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Herding Behavior and Trading Volume: Evidence from the American Indexes

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Abstract

This paper examines the existence of behavioral bias labeled "Herding" in the U.S. market. We studied the turnover effect on herding movement by modifying the Cross Sectional Standard Deviation (CSSD) model and the Cross Sectional Absolute Standard Deviation (CSAD) model. The results indicate that herding is present and is a long-lived phenomenon in the American financial market. We find also that herding is stronger in the S&P 100 index than in the DJIA index. We also find that trading volume contributes in increasing asymmetric herding. By applying VAR and Granger causality test, we find causal link of herding – trading volume. More particularly, we find that trading volume cannot generate herding behavior, except for liquid market. However, contemporaneous herding is a deterministic factor for increasing trading volume. Over the sample period, we examine the herd behavior during Subprime crisis. We find that herding is more intensified during subprime crisis, which contributes to accentuate and elongate it.

Key Words: *Trading volume; Herding; Cross Sectional Standard Deviation; Cross Sectional Absolute Standard Deviation.*

Introduction

Modeling the decision making process of various participants in the market has become a challenge for financial researchers. While conventional efficient theory assumes that markets are informationally efficient and agents are fully rational, there is an increasing empirical insight that agents are not rational and commit systematic errors, which are manifested in the form of inefficient prices. Grullon et al., (2005) and several authors assert that only the behavioral finance (based on psychological biases and emotions) could bring an assuasive apprehension of the complex puzzle of human's decision-making. More particularly, in the recent years, several authors provided direct empirical evidences that investors' stock trading behavior (*e.g.*, stock performance, stock volume, and stock frequency) is affected by their personality traits and psychological biases (*e.g.*, overconfidence, loss aversion, herd behavior, …etc.). However, very limited scholars surveyed the different and subtitle ways in which each of these psychological biases influence the investor trading behavior. One of the most central cognitive biases of behavioral theory is herd behavior. Herding occurs when an investor denies his own information to fell prey into a collective uniformed behavior or group, even if the behavior of this group is not supported by relevant information.

Although the extensive surveys on herding behavior in global financial markets, the deterministic feature that underlies this phenomena remains enigmatic. For instance, herding relation with stock performance is confusing. While one line of research describes herding behavior as a rational behavior in which the investor intentionally imitate other investors' investment decision in order to protect his own interest

(Scharfstein & Stein, 1990; Banerjee, 1992; Devenow & Welch, 1996), a large stream of scholars consider herding as irrational behavior. Indeed under uncertainly and fear to commit wrong decision, individuals emerge into a collective trading (buying or selling) willful blindness ignoring their information and market signals. Herding is a key feature of behavioral finance in explaining market bubbles and crashes because it is considered as a driving force of bubble and price's deviation from its fundamental value. In presence of social connectivity (through conversation, sport activity, commentators, and media), erroneous thought and beliefs can be conveyed from one individual to another generating an increasing bubble and leading to market destabilization (Dawkins, 1976). Thus, detecting herding behavior provides evidence against the theory of rationality (Lao & Singh, 2011), and provides a direct implication of market information efficiency (Yao, Ma, & He, 2014). Bikhchandani, Hirshleifer, & Welch (1992) advanced a herding model based on ― information cascade showing that agents abandon their proper private information to act identically to a group of investors. Such conformity often leads under-diversified portfolio and generates a shift in stock variance and a subsequent high volatility.

Previous surveys of market wide herding on the American market are confused. Actually, Christie & Huang (1995) examined herding behavior in the U.S. market and conclude the absence of this bias. However, Nofsinger & Sias (1999) provides evidence that supports herding among investors in the U.S. markets. Lately, Chiang & Zheng (2010) provided empirical evidence on the absence of herding in the U.S. market, while in the same time Hwang & Salmon (2004) and Zhou & Lai (2009) have detected herding behavior in the NYSE, AMEX and NASDAQ index. These contradicting results on the existence of herding in the U.S. market are an incentive to reexamine this bias and survey its magnitude on American stock prices. Moreover, less is known on how this bias influences investors' trading behavior and whether herding increases trading frequency and stock performance or not. Our point of focus in this research is how herd behavior influences investors' trading behavior and the relationship relaying herding to market trading volume. Furthermore, how herding movement reacts to good or bad news remains an open question. While Christie & Huang (1995) refuted asymmetric herding, Chang, Cheng, & Khorana (2000) provided evidence that herding tendency is greater when market is declining rather when it's advancing, and Henker, Henker, & Mitsios (2006) partially supported this result.

Our objective is to provide a robust survey of herding in the U.S. market by adding trading volume as an explanatory variable in order to investigate whether it is a prevailing factor in fueling herding behavior and its implication on market conditional volatility.

This study applied modified herding measures by introducing trading volume component to both the model of Cross-Sectional Absolute Deviation of returns (CSAD) of Chang, Cheng, & Khorana (2000) and Cross-Sectional Standard Deviation (CSSD) of Christie & Huang (1995). We use daily data from January 4th, 2000 to July 20th, 2012. Our conjecture is that trading volume may present a powerful explanatory feature of herding behavior. We apply VAR (Vector Autoregressive estimation) and Granger causality test in order to investigate the nature of the volume-herding causality relationship. Since our sample period includes the current global financial crisis, which erupted in 2007, we examine the effect of the recent global financial crisis on herding behavior and the contribution of trading volume in increasing herding during the Subprime crisis. The recent global financial crisis was judged as the severest financial crisis that has affected the financial market since the great depression of 1930's (Authers, 2010). During the last global crisis economists have witnessed the collapse of the biggest robust financial investment (Lehman Brothers and Bear Stearns, the bailout of American International Group (AIG), America's largest insurance company), and this collapse have rapidly spread to the greater financial institutions across the world and generated a great recession until today. The interpretation of the main roots of this bubble holds different opinions, but in Akerlof & Shiller (2009)'s eyes each of these interpretations may involve an element of truth and all different explanations have deeper psychological roots. This paper contributes to the literature of behavioral finance by providing robustness measures of herding behavior accounting for the information content in volumes and prices. It should be emphasized that the goal of this paper is not to identify the relationship between prices and volumes, but rather focus on trading volume effect on herding behavior.

The remainder of this paper is as follows. Section 0 will discuss the relevant literature regarding herd behavior and trading volume, Section 0 describes the data and methodology that will be used in this study, Section 0 presents detailed report of the empirical finding, and we conclude in Section 0.

Literature Review

Despite its extensive uses by academic research, trading volume was only recently incorporated in the asset pricing models asset pricing models (Gebka & Wohar, 2013).[1] Trading volume plays an important role in the price formation process and in stock performance. Indeed, empirical finding revealed that trading volume variables capture the quality and the precision of the information in the market and consequently contains information about price movements (Blume, Easley, & O'hara, 1994). Despite the intensive survey of volume-contemporaneous stock price relationship, empirical evidences are controversial (Kramer, 1999; Karpoff, 1987). Financial literature asserts a nonlinear complex relationship relying volume to stock prices (Llorente, Michaely, Saar, & Wang, 2002; Wang, 1993; Campbell & Shiller, 1988).

Additionally, prevailing models of modern capital market trading and pricing shed little light on social interaction and information transmission in which the trading behavior of an investor is affected by others investors (Lux, 1995). Behavioral prediction supposes that herding appears through the correlation in trading as result of individual interaction. Indeed, they assert that herding, as psychological force, influences investor' trading decision and presents a deterministic factor in the spread for pricing of real asset (Hirshleifer & Teoh, 2003). Although the intensive empirical surveys of herding, trading volume has long been playing a second fiddle to herding models. Hirshleifer & Teoh (2003) examined noise traders and find that the irrational correlation in investors' trading activity results mainly from herd behavior. They outline that herding can trigger fed-mode and obsession in noise trader's mind and opinion that leads to market bubbles and crashes. Statman, Thorley, & Vorkink (2006) assert that high stock returns are correlated with a high trading.

Behavioral proponent asserts that when investors ignore their previous beliefs and information to imitate other investors' decisions, they tend to intensify trading on a particular stock leading trading volume to be unusually high. Hence, trading volume may be a vital element in fueling herding movement and is an important factor in explaining herding behavior.

Few studies discussed trading volume effects on herding behavior. The first empirical survey of herding that accounted for trading volume effect was the LSV model developed by Lakonishok, Shleifer, & Vishny (1992). The LSV model investigates the reverberation of herding on stock price using degree of correlation in trades by investors. They evaluated expected trading volume when investors act individually and independently, compared to the trading volume when investors tend to act in-group and trade on the same stock. Hachicha (2010) applied cross-sectional dispersion of trading volume when he examined the herding behavior of investors in the Toronto Stock Exchange. He finds that investors tend to intensely and sustainably herd on this market. Fu & Lin (2010), Lan & Lai (2011) investigated turnover (traded/total shares) effect on herding behavior in the Chinese stock market (China's A and B-markets) using the Christie & Huang (1995)'s model. Their finding supported that trading volume contributes in trigging herding. However, empirical results on how trading volume affects herding are confused. On one hand, Fu & Lin (2010) advanced that low trading volume may influence herding behavior among Chinese equity market; they argue that low trading volume responds more slowly to information and the lack of information is the main trigger of herding behavior (Chen, 2013). On the other hand, Tan, Chiang, Mason, & Nelling (2008) find that herding tends to be stronger in bull market, high trading volume and high volatility. Recently, Lan & Lai (2011), Lao & Singh (2011) find existence of herd behavior in the Chinese

[1] For instance the CAPM pattern go back to early 1960. However, the trading variable was only recently introduced to it (Acharya & Pedersen, 2005).

stock market during periods of down markets and high trading volumes, Yao, Ma, & He (2014) assert that higher trading volume induces more herding in Chinese markets.

There is several insights that excessive trading volume can results from herding behavior, while findings show that agents tend to trade in massive way on particular stock, which creates high trading volume and contributes to increase its volatility (Lux, 1995; Bikhchandani, Hirshleifer, & Welch, 1992; Majand & Yung, 1991). However, several papers had outlined that excessive trading volume may enhance herding, since excessive trading is conducted by psychological biases (*e.g.*, overconfidence) which as result imply high volatility (Lan & Lai, 2011; Tan, Chiang, Mason, & Nelling, 2008; Chuang & Lee, 2006). According to Akerlof & Shiller (2009), investors' reasoning under emotional and psychological pitfalls (*e.g.*, phantasy, optimism or overconfidence) perceive a particular stock, such as housing investment, as highly valuable and profitable. Hence, they tend to trade on this specific stock, which became liquid. At the same time, and under uncertainly and reputational phenomena, this liquid stock keeps other investors' intention who drop their own strategy to blindly follow them. Consequently, a uniform collective investment derive forming meme and leading to herding movement. The more the trading intensified is, the greater the traders' positions will be aligned with the collective market movement (Venezia, Nashikkar, & Shapira, 2011).

Data and Methodology

Data collection

The data in this study is extracted from Wharton Research Database and Chicago Board Options Exchange (CBOE) database, and contains both listed firms specific and market data. The data retains daily market stock prices, volume transaction, market capitalization and individuals firm's share price for all firms listed on Dow Jones Industrial Average (DJIA)[2] and the S&P 100[3] index qualified as the core of the U.S. financial market (Hibbert, Daigler, & Dupoyet, 2008; Low, 2004). The sample period for DJIA and the S&P 100 markets start from January 4th, 2000 to July 20th, 2012; a total of 3157 observations. Estimation of stock performances are calculated based on the log returns: $\mathrm{R_t} = 100 \times \left(\log\left(\mathrm{P_t}\right) - \log\left(\mathrm{P_{t-1}}\right)\right)$ to make the series stationary.

The trading turnover $Vol_{m,t}$ is estimated based on the logarithmic turnover rate for market *m* at day *t*: $Vol_{m,t} = \log\left(V_{m,t}\right) - \log\left(V_{m,t\text{-}1}\right)$ with $V_{m,t}$ is the daily trading volume scaled by market capitalization.

Research Methodology

Christie & Huang (1995)'s Model

Rational theory assumes a linear relationship between stock return dispersion and market return.[4] However, if investors imitate each other, then stock returns would not deviate significantly from market return. So, we should notice a decrease in the dispersion level during turmoil period. Thus, Christie & Huang (1995) suggested CSSD as a proxy for herding and assumed that if an investor adopts a group behavior, the divergence in the dispersion of stock return from the mean value should be very small. CSSD is expressed as follow:

[2] The sample of listed companies is selected based on the Global Industry Classification Standard (GICS). We consider firms from all sectors more particularly industrial, bank and electrical sector.

[3] S&P 100 reflects almost the half of American market since it tracks almost 45% of whole U.S. financial market (CBOE report).

[4] In fact, according to the efficient theory, when the absolute value of overall market return increases, the degree of stock return dispersion should also increase.

$$CSAD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t} - R_{m,t}\right)^2}{N-1}} \tag{1}$$

Where: $R_{i,t}$ is the observed stock return of company *i* at time *t*, $R_{m,t}$ is the cross sectional average of the *N* portfolio return at time *t*.

Christie & Huang (1995) outlined that the CSSD measure is only valid in turmoil period. The authors assert that investors abandon their information and preferences to follow the general tendency during high volatility period. Formally, CSSD pattern is expressed as:

$$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \tag{2}$$

Where α measures the average dispersion of the sample lies out of the two extreme tails of return distribution, dummy variable D_t^L and D_t^U are supposed to capture the degree of variation in investor's behavior during high volatile period (extreme tail). The significant negative sign of β_1 and β_2 parameters capture the existence of herding. However, if these parameters were positive, this will indicate the inexistence of herd behavior.

In this paper, we scrutinize the effect of trading activity on herding. Investors herd when they abandon their own information and beliefs and base their investment decisions on the collective actions in the market, it would be interesting to examine the market liquidity relationship to herding tendency in extreme market condition. During periods of large market price movements, heavy trading volume is expected to be present when the market is extremely good or bad increasing stock's volatility. Thus, it can be argued that if herding behavior exists, there must be a negative correlation between return dispersions and market trading volume squared (Chiang & Zheng, 2010; Yao, Ma, & He, 2014). Hence, introducing turnover component we have:

$$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \beta_3 Vol_{m,t}^2 + \varepsilon_t \tag{3}$$

Where: $Vol_{m,t}$ is the market detrended turnover variable at time *t*. $Vol_{m,t}$ is the calculated daily trading volume on market capitalization and is smoothed out using Hodrick-Prescott Filter (Hodrick & Prescott, 1997).

Chang et al. (2000) Model

Chang et al. (2000) advanced an alternative measure of herd behavior based on Cross-Sectional Absolute Deviation of return (CSAD) derived from the conventional Capital Asset Pricing Model (CAPM).The Chang et al. (2000) pattern conjectures that if herding behavior exists then the linear-relationship between dispersion in individual asset returns and return of market portfolio will be violated. Indeed, when investors exhibit herding behavior, the path of the stock return instead of deviating significantly from market return it should converge toward the average market trend. Thus, the linearity relationship between $ECSAD_t$ and market return will not hold, but this relation will shift to be nonlinear and decreasing. Formally, this nonlinear decreasing relation is expressed as:

$$CSAD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R^2{}_{m,t} + \varepsilon_t \tag{4}$$

In Eq. (4) Chang et al. (2000) defined $CSAD_t$ using the cross-sectional SD of market returns in Eq. (1). The non-linearity between CSAD and market return is captured by the γ_2 coefficient. We expect the decreasing relation is captured by the negative sign of γ_2.

The theoretical behavioral proponent claims that abnormal high trading volume is an irrational investment behavior and enhance herd behavior (Kukacka & Barunik, 2013; Lan & Lai, 2011). He & Wang (1995) suggest that the exogenous information, private or public, can generate excess trading volume. We conjecture that trading volume may be crucial in fueling herding movement and presents an important factor in explaining herding behavior. A modified version of Chang et al. (2000)'s pattern is presented as follow:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R^2{}_{m,t} + \gamma_3 \left| Vol_{m,t} \right| + \gamma_4 Vol^2_{m,t} + \varepsilon_t \quad (5)$$

Where, we expect a negative relation between market return dispersion $CSAD_t$ and market transaction volume squared. Results are presented in Table **3**.

In addition, to provide robustness surveys on trading volume effects on herding behavior, we examine the asymmetric effect of trading volume. Formally, we estimate herding behavior across periods of high trading volume and low trading volume using dummy variables. We add to Eq. (4) dummy variables that capture days with unusual high and low trading volume to yield:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R^2{}_{m,t} + \theta_1 Vol_{High} R^2_{m,t} + \theta_2 Vol_{Low} R^2_{m,t} + \varepsilon_t \quad (6)$$

Where Vol_{High} and Vol_{Low} are respectively dummy variables for days with abnormal high trading volume (top 10th percentile) and for days with abnormal low trading volume (bottom 10th percentile). The estimated variables θ_1 and θ_2 reflect the effect of change in U.S. market liquidity on herding behavior. If θ_1 is statically significant and negative this implies the existence of herd behavior during high market liquidity and the same for θ_2.

Causality between trading volume – Herd Behavior

It is widely admitted that the variation in trading volume often precedes the change in stock price, *e.g.*, high index prices is trigger by high trading volume. However, the degree of delay and the nature of correlation between the price-volume remains an open question. Especially, little is known about the dual influencing relationship relaying volume herding (as detected based on stock return dispersion). According to Granger (1980) a random variable Y_t causes another random variables X_{t+1} if for set I: $Prob\left(X_{t+1} \in I | \Omega_t \right) \neq Prob\left(X_{t+1} \in I | \Omega_t - Y_t \right)$. Where Ω_t variable is the information set comprising all the information available up to and at time *t*. Hence, Y_t can cause X_{t+1} when it detains some unique information about X_{t+1}. Indeed, the random variable X can help to explain Y if the coefficients of the lagged difference of X are jointly statistically significant. Formally, Granger causality equations are expressed as follow:

$$CSAD_t = \gamma_1 + \sum_{i=1}^{p} \alpha_i CSAD_{t-i} + \sum_{j=1}^{p} \beta_j Vol_{m,t-j} + \varepsilon_t \quad (7)$$

$$Vol_{m,t} = \gamma'_1 + \sum_{i=1}^{p} \alpha'_i Vol_{m,t-i} + \sum_{j=1}^{p} \alpha'_j CSAD_{t-j} + \varepsilon'_t \quad (8)$$

Where: γ_1 and γ'_1 are restoring forces into the market equilibrium; *p* is number of lag.

$Vol_{m,t-j}$ and $CSAD_{t-j}$ are respectively lagged market trading volume and lagged herding variables. The rejection of the null hypothesis ($\mathrm{H}_0 : \alpha_j = 0$) that trading volume does not Granger-cause herding (p-value < 5%) imply that market return may enhance herd behavior. It should be highlighted that granger causality model conditions that the two time series of trading volume and herding variable should be cointegrated, *i.e.*, their wavelengths of variation have to be of the same order. Moreover, we ran VAR estimation to provide deeper insight on herding-volume correlation. Results are reported in Table 5.

The effect of Subprime crisis

Several authors pointed out that behavior contagion between investors in markets lead to contagious manias or fads and market bubble and crashes (Lux, 1995; Shiller, 2007). In addition, in periods of large market price movements, we expect the occurrence of large trading volume. Hence, for robustness test of herding measures we examine the possible of 2007-2009 financial crisis on an investor herding behavior by introducing a dummy variable to highlight the fact of global financial crisis 2007-2009 as follow:

$$CSAD_t = \alpha + \gamma'_1 \left|R_{m,t}\right| + \gamma'_2 R^2_{m,t} + \gamma'_3 \left|Vol_{m,t}\right| + \gamma'_4 Vol^2_{m,t} + \gamma'_5 D_t R^2_{m,t} + \varepsilon_t \qquad (9)$$

$$CSAD_t = \alpha + \gamma'_1 \left|R_{m,t}\right| + \gamma'_2 R^2_{m,t} + \gamma'_3 Vol^2_{m,t} + \gamma'_4 R^2_{m,t} D_t + \gamma'_5 Vol^2_{m,t} D_t + \varepsilon_t \qquad (10)$$

We assume that the Subprime crisis' reverberation shows up from July 2007 and its effect was decreasing until the end of 2009. This data has been selected based on the finding of Chow breakpoint test, which prescribes that the start of the subprime crisis corresponds exactly to July 2nd, 2007 (F-statistic = 514.525, p-value = 0.000). Thus, the D_t variable takes the value of one during the financial crisis starting from July 2nd, 2007 to June 29th, 2009 and take null value otherwise. This provides an interesting analysis when the market is moving downward; it shows how the herding behavior and trading frequency of institutional investors differ.

Empirical Results

Descriptive statistics

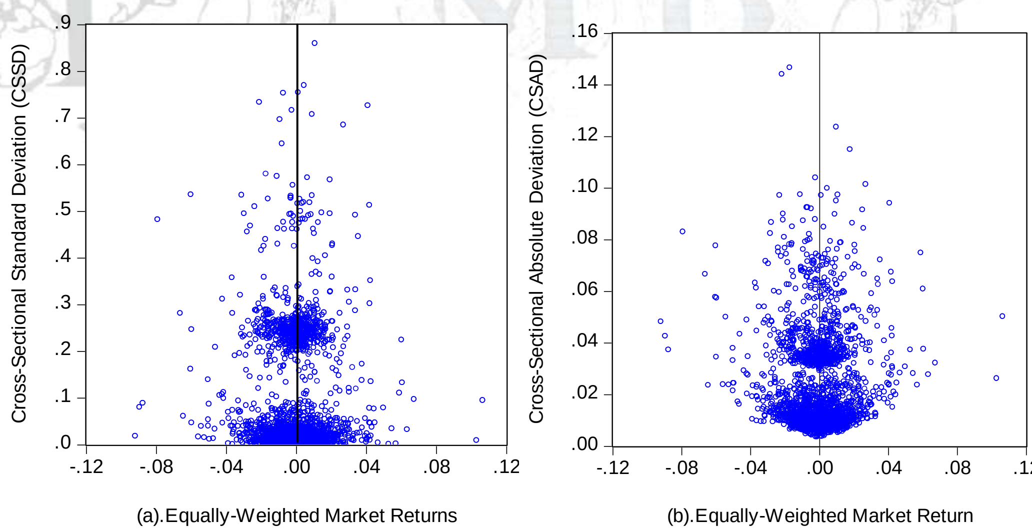

Figure 1. Relationship between daily cross sectional standard deviation (CSSD) and daily cross sectional absolute deviation ($CSAD_t$) and market return $R_{m,t}$ for S&P100 market

Figure 1 shapes the magnitude of non-linearity in the dispersion-market return for the S&P 100 market. It is clear that the linearity assumption is violated, which provides prior insight on the existence of herd behavior in American stock market. More particularly, the ample magnitude of non-linearity is greater in the CSSD dispersion in Figure 1(a) compared with CSAD dispersion in Figure 1(b) which confirm Christie

& Huang (1995)'s prediction that herding is more pronounced during periods of market stress. Under the condition of market disturbance, the average market return becomes larger in absolute term. The return dispersion increases but at a decreasing rate.

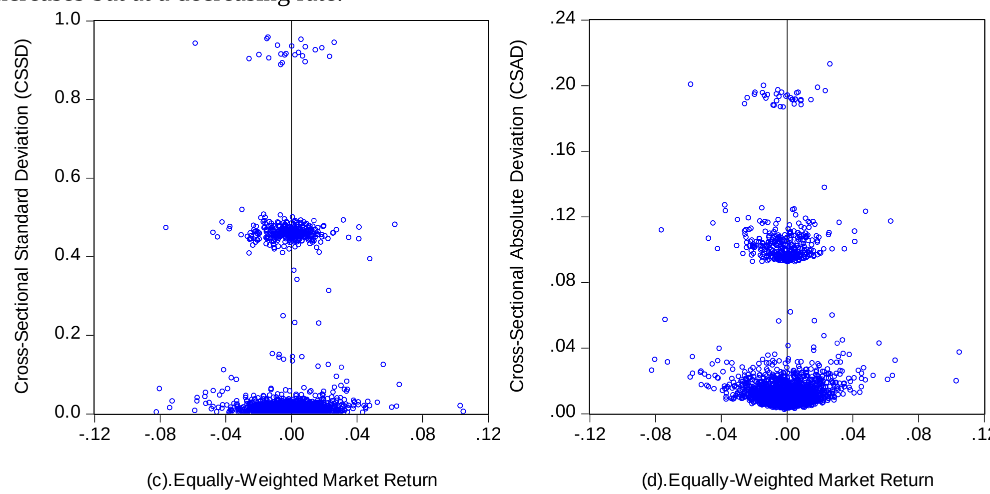

Figure 2. Relationship between daily cross sectional standard deviation (CSSD) and daily cross sectional absolute deviation ($CSAD_t$) and market return $R_{m,t}$ for Dow Jones Industrial Average (DJIA) market.

Regarding

Figure 2 (a) and (b), we can notice that as $\left|R_{m,t}\right|$ surpasses a certain threshold, the path $CSAD_t$ and $CSSD_t$ distribution tends to become narrower. These descriptive findings confirm our prediction of nonlinear reversal relation between $CSSD_t$, $CSAD_t$, and $R_{m,t}$ in U.S. market.

Table 1. Summery statistics of return, volume and herding measure (CSSD) and (CSAD) for U.S. market

	Mean	**Min**	**Max**	**Std.dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**ADF**
Panel A: S&P 100 market								
$\mathbf{R}_{m,t}$	-7.29E-05	-0.091	0.106	0.013	-0.129	10.295	6626.127***	-44.356***
Vol$_m$	0.0004	-2.177	2.306	0.212	0.179	22.189	45801.12***	-20.259***
CSSD	0.075	6.73E-06	0.859	0.116	2.095	8.151	5483.876***	-24.522***
CSAD	0.019	0.003	0.146	0.017	1.999	7.961	5049.095***	-4.756***
Panel B: DJIA market								
$\mathbf{R}_{m,t}$	3.84E-05	-0.082	0.105	0.013	-0.043	10.196	6814.374***	-43.724***
Vol$_m$	6.86E-05	-2.301	2.441	0.272	0.002	15.397	20218.74***	-26.972***
CSSD	0.067	9.11E-07	0.957	0.160	2.723	10.039	10422.80***	-25.443***
CSAD	0.022	0.002	0.212	0.034	2.668	9.954	10108.97***	-10.571***

This table reports summery statistics for the daily mean, standard deviation, skewness, kurtosis, Normality test (Jarque-Bera) and stationarity test (Augmented Dickey-Fuller ADF) of the cross-sectional standard *deviation (CSSD), cross-sectional absolute deviation (CSAD) and the market return $R_{m,t}$ over the sample period for the S&P 100 index and Dow Jones Industrial Average (DJIA) stocks markets.*

*Note: ***, ** and * denote the statistical significant at the 1% level, 5% and 10% level respectively.*

Summary statistics presented in Table 1 provide statistical feature for cross-sectional Standard deviation (CSSD) and cross-sectional Absolute Deviation (CSAD) and market returns $R_{m,t}$ for both S&P 100 and DJIA stocks markets over sample period (04/01/2000-20/07/2012).

The mean return for S&P 100 in Panel A is very small and negative (-7.29E-05) while trading volume have a positive mean (0.0004) which provide insight that investors trade excessively and unprofitably (insight on irrational behavior). S&P 100's return variation is large with a minimum value of (-0.091) and a maximum value (0.106) which indicate the high volatility of U.S. stock market.

The normality test show that all series of market return, volume, $CSSD_t$, and $CSAD_t$ are not normal since their skewness terms are different from zero and their kurtosis coefficients have largely exceed 3 but asymmetric.

Panel B indicates that Dow Jones Industrial Average market has higher mean values (3.84E-05 > -7.29E-05) with lower trading volume average (6.86E-05 < 0.0004) than S&P 100 market, merely the same standard deviation of (0.013). The mean values and standard deviation of the daily $CSSD_t$ for S&P 100 in panel A are larger than of DJIA market in panel B. The Augmented Dickey-Fuller test is significant for all variables across the two markets inducing that the null hypothesis of unit root is rejected and all series are stationary.

Both $CSSD_t$ and $CSAD_t$ in panel A and B are positive in mean with CSSD = 0.075 and CSSD = 0.067 and CSAD = 0.019 and CSAD = 0.022. Indeed, $CSSD_t$ and $CSAD_t$ series are stationary but non-normal and asymmetrical since their kurtosis and Jarque-Bera exceed largely their limited values. Thus, if analytical estimation of $CSSD_t$ and $CSAD_t$ regression presented in Table 2 was valid then U.S. market would exhibit an asymmetric herd behavior for both S&P 100 and DJIA markets.

Estimation Results

Modified regression of herding measure

Analytical analysis presented in Table 2 corroborate the descriptive results.

Table 2. Analysis of herding behavior in U.S. markets based daily cross sectional standard deviation (CSSD) model

Panel A: Regression Results of CSSD for S&P100 market		**Panel B: Regression Results of CSSD for DJIA market**	
$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t$			
A	0.1846 (28.822)***	***α***	0.2163 (26.511)***
β₁	-0.078 (-15.384)***	***β₁***	-0.1085 (-16.194)***
β₂	-0.0668 (-13.890)***	***β₂***	-0.1043 (-16.516)***
Adjusted R²	0.0974		0.1062

Panel C: Regression Results for modified CSSD for S&P100 market		Panel D: Regression Results for modified CSSD for DJIA market	
$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \beta_3 Vol_{m,t}^2 + \varepsilon_t$			
Α	0.185 (28.838)***	***α***	0.2144 (26.136)***
β₁	-0.077 (-15.395)***	***β₁***	-0.1081 (-16.167)***
β₂	-0.0667 (-13.868)***	***β₂***	-0.1040 (-16.475)***
β₃	-0.0113 (-1.1671)	***β₃***	0.0212 (2.219)**
Adjusted R^2	0.0978	Adjusted R^2	0.1076

This table reports the results for Eq.(2) in Panel A and B, and Eq. (3) in Panel C and D. Numbers in parentheses are t-statistics based on Newey-West (1987)'s heteroskedasticity and autocorrelation consistent standard errors.
*Note: ***, ** and * denote the statistical significant at the 1% level, 5% and 10% level respectively.*

Estimation results of Christie & Huang (1995) model using daily data are reported in Table 2.The herding coefficient β_1 and β_2 in Panel A and Panel B are negative and statically different from zero at 1% level. The negative sign of dummy variable refers that equity return dispersion (CSSD) tends to decrease during market turmoil period. This decrease confirms the theoretical assumption of Christie & Huang (1995) on which investors in high volatile period tend to be aligned with the average collective group behavior. The negative and significant sign of β_1 and β_2 imply that the change in investor' behavior during extreme days of upward and down prices movement when herding behavior occurs. More particularly, the estimated value of β_2 is larger than β_1 for both S&P 100 index and DJIA market, which suggests that investors tend to suppress their own beliefs more easily in a down market than in up market. These empirical findings confirm the existence of herd behavior in the American stock market as a developed market although most of previous studies have found no evidence of herding in developed markets (Christie & Huang, 1995; Chang, Cheng, & Khorana, 2000; Henker, Henker, & Mitsios, 2006). More particularly, the herding tendency in U.S. market is stronger in S&P 100 market (β_2 = - 0.0667) than in DJIA market (β_2 = - 0.1040), we refer to the fact that S&P 100 is more liquid and more informed than DJIA market.

Modified regressions of CSSD in presence of trading volume are reported in Table 2 Panel C and Panel D. All variables except for trading volume coefficient are highly significant at 1% threshold. Interestingly, the parameters of return dispersion (β_1; β_2) still significant and negative providing strong evidence on the existence of herding behavior in American stock markets. This evidence along with improved high value of the adjusted R^2 (0.1062 > 0.1076) justify the addition of trading volume as explanatory variable to herding behavior. Scholars (Yao, Ma, & He, 2014; Chen, 2013) supported Christie & Huang (1995)'s assumption that the cross-sectional dispersion should be negatively correlated with trading volume when herding occurs. However, in our case when adding trading volume, we find lower herding behavior in the U.S. markets. This mean that controlling the trading volume variable, herding behavior still exists but in low degree. We find a positive correlation of market return dispersion and trading volume term for DJIA market. This suggests that during extreme market condition the trading volume-equity return dispersion relationship tends to increase rather decrease. We attribute these results to the low liquidity feature of DJIA with only 30 industrial compared the others Americans markets.[5] The non-significance and negative sign of trading volume for S&P 100 market imply that during market disturbance trading volume does not influence herding tendency.

[5] For instance in reference to Table 1, the mean of trading volume of S&P 100 is five times larger than mean trading volume of DJIA (6.86E-05) which indicates the high liquidity of S&P 100 market.

Table 3. Analysis of herding behavior in U.S. markets based daily cross absolute standard deviation (CSAD) model

Panel A: Regression Results for S&P100 market		Panel B: Regression Results for DJIA market	
$CSAD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \varepsilon_t$			
A	0.01536 (30.709)***	**α**	0.017 (17.731)***
γ1	0.6445 (9.213)***	**γ1**	0.6768 (5.402)***
γ2	-2.499 (-2.279)**	**γ2**	-4.5032 (-1.895)*
Adjusted R²	0.0644		0.1752

Panel C: Regression Results for modified CSAD for S&P100 market:		Panel D: Regression Results for modified CSAD for DJIA market:	
$CSAD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \gamma_3 \left|Vol_{m,t}\right| + \gamma_4 Vol^2_{m,t} + \varepsilon_t$			
A	0.0155 (25.809)***	**α**	0.0182 (14.652)***
γ1	0.5627 (9.254)***	**γ1**	0.6753 (5.393)***
γ2	-2.4822 (-2.263)**	**γ2**	-4.4008 (-1.850)***
γ3	0.0009** (0.261)	**γ3**	-0.0064 (-1.197)
γ4	-0.0021** (-0.705)	**γ4**	0.0073* (1.932)
Adjusted R²	0.0655	Adjusted R²	0.0188

This table reports the results for Eq. (4) in Panel A and B, and Eq. (5) in Panel C and D. Numbers in parentheses are t-statistics based on Newey-West (1987)'s heteroskedasticity and autocorrelation consistent standard errors.
*Note: ***, ** and * denote the statistical significant at the 1% level, 5% and 10% level respectively.*

Table **3** Panel A and Panel B present estimation results of daily cross absolute standard deviation (CSAD) model Eq. (4) for S&P 100 and DJIA market. The regression of S&P 100 market suggests if market return $R_{m,t}$ was null, the average degree of equity return dispersion is about zero (α = 0.0153) which prove the absence of systematic risk when market portfolio is inexistent. According to Table **3**, the regression results show the coefficient term of γ_1 on the variable $\left|R_{m,t}\right|$ is positive and highly significant at 1% level indicating the violation of linear condition and suggesting the presence of herd behavior on U.S. market. Furthermore, the coefficient γ_2 is highly significant at 1% threshold and negative, which suggests the presence of herding in both the S&P 100 market and Down Jones Industrial Average (DJIA) market during the whole period. This finding confirms that imitative behavior not only exits in U.S. stock market but as daily phenomena, so herding is a long-lived phenomenon. Additionally, the significant value of γ_2 is larger for S&P 100 market (γ_2 = -2.499) than for DJIA market (γ_2 = 4.5032) suggesting that herding is stronger in S&P 100 market than for DJIA market.

The coherent result in Table 2 and Table **3** is a strong indicator on the presence of herding during both tranquil and turmoil period. Panel C and Panel D report regression results of the modified Chang et al. (2000) using market trading volume as independent variables (Eq. (5)). Estimation results presented in Panel C and D of Table **3** are perfectly consistent with those in Panel A and B. In fact, the coefficient term of non-linearity γ_1 is still positive and highly significant at 1% threshold, and γ_2 variable remains negative and meaningful at 1% level. Furthermore, the adjusted R² is slightly higher (*e.g.*, DJIA's Adjusted R² = 0.0188 > 0.1752) which implies the validity of our model and suggests that our modified pattern provides a better description to herding behavior. The positive and significant sign of γ_3 coefficient in Table **3** Panel C suggests that market return dispersion increases with trading volume; however, the negative significant sign of γ_4 coefficient implies that this increase is at a decreasing degree. This finding is consistent with scholar's assumption that there is a negative correlation between market return dispersion and trading volume component on U.S. stock market (Yao, Ma, & He, 2014; Lan & Lai, 2011; Chiang & Zheng, 2010). Additionally, these results imply that trading volume comprehends incremental information in the market; thus, it can trigger herding movement. However, the effect of trading volume on herding behavior is weaker for DJIA market with γ_4 positive and significant at 10%. For both Panel C and D in Table **3** we can observe that even after controlling the trading volume variable, herding tendency in S&P 100 and DJIA markets remains quite strong and persistent phenomena across days.

Asymmetric effect of trading volume

In order to examine the asymmetric effect of trading volume on herding tendency in the U.S. market, we use a dummy variable for days with abnormal high trading volume (top 10th percentile) and a dummy variable for days with abnormal low trading volume (bottom 10th percentile). Estimation results are reported in
Table **4** Panel A and Panel B. The empirical findings corroborate previous results in Table 2 and Table **3**, suggesting that despite controlling for highest and lowest trading days, herding behavior still exists for both S&P 100 and DJIA markets with γ_2 highly significant and negative. When coefficients for dummy variables are considered, evidence for daily data indicates that S&P 100 displays herding in both high and low trading markets. However, regarding
Table **4** Panel B, the asymmetric effect of herding has not been captured for DJIA market. Indeed, the coefficient of estimated dummy variable in Panel B is not significant, which suggests that the changes in market liquidity do not significantly influence the market return dispersion in DJIA market. Moreover, the Wald test rejects the hypothesis of equality of herding among high and low-trading days. The test results show that the χ^2- statistics are less than 5%. Hence, we can assert that investors in U.S. market have an asymmetric reaction to good news and bad news.

Table 4. Estimation results of asymmetric effects of trading volume on herding in US market using dummy variables

Panel A: Regression Results for S&P100 market:		Panel B: Regression Results for DJIA market:	
$CSAD_t = \alpha + \gamma_1 \left\| R_{m,t} \right\| + \gamma_2 R^2{}_{m,t} + \theta_1 Vol_{High} R^2_{m,t} + \theta_2 Vol_{Low} R^2_{m,t} + \varepsilon_t$			
A	0.0152*** (30.228)	**α**	0.0176*** (17.665)
γ_1	0.5747*** (9.092)	**γ_1**	0.6636*** (5.1517)
γ_2	-3.1242** (-2.418)	**γ_2**	-4.609** (-1.6463)
θ_1	-1.48** (-1.025)	**θ_1**	1.992 (0.7186)
θ_1	-0.685** (-0.441)	**θ_1**	-1.256 (-0.375)
Adjusted R²	0.0648	**Adjusted R²**	0.1780
$\theta_1 - \theta_2$	-0.795	**$\theta_1 - \theta_2$**	3.248
χ^2(p-value)	22.88 (0.01)	***χ^2(p-value)***	19.46 (0.00)

This table reports the estimated coefficients of the regression in Eq. (6). The χ^2-statistic with one degree of freedom is used to test for the null hypothesis H_0: $\theta_1 = \theta_2$. The p-value is the probability of Chi-squared terms. Numbers in parentheses are t-statistics based on Newey-West (1987)'s heteroskedasticity and autocorrelation consistent standard errors.
*Note: ***, ** and * denote the statistical significant at the 1% level, 5% and 10% level respectively.*

Trading volume – herd behavior causality results

Table 5. Volume-herding causality results using Vector Autoregressive Regression (VAR) and Granger Causality tests

Panel A:VAR estimation for S&P 100 market			**Panel B: VAR Estimation for DJIA market**	
	$CSAD_t$	$Vol_{m,t}$	$CSAD_t$	$Vol_{m,t}$
$CSAD_{t-1}$	**0.831*****	0.427*	0.7286***	0.056
	(45.163)	(1.671)	(41.013)	(0.390)
$CSAD_{t-2}$	0.023	-0.637**	-0.070***	-0.236
	(1.294)	(-2.496)	(-3.948)	(-1.643)
$Vol_{m,t-1}$	0.0004	-0.448***	-0.003	-0.473***
	(0.352)	(-25.010)	(-1.473)	(-28.542)
$Vol_{m,t-2}$	-0.0002	-0.221***	-0.0007	-0.225***
	(-0.176)	(-12.422)	(-0.344)	(-27.221)
Adjusted R^2	0.438	0.212	0.305	0.208
F-Statistic	580.612	213.541	326.901	250.490
Panel C:Granger Causality Tests for S&P 100			**Panel D: Granger Causality Tests for DJIA**	
Null Hypothesis	F-Statistic	P-value	F-Statistic	P-value
$CSAD_t$ does not Granger Cause $Vol_{m,t}$	3.883**	0.048	1.690**	0.019
$Vol_{m,t}$ does not Granger Cause $CSAD_t$	0.527	0.467	1.0199	0.312

This table report the estimated coefficient and adjusted R^2 of the Vector Auto-regression Estimation (VAR) and Granger Causality test Eq. (7) and Eq. (8) for the S&P 100 and Dow Jones Industrial Average markets. Numbers in parentheses are t-statistics based on Newey-West (1987)'s heteroskedasticity and autocorrelation consistent standard errors.
*Note: ***, ** and * denote the statistical significant at the 1% level, 5% and 10% level respectively.*

Summarized results of VAR estimation and causality regression of Eq. (7) and Eq. (8) are reported in Table 5. In line with Chuang & Lee (2006), Gebka & Wohar (2013) we set $p = q$ and in order to determine the number of lags "*p*" we use the Akaike Information Criterion (AIC) and Schwarz information criterion (SIC). Consequently, the volume-herding relationship can be assessed based on the estimated parameters of (α_i, β_i) which captures the impact of past one-, two- day's log-volume on current herding (market return dispersion) and vice-versa. Volume-herding relationship is considered in two aspects: herding effect on market trading volume and market trading volume effect on herding tendency.

The first set of results presented in Table 5 Panel A and B are significant respectively to one-day and one-, two- day lagged herding, and suggesting that herding is only influenced by past herding movement. This finding is consistent with empirical results of Hachicha (2010) that the herding behavior in one period depends on the previous herding behaviors periods. Estimation analysis of Eq. (8) shows that trading volume variable correlation to actual and past return dispersion is not significant for DJIA market and weakly significant at 10% for S&P 100 market. This provides insight that although trading volume could

present a potential reason for investor to imitate each other, it is not the main driven force of herding. Herding is enhanced in high liquid market since high trading volume have more available information; thus, investors can earn return faster in high liquid market (Gregoriou & Ioannidis, 2006). Thus, agents tend to herd in liquid market.
On the other side, theoretical proponents assume that herding appears mainly because of individual interaction due to cognitive bias rather than by other factors (Shiller, 2007).[6] This interaction is known as social network that leads to the spread of popular opinion, thoughts and behavior contagion. Under uncertainly or costly information, investors act in conformity with group-thinking[7] based oral conversation, media, common sport activity that allow them the advantage to exploit valuable ideas of others; hence, it provides them an additional relevant information for their financial decisions. The "*groupthink*" phenomenon is an amplification of individual biases and corresponds to members who share the same thought opinion, cognitive biases, same background, have resemblance in behavior, and move in the same social circles. Some individuals are situated close to the center of the social network, they are highly informed and disseminate financial ideas and information; thus, they may have first-hand information to trade. Limited informed investors under uncertainly will choose to follow them and copy their trading strategy; hence, they accentuate rising of trading volume in U.S. market. Especially, herding and information cascade is more pronounced when an investor is confronted to complicated decision (Conlisk, 1996). Kim & Pantzalis (2003) emphasized evidence on herding in diversified firms where analysts' task is more difficult.

In analogy with market's return dispersion decreasing relationship,[8] empirical surveys conditioned negative market volume-return dispersion correlation. Thus, if herding-volume effect exists then the parameters γ_1 and γ_2 should be negative. According to Table 5 Panel A and Panel B, the parameters (γ_1, γ_2) of trading volume for the two previous days are negatively significant at 1%. The estimated values are decreasing suggesting that actual trading volume is mostly explained by actual and previous day's herding tendency. The negative (positive) correlation between CSAD (herding) and market trading volume is highly significant, implying that herding can generate high trading volume. Moreover, estimated coefficient (β_1) in Table 5 Panel A and Panel B are positive and significant suggesting that more contemporaneous herding (smaller CSAD) will generate higher trading volume in the next period. Estimated value of β_i terms are less than one (*e.g.*, $\beta_1 = 0.831$, $\beta_1 = 0.7286$) which suggests that 1% decrease in CSAD will trigger an increase of more than 1% in trading volume degree.
The results reported in Table 5 Panel C and D Granger test show that volume-herding causality is driven in only one sense. The Wald statistics test for S&P 100 market reject the null hypothesis that market return dispersion (CSAD) does not Granger cause market trading volume since p-value (0.048) < 5%; F-statistic = 3.883. According to VAR and Granger test, we conclude that trading volume cannot generate herding behavior except for liquid market. However, we find that contemporaneous herding is a deterministic factor for excessive trading volume.

The results are consistent with the theoretical behavior predictions, which assume that herding is information disseminative. Under uncertainly, especially during market disturbance, traders do not know the value of new information and have to make decision in a short period, they often fail in determining the correct fundamental value; thus, they interpret signals relative to stock price wrongly. These traders, known as "*noise traders*",[9] tend to make irrational trading strategies and will herd and fuel the market with an abnormal high trading volume that contributes to the increase of excessive stock's volatility (Black, 1986; Shiller, 2007).

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[6] Cognitive biases in conversation stimulate the diffusion of mistaken beliefs phenomena: a collective confirmatism.
[7] This mean when CSAD is small the market return dispersion will be low and herding degree will be higher.
[8] Uniformity biases for all group.
[9] Noise traders correspond to those who use uninformative uncertain signals in their trading and who make their strategy based on anything other than information.

The effect of Subprime crisis

The 2007-2009 crisis is qualified as the most dramatic and critic crisis that the history of financial market have witnessed since the great depression of 1930s. Where, almost all index values fall by 30% to 40% during 2008. In addition, this crisis has left a considerable long-term effect on market volatility (great recession until today).

Table 6. Regression results of herding behavior during the Subprime crisis

Panel A: Regression Results for S&P100 market			**Panel B: Regression Results for DJIA market**	
$CSAD_t = \alpha + \gamma'_1 \lvert R_{m,t} \rvert + \gamma'_2 R^2_{m,t} + \gamma'_3 \lvert Vol_{m,t} \rvert + \gamma'_4 Vol^2_{m,t} + \gamma'_5 D_t Vol^2_{m,t} + \varepsilon_t$				
	C	Adjusted R^2	C	Adjusted R^2
α	0.015*** (25.720)		0.0189*** (14.328)	
$\lvert R_{m,t} \rvert$	0.563*** (9.264)		0.679*** (5.427)	
$R^2_{m,t}$	-2.463*** (-2.246)		-4.146*** (-1.742)	
$\lvert Vol_{m,t} \rvert$	-0.0007** (-0.217		-0.004 (-0.692)	
$Vol^2_{m,t}$	-0.002** (-0.565)		0.007 (1.821)	
$D_t Vol^2_{m,t}$	-0.003* (-0.682)	0.065	-0.018** (-2.139)	0.0202
Panel C: Regression Results for S&P100 market			**Panel D: Regression Results for DJIA market**	
$CSAD_t = \alpha + \gamma'_1 \lvert R_{m,t} \rvert + \gamma'_2 R^2_{m,t} + \gamma'_3 \lvert Vol_{m,t} \rvert + \gamma'_4 Vol^2_{m,t} + \gamma'_5 R^2_{m,t} D_t + \gamma'_6 Vol^2_{m,t} D_t + \varepsilon_t$				
	C	Adjusted R^2	C	Adjusted R^2
α	0.015*** (25.379)		0.0186*** (14.642)	
$\lvert R_{m,t} \rvert$	0.503*** (7.177)		0.496*** (3.557)	
$R^2_{m,t}$	-2.467** (-2.253)		-5.444*** (-1.349)	
$\lvert Vol_{m,t} \rvert$	0.0013** (0.367)		0.0071 (1.864)	
$Vol^2_{m,t}$	-0.0014* (-0.509)		-0.0046 (-0.843)	
$D_t Vol^2_{m,t}$	-0.0016* (-0.4316)		-0.0139 (-1.571)	
$R^2_{m,t} D_t$	-2.584 (-1.702)	0.066	-8.922** (-2.941)	0.023

This table reports the results of Eq. (9) in Panel A and B, and Eq. (10) in Panel C and D. Numbers in parentheses are t-statistics based on Newey-West (1987)'s heteroskedasticity and autocorrelation consistent standard errors.
*Note: ***, ** and * denote the statistical significant at the 1% level, 5% and 10% level respectively*

In order to study the potential effect of 2007-2009 global financial crisis on investors' behavior, we add to Eq. (5) a dummy variable. Estimation results are reported in Table 6. Regression results of the Eq. (9) and Eq. (10) reported in Table 6 confirm that even the Global Financial Crisis is controlled for both S&P 100 and DJIA, which still exhibit strong herding behavior during crisis period. In fact, after adding the dummy variable D_t we notice that all coefficients such as $\left|R_{m,t}\right|$, $R^2_{m,t}$ and $Vol^2_{m,t}$ remain highly significant at 1% level and consistent with their value in Eq. (5), which suggest the prevalent influence of market disturbance on herding movement. The estimated coefficient for the dummy variable that captures financial crisis effect γ'_4 is highly and negatively meaningful at 5% and 10% threshold, which indicates that over the global financial crisis period the market return dispersion on U.S. market tends to decrease.

This finding suggests that herding is intensified during the subprime crisis period, which accentuates market disturbance and elongate volatility increasing. We outline that our prior empirical results presented in Table 2 confirm our results and support Christie & Huang (1995)'s prediction that herding is more profound in the extreme market turbulence in the U.S. financial market. This finding is perfectly consistent with our theoretical prediction that under high risk, fear and panic, investors spontaneously abundant their positions and their strategies to blindly copy others strategy, which leads the market to be blind to disaster (Orléan, 2004).

Furthermore, the controlled variable on trading volume γ'_5 during crisis period is negative and significant at 10% level suggesting a decreasing relationship of trading volume and market return dispersion. This imply that trading volume, by increasing market liquidity, may be an stimulus for investors to herd, even during crisis period, and may play a relevant role in extending the herding effect. This finding appears to be consistent with Shiller (2007) perception of Subprime crisis.

Shiller (2007) examined the boom in the U.S. housing bubble and attributed its origin to thought and behavior contagion among agents who are too optimistic with magic thinking or rosy idea that home prices always increase and never fall. These biased beliefs spread among investors due to social network's process that leads them to abandon their private information and generate a spread of imitative behavior and delusions. The contagious spread of beliefs (herding) influences agents' perceptions and derives their behaviors to ignore the signal of financial market and trade excessively on housing investment. Consequently, they generate abnormal trading volume and creates abnormal increasing in market volatility.

Conclusion

Our findings provide response to debate on existence of herding behavior in U.S. market. Herding not only exists in U.S. financial market, but it a persistent phenomenon, since we use two different measures of herding CSSD and CSAD. The results were perfectly coherent and valid, indicating that the American market exhibit an irrational behavior (or herding). Some authors such Zhou & Lai (2009) employed intra-day sample and claimed that herding have a short-life, and is restricted on some industries. However, our analysis using daily data of companies from all sectors showed that herding is a persisting phenomenon across days. Research find a positive and significant correlation between market trading volume and herding, in addition to positive Granger causality in one sense which indicates that herding is the main factor in increasing excessive trading volume, and in fueling the Subprime crisis bubble. Empirical survey of herding during the 2007-2009 crisis confirms that herding is the main driven force of Subprime crisis. As a whole, our empirical investigation on herding bias provides a potential explanation to the excessive market trading. However, the statistical analysis reveals that the non-conditional density function of return series follow an asymmetric shape with abnormal high fat tails. Thus, herding in U.S. market is asymmetric with heavy tails.

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