132) in a week when the underlying stock reaches the upper limit boundary, meaning that the market is experiencing a bullish state. Conversely, individual sell order herding behavior occurs more often in a week (Order *Herd_S*=4.668.) when the underlying stock reaches the lower limit boundary, meaning that the market is experiencing a bearish state. The figure for the abnormal search volume index (*ASVI*) is higher when the underlying stock reaches the upper (lower) price limit during a week (Mean =0.178 (0.136)), than over the sample period as a whole (0.097). These preliminary results show that both *ASVI* and Herding occur more often in a bullish/bearish market.

[Insert Table 1 about here]

4.2 Herding Behavior Regression Estimates

To better quantify the relation between investors' intention for stocks and their herding behavior, we estimate pooled OLS and panel regressions[14] model as in equation (3). In the regression specification, the *Herd* measure is the dependent variable, and the *ASVI* along with a set of stock characteristics variables are employed as independent variables. The choice of independent variables other than *ASIV* is motivated by Zhou and Lai (2009), who show that the level of herding behavior is related to a variety of stock characteristics. The overall order and trade herding behavior of pooled OLS and panel regression estimates for individual investors are reported in Panel A of Table 2, which indicate that the *ASVI* coefficient estimate is positive and strongly significant (*ASVI* coefficient=0.029, 0.029).[15] Similarly, estimations of buy-side and sell-side order herding behavior demonstrate that the *ASVI* measure can explain a considerable portion of the variation in the herding behavior (*ASVI* coefficient=0.073, 0.071 for buy-side; 0.036, 0.035 for sell-side).

[14] By using the Hausman test, we accept the null hypothesis that the residuals are correlated with any independent variables. Thus, the panel regression model with random effect is employed in the analysis of herding behavior as well.
[15] We apply the White heteroscedasticity-consistent variance covariance matrix whenever applicable.

Furthermore, comparing the *ASVI* coefficient estimate in buy-side regression with the coefficient estimate in the sell-side and overall regression, we find that the *ASVI* coefficient estimate in the buy-side regression is the strongest determinant of herding behavior. As a result, individual investors exhibit stronger order buy-side herding behavior than sell-side when there is higher *ASVI*.

Panel B of Table 2 depicts results of pooled OLS and panel regressions on the association of institutional herding behavior and *ASVI*. We can see that for all the regressions, there are no significant correlation between *ASVI* and institutional herding. Therefore, we shift the focus of this paper to an analysis of the association between *ASVI* and individual herding behavior.[16]

The herding regression estimates provide significant evidence of a positive relation between Google search volume index and the individual investors' order herding measure. This result is consistent with our first and second hypothesis, which posits that individual investors who use internet search engines exhibit stronger order herding behavior because they are apt to obtain similar information from the internet more easily when researching an order to trade a stock. Da et al. (2011) argue that the Google search volume index reflects only the activity of noise traders, individual investors are more likely to search for financial information regarding a stock in Google. Our finding is consistent with their argument. Da et al. (2015) further argue that institutional investors have access to more sophisticated information services such as Reuters or Bloomberg terminals. Therefore, it is not surprising that we do not observe a significant relationship between Google *ASVI* and herding behavior for the

[16] From Table 3 to Table 9, we also examine the relationship between *ASVI* and institutional herding behavior, but such results are almost all not significant. We do not report them because of space constraints. The above robustness results are available from the authors upon request.

institutional investors. In sum, the results shown in Table 2 confirm our hypotheses 1 and 2.

[Insert Table 2 about here]

4.3 Herding Behavior Regression Estimates between Events and Non-events Period

To assess whether individual investors are more likely to increase their Google search volume index during event periods, we include upper price and lower price limit events and explore whether *ASVI* has stronger impact on herding behavior during bull and bear markets.

In Table 3 Panel A, we estimate the regression as in equation (4) by including a dummy variable equal to 1 if a stock reaches the upper price limit in a given week, and 0 otherwise. Panel A of Table 3 confirms that individual investors are more inclined to increase their Google search volume index when they submit a buy order, which results in more herding behavior during the upper price limit period. However, sell order herding does not occur when the price reaches the upper limit. The coefficients on the *ASVI* plus interactions between the upper price limit dummy and *ASVI* (*ASVI+Up×ASVI*) of overall and buy-side order pooled OLS regression are 0.116 and 0.254, respectively, both significant at the 1% level. In the panel regression, the coefficients of *ASVI+Up×ASVI* for overall and buy-side order are 0.116 and 0.251 respectively, both also significant at the 1% level.

Moreover, we also examine the marginal effect of *ASVI* on individual herding measures between the lower and non-lower price limit period in Panel B of Table 3 as in equation (5). The coefficients of the *ASVI* plus the interactions between the lower price limit dummy variable (*Lo*) and *ASVI* (*ASVI+Lo×ASVI)* of overall and sell-side order pooled OLS regression are 0.135 and 0.238, respectively, significant at the 1%

level, while in the overall and sell-side order panel regression they are 0.135 and 0.240, respectively. This finding provides strong evidence that in a down market, individual investors prefer to increase their search frequency in Google when submitting a sell order, resulting in more herding behavior during a bearish market when the likelihood reaching the lower price limit is higher. Furthermore, in Table 2 and Table 3, herding coefficients are more significant in the order statistics than the trade statistics, which confirms our hypothesis 3, which states: *The degree of positive relationship between the Google search volume index (investor attention index) and herding is more significant when observing individual herding behavior with order book data than with trade data.* The findings in Table 3 also strongly support Hypothesis 4*: When the market price is close to the upper (lower) limit, the investor attention proxy (ASVI) has a more significant association with the buy (sell) order herding behavior.*

[Insert Table 3 here]

4.4 Impact of Stock Capitalization on the association between *ASVI* and Herding Behavior

In Tables 4 to 6, we examine the association between *ASVI* and herding behavior for large capitalization and small capitalization underlying stocks using equations (3), (8), and (9). In hypothesis 5, we posit that as the small capitalization stocks have lower tick size, and lower stock prices, information flow may cause stronger herding for small cap firms, especially for retail investors in general.

Table 4 Panel A we compare the results of herding equation (3) for the Pooled OLS between above median capitalization and below median capitalization. The coefficient of *ASVI* is more significant and the magnitude is also larger for the Below Median Capitalization sample than the Above Median Capitalization sample

(All_Order: 0.049 vs. 0.020, Buy_order: 0.129 vs. 0.035) for individual investors. Panel B of Table 4 shows the consistent results generated using the panel regression model (All_Order: 0.047 vs. 0.017, Buy_order: 0.129 vs. 0.031). In sum, Table 4 confirms hypotheses 1, 3, and 5, showing that there is a positive association between *ASVI* and individual herding, in particular for order herding behavior. The association between *ASVI* and *Herd* is further enhanced for firms with smaller capitalization, in particular for buy order herding.

[Insert Table 4 here]

To assess whether market capitalization influences the impact of *ASVI* on herding behavior for upper and non-upper price limit weeks and for high and low market capitalization, we apply equation (8), which includes a market capitalization dummy variable (*MC*) which equals 1 for the below median capitalization group, and 0 otherwise in Table 5. To confirm hypothesis 6, we expect that (*ASVI*+*Up*×*ASVI*) for the above median capitalization group and (*ASVI*+*MC*×*ASVI*+*Up*×*ASVI*+ *MC*×*Up*×*ASVI*) for the below median capitalization group in equation (8) to be significantly positive for all and buy order herding in a bullish market. Further, in a bullish market the magnitude of buy order herding in small capitalization stocks (*ASVI*+*MC*×*ASVI*+*Up*×*ASVI*+*MC*×*Up*×*ASVI))* will be larger than in large capitalization stocks (*ASVI* +*Up*×*ASVI*) herding. In a bullish market both large capitalization and small capitalization groups generate significantly positive buy order herding (Above Median Capitalization: *ASVI*+*Up*×*ASVI*: All_Order = 0.084, Buy_Order=0.201, Below Median Capitalization: *ASVI* + *MC*×*ASVI* + *Up*×*ASVI* + *MC*×*Up*×*ASVI*: All_Order= 0.170, Buy_Order=0.307). We could observe that *MC* increases the effect of *ASVI* on herding behavior, especially for individual investor buy orders (*ASVI*+*MC*×*ASVI*+*Up*×*ASVI*+*MC*×*Up*×*ASVI* = 0.307, 0.296, respectively for pooled OLS and panel models). These results are consistent with the hypothesis 6, which posits that *ASVI is* more strongly associated with buy order herding when the market price is near the upper limit, especially for small capitalization firms.

[Insert Table 5 here]

In Table 6 we show the results of equation (9), which explores down markets, to determine whether *ASVI* affects sell orders and is more pronounced for large capitalization firms. Table 6 shows that the association between *ASVI* and *Herd* is further enhanced for firms with greater capitalization (*(ASVI+Lo×ASVI)*= 0.151, 0.253, 0.303 and 0.197 in the Pooled OLS, respectively, for all, buy, sell order and sell trades (the random effect model yields similar findings)), when the lower price limit dummies are taken into account. Compared to the below median group (*ASVI+MC×ASVI+Lo×ASVI+ MC×Lo×ASVI*=0.114, 0.108, 0.027, 0.179*)*, the large capitalization firms have more significant results in a down market.

[Insert Table 6 here]

The results from Tables 5 and 6 confirm our hypothesis 6, which states that "*The investor attention proxy (ASVI) exhibits asymmetric effects under different market conditions. In a bullish market the ASVI has a more significant association with individual buy order herding behavior in small capitalization firms. In a bearish market, the ASVI has a more significant association with individual sell order herding behavior in large capitalization firms*". The results shown in Tables 5 and 6 are consistent with the contention of Daniel et al. (2001) and Gervais and Odean (2001) that the degree of overconfidence can vary over time, and asymmetric relations between the upper price and lower price limits may exist (Kim et al. (2008)).

4.5 Robustness Test

In Table 7 we next examine whether reaching the upper (lower) price limit for several days in a given week enhances the relationship between Google search volume index and herding behavior, as a robustness check. We replicate the regression specification by replacing the upper (lower) price limit dummy variable in equations (6) and (7) with two dummy variables which are *Uu1* (*Ll1*) and *Uu2* (*Ll2*). *Uu1* (*Ll1*) equals 1 if the upper (lower) price limit is reached one or two days in a given week, and 0 otherwise. *Uu2* (*Ll2*) equals 1 if the upper (lower) price limit is reached three, four, or five days in a given week, and 0 otherwise. To save space, Table 7 only reports the coefficients of *ASVI*, *Uu1* (*Ll1*) ×*ASVI*, and *Uu2* (*Ll2*)×*ASVI*. To investigate the effect of the upper (lower) price limit, we separately test the null hypotheses that the sum of *ASVI* and *Uu1* (*Ll1*)×*ASVI* is zero, and the sum of *ASVI* and *Uu2* (*Ll2*)×*ASVI* is zero. In Panel A of Table 7, we reject the second hypothesis for overall and buy-side order herding in the pooled OLS and Panel regression models. The sum of the coefficients on *ASVI* and *Uu2*×*ASVI* is significantly positive and greater than the sum of the coefficients on *ASVI* and *Up*×*ASVI* for overall and buy-side order herding in Panel A of Table 3 (0.896 vs. 0.116 and 1.083 vs. 0.254 in pooled OLS model; 0.919 vs. 0.116 and 1.073 vs. 0.251 in Panel regression model). The results show that the number of days in which the upper price limit is reached in a given week will increase the strength of the relationship between Google search volume index and herding behavior. In Panel B of Table 7, we also find that the sum of the coefficients on *ASVI* and *Ll2*×*ASVI* are significantly positive for sell-side order herding measures and greater than the sum of the coefficients on *ASVI* and *Lo*×*ASVI* for sell-side order herding in Panel B of Table 3 (1.857 v.s. 0.238 in pooled OLS model; 1.907 v.s. 0.240 in Panel regression model), implying individual traders are likely to make use of Google during an above 3-day lower price limit week, resulting in more stronger sell-side order herding behavior. The results show that retail traders are inclined to increase their sell-side order herding behavior when using Google online search during a 3-5-day lower price limit week.

In sum, the results in Table 7 confirm hypotheses 1, 2, and 3, which posit that there is a significant association between *ASVI* and individual investor herding. Moreover, if the upper (lower) price limit is reached three, four, or five days in a given week, the impact of *ASVI* on the overall and buy-side (sell-side) order herding behavior for individual investors will increase.

[Insert Table 7 about here]

Table 8 shows the results of two robustness tests. In the first we replaced *ASVI* by applying all positive *ASVI* to estimate an empirical analysis of Table 2 and Table 3, while the second one replaced the individual/institutional Herding statistics by computing Abnormal individual/institutional Herding statistics following the same method as estimating *ASVI* in equations (10), (11), and (12). Panel A of Table 8 shows that there is a positive association between investor attention (*ASVI*) and individual herding behavior (*Herd*) (0.073, 0.084), and buy order herding is more significant than sell order herding, findings consistent with Table 2. Results from Panel A again confirm hypotheses 1 and 3.

Panel B and Panel C of Table 8 replicate the empirical analysis of Table 3 using a different *Herding* measure in equations (11) and (12). Panel B of Table 8 shows that in general in a bullish market buy orders generate higher Herding statistics than sell orders in the pooled OLS and Panel regression models ($ASVI+Up\times ASVI$=0.597 vs. -0.018 for ASVI>0 group, 0.153 vs. -0.036 using abnormal herding measure; $ASVI+Up\times ASVI$=0.625 vs. 0.006 for ASVI>0 group, 0.154 vs. -0.035 using abnormal herding measure), supporting hypothesis 4. In addition, Panel C of Table 8 shows that results confirm hypothesis 6 only when using a positive *ASVI* and abnormal herding proxy (*ASVI+Lo×ASVI*=0.558 vs. 0.454 for ASVI>0 group, 0.098 vs. 0.130 using the abnormal herding measure). It is possible that in a down market, with price distortion there is more noise trading as investors may attempt to herd when stock price go down, while investors who own the shares in the first place may also try to herd (sell order) when price of the stock decreases. But in general, *when the market price is close to the upper limit, the investor attention proxy (ASVI) has a more significant association with the buy order herding behavior.*

[Insert Table 8 here]

Table 9 shows the results of testing the results in Tables 5 and 6 by substituting *ASVI* for *ASVI*>0 only data in equations (8) and (9) and applying abnormal herding instead of herding in equations (13) and (14). In Panel A of Table 9 results for herding with large firms are significant for both all and buy orders ((*ASVI+ Up×ASVI*) = 0.135, 0.505, 0.080, 0.497, 0.080) for the large capitalization group. Conversely, (*ASVI+MC×ASVI+Up×ASVI+MC×Up×ASVI*) for the small capitalization group is also significantly positive in a bullish market (0.453, 0.602, 0.138, 0.489, 0.674, 0.138). Consistent with Table 5, in a bullish market the magnitude of herding in small capitalization stocks (*ASVI+MC×ASVI+Up×ASVI+ MC×Up×ASVI)*) is larger than for large capitalization stock (*ASVI +Up×ASVI*) herding. These results again confirm hypotheses 6, which posits that *ASVI is* more strongly associated with buy order herding when the market price is near the upper limit, especially for small capitalization firms.

In Panel B of Table 9, we run equation (9) by retaining only positive *ASVI* data and by computing abnormal herding statistics. The results shown in Panel B of Table 9 demonstrate partial consistency with the results presented in Table 6. When applying positive *ASVI* group only in the empirical analysis (Columns 1 and 3), results show that in a down market, the association between *ASVI* and *Herd* is further enhanced for firms with smaller capitalization ((*ASVI+MC×ASVI+Up×ASVI+ MC×Up×ASVI)*= 0.344, 0.624, 0.398, 0.937 and 0.596 in the Pooled OLS and Panel models, respectively). When applying positive *ASVI* to the groups only sample set, small capitalization firms generate more significant herding behaviors than large cap firms. Further, the results shown in Columns 2 and 4 in Panel B of Table 9 are consistent with the results shown in Table 6. In a bearish market, large capitalization firms may exhibit more significant herding in both buy and sell order than small capitalization firms. ((*ASVI+Lo×ASVI*=0.122, 0.219, 0.122, 0.220), while *ASVI+MC×ASVI+Lo×ASVI+ MC×Lo×ASVI* are not significant in Columns 2 and 4 of Panel B in Table 9.) The findings shown in Columns 2 and 4 are consistent with the results in Table 6 and confirm hypothesis 6, which states that "*The investor attention proxy (ASVI) exhibits asymmetric effects under different market conditions. In a bullish market the ASVI has a more significant association with individual buy order herding behavior in small capitalization firms. In a bearish market, the ASVI has a more significant association with both individual buy and sell order herding behavior in large capitalization firms*". Results from Table 9 in general confirm the findings shown in Tables 5 and 6. In a bullish market, the total and buy order herding is a more palpable phenomenon. However, in a bearish market, because market conditions are unstable, herding behavior occurs in both the total and sell orders for large and small capitalization firms.

[Insert Table 9 here]

5. Conclusion

Researchers argue that when cost of information search is low, investors obtain free information and herd (Bikhchandani et al. (1992), Sgroi (2002) and Kultti and Miettinen (2006)). Our paper represents the first attempt in the individual herding behavior literature to show that the Google search volume index can serve as a source of free information and indicate the degree of attention of retail investors. It may thus induce individual herding behavior. Further, the literature proposes that market trading outcomes such as past returns and abnormal trading volume are useful proxies of individual herding. Our study suggests that these two factors carry more "ex-post" features, as the past returns and trading volume implies certain investors are already engaged in the trading of the underlying stocks, making it difficult to identify the motives for herding initiation.

In response, based on the information grabbing hypothesis, our study uses a more "ex-ante" proxy under which we suggest that for individual investors with limited sources of information and easy access to the internet, the Google search volume index can serve as a pertinent investor attention proxy. Thus, our study contributes to the literature by using the abnormal *SVI* as an investor attention proxy to observe individual herding behavior. We further posit that the information grabbing effect represented by the abnormal *SVI* can lead to more buying orders. Hence, we observe more significant individual herding phenomenon in buying behavior than in selling behavior, and more in order behavior than in trade.

We conduct an analysis using intraday Taiwanese stocks trading data, since stock trading in the Taiwanese market is dominated by individual investors, there is an urgent need to understand individual herding in depth. These results thus make a substantial contribution to the literature. By applying intraday data to estimate the individual investor herding measure, and constructing a weekly abnormal search volume index, our paper shows that the Google search volume index can be a proxy for individual investor attention. In addition, the measure of *ASVI* shows that individual investors become more attentive to the information than the institutional investors and hence exhibit more significant herding behavior. Following the suggestion of Barber et al. (2008) and Degryse et al. (2005), that order aggressiveness can capture investor trading intentions, we further classified the herd measure into buy and sell order herding, and buy and sell trade herding, and finds that in general, order submission reflects order aggressiveness and exhibits more significant herding behavior.

We further expand our research on the impact of *ASVI* on herding phenomenon by including the event of the underlying stock price reaching the upper and lower limits in a week. Evidence shows that reaching the limit generates an information-grabbing effect which further enhances the impact of investor attention on individual investor herding behavior. Further, while in general small cap firms generate more intensive herding, we explore the asymmetric impact of market capitalization on the association of *ASVI* and herding behavior in bull and bear markets. We confirm that the individual investor buy herding phenomenon is stronger in bull markets, especially for small capitalization firms. Further, in bear markets, with greater price deterioration for large cap firms, we detect herding behavior on both the buy and sell sides. In sum, this study contributes to the literature on individual herding behavior by finding that the Google search index can serve as an investor attention proxy in identifying individual investor herding.

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Table 1 Descriptive Statistics of Herding measure, *ASVI*, and Other Control Variables

Herd is individual herding measures for a stock in a given week which is classified as overall order/trade herding, buy-side order/trade herding, and sell-side order/trade herding. *ASVI* is abnormal *SVI* for a stock in a given week. *CAP* is market capitalization of a stock. *RET* is past returns of a stock during the prior 1 week. *EP* is the inverse of the P/E ratio for a stock in a given week. *VOL* is the trading volume of a stock in a given week. *STD* is the standard deviation of daily returns for a stock during the prior 3 months. *VIX* is the mean value of daily *VIX* during a week.

	Individual herding measure						Control variables						
	ALL		BUY		SELL								
	Order	Trade	Order	Trade	Order	Trade							
Variable	*Herd*	*Herd*	*Herd_B*	*Herd_B*	*Herd_S*	*Herd_S*	*ASVI*	*CAP*	*RET*	*EP*	*VOL*	*STD*	*VIX*
All Sample													
Mean	4.471	4.463	4.386	4.357	4.539	4.561	0.097	8.799	0.496	0.057	8.471	2.159	20.702
Median	3.230	3.040	3.036	2.961	3.378	3.109	0.000	8.666	0.000	0.054	8.506	2.079	18.176
Max.	53.274	49.010	52.513	44.552	53.274	49.010	4.615	14.903	2,062.7	4.000	14.223	23.477	43.972
Min.	-14.337	-14.718	-11.720	-14.630	-14.337	-14.718	-4.615	3.273	-95.014	0.000	0.000	0.000	9.820
S. D.	4.859	5.415	4.984	5.250	4.756	5.560	1.339	1.468	11.392	0.070	1.764	0.858	6.954
Skew.	2.097	1.692	2.194	1.628	2.011	1.733	0.435	0.545	82.638	15.310	-0.226	0.838	1.004
Kurt.	10.871	7.241	11.387	6.861	10.364	7.456	7.356	3.775	11,572	526.353	3.212	8.865	3.265
N	184,992	184,744	82,156	88,157	102,836	96,587	214,796	188,706	188,607	188,517	188,374	187,305	211,400
When stock i reaches the upper price limit in a given week (Weekly Frequency)													
Mean	5.179	3.886	6.132	2.366	3.484	4.551	0.178	8.397	1.848	0.047	9.355	2.846	24.042
Median	3.479	2.907	4.203	1.700	2.417	3.577	0.000	8.333	0.483	0.032	9.491	2.808	21.014
Max.	52.513	38.313	52.513	30.463	38.853	38.313	4.615	14.781	1,458.4	4.000	14.092	23.477	43.972
Min.	-9.299	-14.717	-9.299	-14.630	-7.871	-14.717	-4.615	3.346	-95.014	0.000	0.000	0.329	9.820
S. D.	6.175	4.310	6.880	3.073	4.156	4.595	1.426	1.381	18.883	0.092	1.677	0.886	8.450
Skew.	2.631	1.600	2.392	1.380	2.594	1.490	0.631	0.215	42.277	15.013	-0.922	1.212	0.518
Kurt.	12.919	8.575	10.818	10.027	14.402	7.777	7.009	3.490	2,640.7	421.998	5.440	22.929	2.155
N	18,250	18,236	11,684	5,548	6,566	12,688	18,669	18,669	18,232	18,645	18,669	18,423	18,669
When stock *i* reaches the lower price limit in a given week (Weekly Frequency)													
Mean	4.562	3.870	4.417	4.504	4.668	3.019	0.136	8.382	1.436	0.053	9.004	3.027	25.976
Median	3.058	2.812	3.008	3.344	3.066	2.236	0.000	8.407	0.000	0.033	9.257	2.984	24.864
Max.	51.764	40.863	39.414	40.863	51.764	38.313	4.615	14.827	652.322	4.000	14.223	15.262	43.972
Min.	-11.585	-14.604	-9.299	-14.604	-11.585	-14.272	-4.605	3.273	-67.350	0.000	0.000	0.590	9.820
S. D.	5.639	4.881	5.081	5.174	6.014	4.316	1.445	1.551	16.115	0.123	1.945	0.905	7.966
Skew.	2.743	1.490	2.028	1.398	3.009	1.562	0.420	-0.036	20.597	15.150	-1.024	0.563	0.159
Kurt.	14.213	8.276	9.117	7.228	15.513	10.538	6.639	3.227	717.892	346.922	4.884	7.131	1.780
N	7,459	7,440	3,157	4,261	4,302	3,179	7,573	7,573	7,527	7,563	7,573	7,511	7,573

Table 2. Impact of *ASVI* on individual/institutional herding measures.

Herd_ind (*Herd_ins*) is individual (institutional) herding measures for a stock in a given week. *ASVI* is abnormal *SVI*. *CAP* is market capitalization of a stock. *RET* is past returns of a stock during the prior 1 week. *EP* is the inverse of the P/E ratio. *VOL* is the trading volume of a stock. *STD* is the standard deviation of daily returns for a stock during the prior 3 months. *VIX* is the mean value of daily *VIX* during a week. We apply the White heteroscedasticity-consistent variance covariance matrix and also control industry dummy variables. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Pooled OLS						Panel - Random effect					
Panel A Dependent Variable: Individual herding measure												
	Order			Trade			Order			Trade		
	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL
Inter.	-2.326***	2.186***	0.823***	-7.244***	-3.310***	-4.891***	-0.593	2.457***	0.826	-5.100***	-3.200***	-4.325***
ASVI	0.029***	0.073***	0.036***	0.004	-0.019	0.007	0.029***	0.071***	0.035***	0.005	-0.017	0.013
Herd_ins	0.036***	-0.004	-0.013***	0.073***	-0.028***	-0.022***	0.036***	-0.005	-0.015***	0.078***	-0.026***	-0.022***
CAP	0.865***	-0.100***	0.576***	1.435***	0.644***	0.898***	0.529***	-0.371***	0.563***	1.080***	0.587***	0.758***
RET	0.004	0.002	0.003	-0.008***	-0.020***	-0.011***	-0.003	-0.006	0.003	-0.013***	-0.023***	-0.012**
EP	-1.324***	0.324	-3.019***	-1.103***	1.182***	-2.325***	-1.906***	0.160	-2.895***	-1.295***	1.282***	-1.947***
VOL	0.008	0.350***	-0.144***	-0.019*	0.399***	0.220***	0.222***	0.614***	-0.124***	0.140***	0.430***	0.288***
STD	-0.546***	-0.269***	-0.411***	-0.622***	-0.503***	-0.440***	-0.656***	-0.370***	-0.428***	-0.669***	-0.408***	-0.500***
VIX	0.024***	0.045***	0.020***	0.020***	-0.019***	0.002	0.021***	0.042***	0.022***	0.014**	-0.027***	0.005
N	177,107	31,330	38,372	174,457	29,942	34,199	177,107	31,330	38,372	174,457	29,942	34,199
Adj. R^2	0.0794	0.0214	0.0506	0.1717	0.1338	0.1368	0.0200	0.0235	0.0201	0.0548	0.0571	0.0410
Panel B Dependent Variable: Institutional herding measure												
Inter.	35.795***	32.573***	38.923***	24.944***	16.750***	17.640***	38.485***	32.746***	40.452***	27.034***	16.453***	20.099***
ASVI	-0.005	0.011	0.043	0.003	-0.005	0.020	-0.008	0.010	0.050	-0.009	0.006	0.018
Herd_ind	0.222***	-0.023	-0.122***	0.417***	-0.204***	-0.178***	0.226***	-0.028	-0.142***	0.455***	-0.193***	-0.177***
CAP	-2.146***	-2.335***	-2.282***	-1.670***	-1.064***	-1.339***	-2.468***	-2.445***	-2.522***	-1.804***	-0.867***	-1.544***
RET	0.016***	0.050***	-0.002	-0.015***	0.038***	-0.063***	0.015	0.046***	-0.004	-0.010	0.043***	-0.063***
EP	0.215	0.881	-2.766**	4.761***	4.771***	0.253	-0.464	-0.319	-2.961*	2.453***	4.682***	0.463
VOL	-0.285***	0.260***	-0.542***	0.440***	0.942***	1.051***	-0.228***	0.348***	-0.453***	0.281***	0.672***	0.992***
STD	-0.080*	-0.799***	0.404***	-0.527***	-1.251***	-0.277***	-0.080	-0.745***	0.330**	-0.213**	-0.806***	-0.295*
VIX	-0.106***	-0.074***	-0.109***	-0.120***	-0.119***	-0.192***	-0.107***	-0.076***	-0.103***	-0.128***	-0.130***	-0.194***
N	177,107	31,330	38,372	174,457	29,942	34,199	177,107	31,330	38,372	174,457	29,942	34,199
Adj. R^2	0.0844	0.0792	0.1098	0.0470	0.0298	0.0359	0.0284	0.0398	0.0466	0.0440	0.0193	0.0264

Table 3. Impact of *ASVI* on individual herding measures with touching upper/lower price limit dummies.

Herd_ins is institutional herding measures for a stock in a given week. *ASVI* is abnormal *SVI*. The upper/lower price limit (*Up/Lo*) which is defined as 1 while a stock reaches the upper/lower price limit in a given week, otherwise 0. For brevity, the coefficient estimates of these control variables as in Table 2 are suppressed. We apply the White heteroscedasticity-consistent variance covariance matrix and also control industry dummy variables. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Pooled OLS						Panel - Random effect					
Dependent Variable: Individual herding measure												
Panel A Upper and non- upper price limit weeks												
	Order			Trade			Order			Trade		
	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL
Inter.	-2.330***	2.015***	0.777***	-7.245***	-3.330***	-4.871***	-0.705**	2.223***	0.800*	-5.124***	-3.210***	-4.313***
Up	1.610***	3.526***	-0.551***	0.379***	-1.023***	0.993***	1.475***	3.461***	-0.589***	0.260***	-1.087***	1.011***
ASVI	0.013*	0.016	0.040***	0.005	-0.025	0.010	0.015*	0.018	0.039***	0.006	-0.020	0.017
$Up \times ASVI$	0.103***	0.238***	-0.046	-0.020	0.089*	-0.037	0.102***	0.233***	-0.047	-0.020	0.054	-0.041
Herd_ins	0.037***	-0.011***	-0.013***	0.073***	-0.029***	-0.023***	0.036***	-0.012***	-0.015***	0.078***	-0.027***	-0.022***
	(Other coefficient estimates have been suppressed.)											
H_0: $ASVI + Up \times ASVI = 0$	0.116***	0.254***	-0.006	-0.015	0.064	-0.027	0.116***	0.251***	-0.007	-0.013	0.034	-0.024
N	177,107	31,330	38,372	174,457	29,942	34,199	177,107	31,330	38,372	174,457	29,942	34,199
Adj. R^2	0.0887	0.0918	0.0516	0.1721	0.1366	0.1429	0.0282	0.0881	0.0213	0.0550	0.0606	0.0479
Panel B Lower and non- lower price limit weeks												
Inter.	-2.306***	2.162***	0.906***	-7.208***	-3.246***	-4.905***	-0.582*	2.432***	0.876**	-5.067***	-3.139***	-4.351***
Lo	0.267***	-0.341**	0.939***	0.466***	0.710***	-0.260**	0.195***	-0.402**	0.914***	0.479***	0.764***	-0.324***
ASVI	0.024***	0.068***	0.021	0.000	-0.031*	-0.001	0.023***	0.067***	0.020	0.001	-0.028*	0.004
$Lo \times ASVI$	0.111**	0.129	0.217**	0.078**	0.231***	0.182**	0.112***	0.107	0.219**	0.074**	0.235***	0.193***
Herd_ins	0.036***	-0.005	-0.013***	0.073***	-0.028***	-0.023***	0.036***	-0.006*	-0.015***	0.078***	-0.025***	-0.022***
	(Other coefficient estimates have been suppressed.)											
H_0: $ASVI + Lo \times ASVI = 0$	0.135***	0.197	0.238**	0.078**	0.200**	0.181**	0.135***	0.174	0.240***	0.075**	0.206***	0.197***
N	177,107	31,330	38,372	174,457	29,942	34,199	177,107	31,330	38,372	174,457	29,942	34,199
Adj. R^2	0.0796	0.0215	0.0539	0.1720	0.1354	0.1370	0.0202	0.0236	0.0236	0.0552	0.0589	0.0413

Table 4. Impact of *ASVI* on individual herding measures separated into different market capitalization groups.

Herd_ins is institutional herding measures for a stock in a given week. *ASVI* is abnormal *SVI*. *CAP* is market capitalization of a stock. *RET* is past returns of a stock during the prior 1 week. *EP* is the inverse of the P/E ratio. *VOL* is the trading volume of a stock. *STD* is the standard deviation of daily returns for a stock during the prior 3 months. *VIX* is the mean value of daily *VIX* during a week. We apply the White heteroscedasticity-consistent variance covariance matrix and also control industry dummy variables. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A Dependent Variable: Individual herding measure (Pooled OLS)												
	Above Median Market Capitalization						Below Median Market Capitalization					
	Order			Trade			Order			Trade		
	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL
Inter.	-6.697***	0.059	-2.134***	-12.662***	-5.864***	-9.661***	3.301***	4.725***	3.660***	-1.187***	-1.197***	-0.505
ASVI	0.020**	0.035	0.034*	0.002	-0.030	0.026	0.049***	0.129***	0.041**	0.015	0.007	-0.001
Herd_ins	0.076***	-0.027***	-0.024***	0.111***	-0.047***	-0.028***	0.017***	0.007*	-0.011***	0.063***	-0.012***	-0.012***
CAP	1.348***	0.397***	0.927***	2.079***	1.071***	1.634***	0.019	-0.689***	0.117**	0.421***	0.136***	0.007
RET	-0.001	-0.007	0.005	-0.010***	-0.024***	-0.004	0.007**	0.009	0.001	-0.009***	-0.021***	-0.020***
EP	-1.071***	-1.005	-4.782***	0.461	1.593**	-4.104***	-0.090	1.707*	-1.451***	-0.171	1.934***	-0.289
VOL	0.029*	0.150***	-0.144***	-0.087***	0.274***	0.023	0.048***	0.509***	-0.096***	0.117***	0.561***	0.437***
STD	-0.973***	-0.512***	-0.751***	-1.031***	-0.842***	-0.821***	-0.206***	-0.100	-0.219***	-0.293***	-0.258***	-0.254***
VIX	0.017***	0.030***	0.037***	0.018***	0.001	0.014**	0.026***	0.056***	0.012***	0.019***	-0.034***	0.002
N	88,393	14,124	16,879	88,373	14,189	14,887	88,714	17,206	21,493	86,084	15,753	19,312
Adj. R^2	0.1277	0.0429	0.0841	0.1702	0.131	0.1617	0.0097	0.0342	0.0126	0.0607	0.0554	0.031
Panel B Dependent Variable: Individual herding measure (Panel - Random effect)												
Inter.	-5.380***	0.514	-1.642**	-10.567***	-4.884***	-7.921***	4.162***	5.682***	3.138***	0.064	-1.604***	-0.189
ASVI	0.017*	0.031	0.034*	-0.001	-0.027	0.028	0.047***	0.129***	0.036**	0.014	0.006	0.000
Herd_ins	0.078***	-0.031***	-0.029***	0.114***	-0.048***	-0.037***	0.017***	0.007	-0.011***	0.060***	-0.013***	-0.013***
CAP	1.101***	0.192***	0.878***	1.760***	0.939***	1.450***	-0.213***	-1.061***	0.198**	0.206**	0.185**	-0.064
RET	-0.006	-0.010	0.004	-0.015***	-0.026***	-0.006	-0.001	-0.001	0.001	-0.013***	-0.021***	-0.021***
EP	-2.949***	-0.511	-5.278***	-1.854***	1.137	-4.502***	-1.110**	1.206	-1.644***	-0.725**	1.606***	-0.394
VOL	0.159***	0.302***	-0.171***	0.033	0.294***	0.004	0.282***	0.794***	-0.073*	0.265***	0.548***	0.488***
STD	-0.897***	-0.481***	-0.667***	-0.936***	-0.687***	-0.747***	-0.389***	-0.236***	-0.267***	-0.389***	-0.217***	-0.299***
VIX	0.004	0.022**	0.034***	0.004	-0.010	0.011	0.029***	0.055***	0.015**	0.020***	-0.036***	0.003
N	88,393	14,124	16,879	88,373	14,189	14,887	88,714	17,206	21,493	86,084	15,753	19,312
Adj. R^2	0.0496	0.0202	0.0372	0.0709	0.0586	0.0568	0.0087	0.0432	0.0072	0.0441	0.0431	0.0278

Table 5. Impact of *ASVI* on individual herding measures with touching upper price limit dummies and market capitalization dummies.

Herd_ins is institutional herding measures for a stock in a given week. *ASVI* is abnormal *SVI*. *MC* is a market capitalization dummy variable which equals 1 if market capitalization is below the median and 0 otherwise. The upper price limit (*Up*) which equals 1 when a stock reaches the upper price limit in a given week, otherwise 0. For brevity, the coefficient estimates of these control variables as in Table 2 are suppressed. We apply the White heteroscedasticity-consistent variance covariance matrix and also control industry dummy variables. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Individual herding measure												
	Pooled OLS						Panel - Random effect					
	Order			Trade			Order			Trade		
	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL
Inter.	-3.690***	1.419***	-0.880**	-9.210***	-4.754***	-7.441***	-0.892*	2.160***	-0.652	-5.245***	-3.980***	-5.588***
MC	0.299***	-0.120	0.567***	0.629***	0.446***	0.808***	-0.094	-0.278**	0.604***	-0.010	0.253*	0.471***
Up	0.456***	2.435***	-0.658***	-0.068	-1.669***	0.648***	0.517***	2.454***	-0.631***	0.045	-1.566***	0.812***
MC×*Up*	2.235***	1.939***	0.212	0.856***	1.169***	0.578***	1.904***	1.821***	0.084	0.432***	0.872***	0.353***
ASVI	0.018*	0.009	0.048**	0.009	-0.044*	0.030	0.017*	0.007	0.047**	0.009	-0.035	0.036
MC×*ASVI*	-0.010	0.019	-0.017	-0.010	0.053	-0.041	-0.006	0.028	-0.018	-0.006	0.040	-0.046
Up×*ASVI*	0.067	0.192*	-0.050	-0.035	0.044	-0.049	0.072*	0.201**	-0.043	-0.027	-0.001	-0.038
MC×*Up*×*ASVI*	0.096	0.087	0.007	0.039	0.056	0.039	0.080	0.060	-0.010	0.020	0.088	0.005
Herd_ins	0.036***	-0.011***	-0.014***	0.074***	-0.028***	-0.022***	0.037***	-0.011***	-0.016***	0.078***	-0.026***	-0.022***
	(Other coefficient estimates have been suppressed.)											
H_0: *ASVI* + *Up*×*ASVI*=0	0.084**	0.201**	-0.001	-0.025	0.000	-0.019	0.089**	0.208**	0.004	-0.018	-0.036	-0.002
H_0: *ASVI* + *MC*×*ASVI* + *Up*×*ASVI* + *MC*×*Up*×*ASVI*=0	0.170***	0.307***	-0.012	0.004	0.109	-0.021	0.163***	0.296***	-0.024	-0.004	0.092	-0.043
N	177,107	31,330	38,372	174,457	29,942	34,199	177,107	31,330	38,372	174,457	29,942	34,199
Adj. R^2	0.0955	0.1029	0.0528	0.1738	0.1401	0.1478	0.0339	0.0978	0.0215	0.0562	0.0646	0.0524

Table 6. Impact of *ASVI* on individual herding measures with touching lower price limit dummies and market capitalization dummies.

Herd_ins is institutional herding measures for a stock in a given week. *ASVI* is abnormal *SVI*. *MC* is a market capitalization dummy variable which equals 1 if market capitalization is below the median and 0 otherwise. The lower price limit (*Lo*) which equals 1 when a stock reaches the lower price limit in a given week, otherwise 0. For brevity, the coefficient estimates of these control variables as in Table 2 are suppressed. We apply the White heteroscedasticity-consistent variance covariance matrix and also control industry dummy variables. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Individual herding measure												
	Pooled OLS						Panel - Random effect					
	Order			Trade			Order			Trade		
	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL
Inter.	-3.784***	1.351***	-0.711*	-9.204***	-4.691***	-7.591***	-0.929**	2.028***	-0.512	-5.206***	-3.935***	-5.737***
MC	0.494***	0.267***	0.500***	0.683***	0.491***	0.897***	0.091	0.140	0.528***	0.012	0.296**	0.541***
Lo	-0.413***	-0.509***	0.170	0.010	0.443**	-0.788***	-0.279**	-0.461**	0.258	0.247	0.643***	-0.693***
$MC \times Lo$	1.477***	0.419	1.360***	1.002***	0.611***	0.988***	1.030***	0.144	1.163***	0.505***	0.257	0.684***
ASVI	0.018*	0.035	0.028	0.004	-0.045*	0.017	0.016	0.033	0.027	0.004	-0.039*	0.024
$MC \times ASVI$	0.018	0.080*	-0.015	-0.009	0.038	-0.036	0.020	0.082**	-0.016	-0.008	0.027	-0.046
$Lo \times ASVI$	0.133***	0.218	0.275*	0.027	0.101	0.180***	0.146***	0.184	0.283**	0.038	0.113	0.208***
$MC \times Lo \times ASVI$	-0.055	-0.224	-0.081	0.124*	0.301	0.017	-0.083	-0.192	-0.101	0.093	0.281	-0.019
Herd_ins	0.036***	-0.005	-0.014***	0.074***	-0.027***	-0.022***	0.036***	-0.006	-0.015***	0.078***	-0.025***	-0.022***
	(Other coefficient estimates have been suppressed.)											
H_0: $ASVI + Lo \times ASVI = 0$	0.151***	0.253*	0.303**	0.032	0.057	0.197***	0.162***	0.216	0.310**	0.042	0.074	0.232***
H_0: $ASVI + MC \times ASVI + Lo \times ASVI + MC \times Lo \times ASVI = 0$	0.114	0.108	0.207	0.147**	0.396**	0.179	0.099	0.107	0.193	0.127**	0.383**	0.166
N	177,107	31,330	38,372	174,457	29,942	34,199	177,107	31,330	38,372	174,457	29,942	34,199
Adj. R^2	0.0811	0.0223	0.0568	0.1733	0.1380	0.1414	0.0212	0.0239	0.0254	0.0561	0.0623	0.0447

Table 7. Impact of *ASVI* on individual herding measures with multiple weekdays touching upper/lower price limit dummies.

ASVI is abnormal *SVI*. *Uu1* (*Ll1*) equals 1 if upper (lower) price limit occurs for one or two days in a given week and 0 otherwise. *Uu2* (*Ll2*) equals 1 if upper (lower) price limit occurs three, four, or five days in a given week and 0 otherwise. For brevity, the coefficient estimates of these control variables as in Table 2 are suppressed. We apply the White heteroscedasticity-consistent variance covariance matrix and also control industry dummy variables. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Individual herding measure												
	Pooled OLS						Panel - Random effect					
Panel A Numerous upper and non- upper price limit weeks												
	Order			Trade			Order			Trade		
	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL
ASVI	0.013*	0.016	0.040***	0.005	-0.025	0.010	0.015**	0.017	0.039***	0.006	-0.020	0.017
Uu1×ASVI	0.009	0.070	-0.046	-0.028	0.053	-0.045	0.009	0.072	-0.048	-0.028	0.015	-0.050
Uu2×ASVI	0.883***	1.067***	-0.068	-0.007	0.491***	0.049	0.904***	1.056***	0.105	0.023	0.504***	0.074
	(Other coefficient estimates have been suppressed.)											
H_0: *ASVI+ Uu1×ASVI=0*	0.022	0.086	-0.006	-0.023	0.028	-0.035	0.025	0.088	-0.009	-0.021	-0.005	-0.033
H_0: *ASVI+ Uu2×ASVI=0*	0.896***	1.083***	-0.028	-0.002	0.466***	0.059	0.919***	1.073***	0.144	0.030	0.484***	0.091
Panel B Numerous lower and non- lower price limit weeks												
ASVI	0.024***	0.068***	0.021	-0.000	-0.031*	-0.001	0.024***	0.067***	0.021	0.001	-0.028*	0.004
Ll1×ASVI	0.054	0.128	0.016	0.043	0.144**	0.130**	0.061*	0.107	0.027	0.047	0.156**	0.152**
Ll2×ASVI	0.729	3.713	1.836***	0.452	1.263**	1.776	0.699	3.331	1.886***	0.367	1.181*	1.514
	(Other coefficient estimates have been suppressed.)											
H_0: *ASVI+ Ll1×ASVI=0*	0.078**	0.196	0.037	0.043	0.113*	0.129**	0.085**	0.174	0.048	0.048	0.128*	0.157***
H_0: *ASVI+ Ll2×ASVI=0*	0.753	3.781	1.857***	0.452	1.232**	1.775	0.723	3.398	1.907***	0.368	1.152*	1.518

Table 8. Robustness Test: Application of Positive *ASVI* and Abnormal individual herding measures.

The columns (1) and (3) of Table 8 conduct one robustness test which replace the *ASVI* by applying all positive *ASVI* to estimate empirical analysis of Table 2 and Table 3, and the columns (2) and (4) of Table 8 conduct another robustness test which replace the individual Herding measures by computing Abnormal individual Herding statistics following same method as estimating *ASVI* in equations (10), (11), and (12). *ASVI* is abnormal *SVI*. *CAP* is market capitalization of a stock. *RET* is past returns of a stock during the prior 1 week. *EP* is the inverse of the P/E ratio. *VOL* is the trading volume of a stock. *STD* is the standard deviation of daily returns for a stock during the prior 3 months. *VIX* is the mean value of daily *VIX* during a week. We apply the White heteroscedasticity-consistent variance covariance matrix and also control industry dummy variables. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Pooled OLS						Panel - Random effect					
Dependent Variable	Individual order herding measure			abnormal order herding measure			Individual order herding measure			abnormal order herding measure		
	(1) while *ASVI*>0			(2)			(3) while *ASVI*>0			(4)		
	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL
Panel A Whole period												
ASVI	0.003	0.073*	0.012	0.025**	0.084***	0.024*	0.031	0.095**	0.038	0.025***	0.084***	0.024*
	(Other coefficient estimates have been suppressed.)											
Panel B Upper and non- upper price limit weeks												
ASVI	-0.042**	-0.063*	0.015	0.011	0.058***	0.030*	-0.006	-0.049	0.041	0.011	0.058***	0.030*
Up×*ASVI*	0.364***	0.660***	-0.033	0.089***	0.095	-0.064	0.319***	0.674***	-0.035	0.089***	0.096	-0.065
	(Other coefficient estimates have been suppressed.)											
H_0: *ASVI* +*Up*×*ASVI* =0	0.322***	0.597***	-0.018	0.100***	0.153**	-0.036	0.313***	0.625***	0.006	0.100***	0.154**	-0.035
Panel C Lower and non- lower price limit weeks												
ASVI	-0.009	0.057	-0.013	0.021***	0.083***	0.016	0.022	0.078*	0.020	0.021***	0.083***	0.016
Lo×*ASVI*	0.282***	0.501*	0.467**	0.081*	0.015	0.113	0.232***	0.493*	0.389*	0.081*	0.012	0.113
	(Other coefficient estimates have been suppressed.)											
H_0: *ASVI* +*Lo*×*ASVI* =0	0.273***	0.558**	0.454**	0.102**	0.098	0.130	0.254***	0.571**	0.409**	0.102**	0.096	0.129

Table 9. Robustness Test: Application of Positive *ASVI* and Abnormal individual herding measures including high and low market capitalization dummy.

The columns (1) and (3) of Table 9 conduct one robustness test which replace the *ASVI* by applying all positive *ASVI* to estimate empirical analysis of Table 5 and Table 6, and the columns (2) and (4) of Table 9 conduct another robustness test which replace the individual/institutional Herding measures by computing Abnormal individual/institutional Herding statistics following same method as estimating *ASVI* in equations (13), and (14). *ASVI* is abnormal *SVI*. *CAP* is market capitalization of a stock. *RET* is past returns of a stock during the prior 1 week. *EP* is the inverse of the P/E ratio. *VOL* is the trading volume of a stock. *STD* is the standard deviation of daily returns for a stock during the prior 3 months. *VIX* is the mean value of daily *VIX* during a week. We apply the White heteroscedasticity-consistent variance covariance matrix and also control industry dummy variables. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Pooled OLS						Panel - Random effect					
Dependent Variable	Individual order herding measure			abnormal order herding measure			Individual order herding measure			abnormal order herding measure		
	(1) while *ASVI*>0			(2)			(3) while *ASVI*>0			(4)		
	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL	ALL	BUY	SELL
Panel A Upper and non- upper price limit weeks												
ASVI	-0.046**	-0.078*	-0.025	0.013	0.053**	0.048**	-0.040*	-0.083*	-0.015	0.013	0.053**	0.048**
MC×ASVI	0.049	0.087	0.111*	-0.005	0.013	-0.042	0.122***	0.129*	0.159**	-0.005	0.013	-0.043
Up×ASVI	0.181**	0.583***	-0.082	0.067	0.071	-0.069	0.159**	0.580***	-0.051	0.067	0.073	-0.070
MC×Up×ASVI	0.269**	0.010	0.131	0.063	0.039	0.003	0.248**	0.048	0.050	0.063	0.039	0.002
	(Other coefficient estimates have been suppressed.)											
H_0: *ASVI + Up×ASVI=0*	0.135*	0.505**	-0.107	0.080*	0.124	-0.021	0.119	0.497**	-0.066	0.080*	0.126	-0.022
H_0: *ASVI + MC×ASVI + Up×ASVI + MC×Up×ASVI=0*	0.453***	0.602***	0.135	0.138**	0.176	-0.060	0.489***	0.674***	0.143	0.138**	0.178	-0.063
Panel B Lower and non- lower price limit weeks												
ASVI	-0.040*	-0.009	-0.044	0.015	0.064**	0.031	-0.036	-0.006	-0.028	0.015	0.064**	0.031
MC×ASVI	0.112***	0.179**	0.092*	0.015	0.045	-0.035	0.183***	0.223**	0.134**	0.015	0.045	-0.036
Lo×ASVI	0.189*	0.466	0.327	0.107**	0.040	0.188*	0.166	0.417	0.275	0.107**	0.037	0.189*
MC×Lo×ASVI	0.083	0.100	0.249	-0.065	-0.057	-0.131	0.085	0.303	0.215	-0.065	-0.056	-0.132
	(Other coefficient estimates have been suppressed.)											
H_0: *ASVI + Lo×ASVI=0*	0.149	0.457	0.283	0.122***	0.104	0.219**	0.130	0.411	0.247	0.122***	0.101	0.220**
H_0: *ASVI + MC×ASVI + Lo×ASVI + MC×Lo×ASVI=0*	0.344**	0.736	0.624**	0.072	0.092	0.053	0.398***	0.937**	0.596**	0.072	0.090	0.052