Herding behaviour and market dynamic volatility: evidence from the US stock markets

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Abstract: This paper documents the effect of herd behaviour on the US S&P100 and US DJIA stock market’s stocks volatility. We investigated the presence and the change of herding behaviour in the US S&P100 and US DJIA stock markets during January 2000 to July 2012. Results provide strong and coherent evidence on the occurrence of herding at only daily frequency. In particular, the findings indicated a significant change in herding tendency across sub-periods of the subprime crisis. The different tests report that herding is only prevailing during bull period and during days of high trading volumes. Moreover, empirical evidences report a significant relationship between market sentiment and herd behaviour. We show that herding contributes not only in fuelling market excessive volatility but also in raising the housing bubble during the subprime crisis. Surprisingly, we find that asymmetric herding exists during days of low volatility.

Keywords: excessive volatility; subprime crisis; cross sectional absolute standard deviation; market sentiment.


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1 Introduction

The last global financial crisis (GFC) erupted in 2007 is qualified as the worst and heaviest financial crisis since the great depression of the 1930s. Almost all indices values sharply declined by 40% to 50% during 2008 across global financial markets (Dungey and Gajurel, 2014; Authers, 2010). A stylised fact of this crisis lead to an ample persistent shift in stock price from fundamentals and has left a considerable worldwide heavy recession until today. One of the concrete features of thought and behaviour contagion among investors is Herd behaviour. Indeed herding elucidate the manner through which thought or beliefs are conveyed from an investor to another leading to the spread of imitative, uniform (erroneous) investment behaviour. It is widely admitted that herd behaviour is a vital ingredient of rising bubble and aggregate stock’s increasing price.

Herd corresponds to an investor who intentionally abandons their own beliefs and their own private information to act in conformity with market consensus regardless of market relevant information. Herding behaviour was first mentioned by Keynes (1936) where he described this bias by referring to the metaphors of Beauty Contest. However the seminar patter of Christie and Huang (1995) made a significant methodological departure from those in the existent literature by modelling herd behaviour based on cross-sectional dispersion in individual stock return (CSSD). Lately Chang et al. (2000) extended Christie and Huang’s (1995) herding pattern using market cross-sectional absolute deviation (CSAD) of assets returns.

regression to examine herding behaviour in US RETs market. Both of them provided evidence in favour of herding in this market. In particular, they find herding is more pronounced in the high quintiles of REIT return dispersion during 1980–2010.

Therefore, whether the US financial market as a developed market exhibits herding behaviour remains an open question. This study contributes to the existent empirical survey by re-examining this behavioural bias and its magnitude on the US S&P100 and US Dow Jones Industrial Average (DJIA) stock markets. To the best of our knowledge, herding surveys have not been conducted on the S&P100 and DJIA markets.

Furthermore, few studies on herding behaviour shed light on the potential effect of markets return in fuelling herding and the relationship between herding and market volatility return. Our study contributes to the limited existing literature by applying VAR and Granger causality pattern to evaluate the return-herding relationship and to evaluate herding effect on market implied volatility.

Our focus is how herd behaviour shifts during the Global financial 2007–2009 crisis. Moreover, although US market sentiment index ‘VIX’ is widely admitted as market fear sentiment, the effect of market sentiment on herd behaviour have received very limited research attention. We add to the existent literature by incorporating market sentiment index into Chang et al. (2000) herding regression model. This modified model allows to examine how herding as psychological pitfalls under fear sentiment impedes investor’s abilities to reason and respond rationally and increase market volatility.

This paper provides a direct empirical link between market return dispersion and market conditional volatility and provides additional evidence on the response of herding behaviour to the market’ asymmetric volatility in S&P100 and DJIA stocks markets. Furthermore our study contributes to the present studies by taking in consideration several variables relative to the real economy across herding regression in order to provide a deeper apprehension of the real essence of herding tendency.

Our objective is not only to provide a robust survey of herding in the US market but also aims to test whether this psychological pitfall may contribute to explaining the observed clustered and excessive conditional volatility in the US financial market.

The remainder of this paper is organised as follows: Section 2 describes the data set. Section 3 presents the research methodology. Section 4 discusses the empirical findings. Section 5 provide the summery and conclusion.

2 Data collection

Since we are interested in studying herd behaviour during the last global financial crisis, we chose the US stock market as the main trigger of this crisis. More precisely, we surveyed listed firms on S&P100, a sub-set of the S&P500 index qualified as the core of the US financial market (Hibbert et al., 2008) and 30 listed firms on the Dow Jones Industrial Average markets.

We use daily and monthly data to construct the variables of our empirical work. The daily and monthly data are extracted from Wharton Research Database and Chicago Board Options Exchange (CBOE) database. The sample period covers the 4th January 2000 to 20th July 2012, a total of 3157 daily and 150 monthly observations. The date set retain market stock prices, volume transaction, market capitalisation, individual firm’s share price and market implied volatility index (the ‘VXO’ volatility index for the
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S&P100 market and ‘VXD’ volatility index for the DJIA markets). The S&P100 (DJIA) implied volatility index VXO (VXD) are extracted from historical options Data. The VXO (VXD) index is calculated through the bid and ask price of the S&P100 (DJIA) markets. The VXO (VXD) is known as – the fear gauge or – the sentiment index according to the Wall Street Journal. Market sentiment is detected through an acceleration of VXO (VXD) increase² (Low, 2004).

3 Empirical methodology

3.1 Herding measure

There is a wide range of empirical herding models. However, the most robust and well-know herding measure is Chang et al. (2000) cross-sectional absolute deviation (CSAD) model. Chang et al. (2000) CSAD pattern was inspired from Rational Capital Asset Pricing Model (CAPM) and expressed:

\[
CSAD_t = \frac{\sum_{i=1}^{N} |R_{it} - R_{mt}|}{N}
\]

where \(R_{it}\) is the observed stock return of firm \(i\) at time \(t\), \(R_{mt}\) is the cross-sectional average return of all stock returns in the portfolio at time \(t\), \(N\) is the number of firms in the portfolio.

The capital asset pricing model’s assumption is: if investors are rational (absence of herding) and estimate price with reference to the CAPM model the relationship between individual asset return dispersion and market portfolio return should be linear and increasingly positive. However, when investors exhibit herding behaviour, the path of the stock return should converge toward the average of the market trend, instead of deviating significantly from market return. Thus the linear relationship between stock return dispersion and market return will not hold but will shift to be nonlinear and decreasing. Formally, this nonlinear decreasing relationship is expressed as

\[
CSAD_t = \alpha + \gamma_1 |R_{mt}| + \gamma_2 R_{mt}^2 + \epsilon_t
\]

Chang et al. (2000) assume that during periods of extreme price movements, in the presence of herding behaviour investors will abandon their own private beliefs and base their individual investment decision-making on the collective actions in the market.

In equation (2) the non-linearity between CSAD and market return is captured by the \(\gamma_2\) parameter. We expect the decreasing relationship to be captured by the negative sign of \(\gamma_2\).

H1: If herding behaviour is not observed we expect \(\gamma_1 > 0\) and \(\gamma_2 = 0\) in model (2). If herding exists in US S&P100 and US DJIA markets, then \(\gamma_2\) should be negatively significant.

Furthermore, we examine herding under different market conditions. There is a bulk of empirical papers that highlight the asymmetric effect of market return and trading volume on herd behaviour. We survey separately whether herding is more observable in
bull market with positive market return and whether herding reacts asymmetrically during a downward market trend with negative returns, using dummy variables as expressed in the following regression model:

$$CSAD_t = \alpha + \gamma_1 (1 - D) R_m^t + \gamma_2 D R_m^t + \gamma_3 (1 - D) R_{m,\text{CSAD}}^t + \gamma_4 D R_{m,\text{CSAD}}^t + \epsilon_t$$  \hspace{1cm} (3)$$

where $CSAD_t$ is the average absolute value of the deviation of each stock relative to the return of the equally-weighted market portfolio $R_m$ at time $t$. $R_m$ are equally-weighted market return on day (month) $t$ when the market is up (down). The asymmetric effect is captured at both linear and nonlinear terms using the dummy variable $D$ with $D = 1$ if $R_m < 0$ and 0 otherwise.

Moreover, since we employ an equally weighted measure, our results may have been influenced by the presence of positive trading stocks in the portfolio. Thus for robustness analysis we study the relative influence of small trading volume (low) and large trading volume stocks (high) on investor herding behaviour. The following model is estimated separately across daily (monthly) high trading volume and daily (monthly) low trading volume:

$$CSAD_t = \alpha + \delta_2 Vol_H + \delta_1 Vol_L + \delta_2 Vol_{t-1} + \delta_1 Vol_{t-1} (R_{m,\text{CSAD}}^t) + \delta_2 Vol_{t-1} (R_{m,\text{CSAD}}^t) + \epsilon_t$$  \hspace{1cm} (4)$$

where $Vol_m$ is market detrended return at time $t$. $Vol_H$ and $Vol_L$ are dummy variables that respectively capture unusual high and low trading volume periods. The trading volume is considered high if at time $t$ it is greater than the previous 30-day (or 12-month) moving average. Low trading volume corresponds to trading volume that is less than the previous 30-day (or 12-month) moving average.

H2: If herding effect is prevailing, the coefficient $\delta_2$ should be significant and negative.

If $\delta_2 Vol_H > \delta_2 Vol_L$ this will indicate that herding is more observable during days (months) with high trading volume and the information driving their behaviour is more diverse during the high volume period relatively to the low volume period.

### 3.2 Herding and the global financial subprime crisis

In this section we examine how cross sectional returns in the US S&P100 and DJIA stock markets are affected during the recent global financial crisis. Scholars assert that the housing bubble was fuelled by an adaptive and imitative mechanism (herding) (Harras and Sornette, 2011). Since high return may fuel a bubble we conduct series of other tests in order to determine the financial crisis effect on the cross sectional dispersion of S&P100 and DJIA stocks return. First, we adopt a granger causality test and a VAR (vector auto-regressive) test to provide insight on the predictable relationship between market increasing return (as proxy for bubble) and herd behaviour $CSAD_t$ (as proxy of herding co-movement). To test the robustness of the evidence, we apply the granger causality approach to herding behaviour ($CSAD_t$) – market implied volatility index (VXO, XVD). Formally, we apply the following models:

$$CSAD_t = \gamma_{CSAD} + \sum_{i=1}^{p} \alpha_i CSAD_{i-1} + \sum_{j=1}^{d} \alpha_j R_{m,i-j} + \epsilon_t$$  \hspace{1cm} (5a)$$

$$R_{m,i} = \gamma_{R} + \sum_{i=1}^{p} \alpha_i R_{m,i-1} + \sum_{j=1}^{d} \alpha_j CSAD_{i-j} + \epsilon_t$$  \hspace{1cm} (5b)$$
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\[ CSAD_t = \gamma_1' + \sum_{j=1}^{p} \alpha_{ij} CSAD_{t-j} + \sum_{j=1}^{p} \alpha_{ij} VX_{t-j} + \varepsilon_t \]  

(6a)

\[ VX_t = \gamma_1' + \sum_{j=1}^{p} \alpha_{ij} VX_{t-j} + \sum_{j=1}^{p} \alpha_{ij} CSAD_{t-j} + \varepsilon_t' \]  

(6b)

where \( \gamma_1 \) and \( \gamma_1' \) are restoring forces into market equilibrium; \( p \) is number of lags. \( R_{m,t-j} \) and \( CSAD_{t-j} \) are respectively lagged market return and lagged herding measure. The rejection of the null hypothesis (H0: \( \alpha_j = 0 \)) that market return does not granger-cause herding implies that market return may trigger herd behaviour. The results are reported in Table 5.

Several authors outlined that herding conveys erroneous thought and contagious mania or fads in speculative markets leading to bubbles and crashes (Lux, 1995; Shiller, 2000). Christie and Huang (1995) reported that herding is more intense during period of market disturbance. Thus, we revised model (2) by introducing a slope dummy variable to include the 2007–2009 global financial crisis as follows:

\[ CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 D^{crisis}_t R^2_{m,t} + \varepsilon_t \]  

(7)

The \( D^{crisis}_t \) variable takes the value of unity during the financial crisis and 0 otherwise.

We assume that the subprime crisis boom exploded on 2 July 2007 (Authers, 2010; Phillips and Yu, 2011) and its effect was decreasing until mid (June) of 2009 (NBER reports, 2010; Philippas et al., 2013). The recent global financial crisis was judged as the severest financial crisis since the 1930s great depression (Authers, 2010). During the crisis, economists witnessed the collapse of the biggest robust financial investments (Lehman Brothers and Bear Stearns, the bailout of American International Group (AIG), America’s largest insurance company). This collapse rapidly spread to the greater financial institutions across the world and has generated a great recession until today. Therefore, we applied a deeper analysis of the global financial crisis by dividing the 2007–2009 crisis period into three sub-periods. Following Authers (2010), we use a narrower definition of the subprime crisis based on the big events of Lehman Brothers collapse on September 2008; the Global correlated crash on October 2008 and the great recession period of more than 18 months until June 2009 as suggested by NBER reports. The first sub-period starts from July 2007 until September 2008; the second sub-period goes from September to October 2008 and finally the third sub-period known as the great recession period and goes from December 2007 to June 2009. The results are presented in Table 6.

3.6 Herd behaviour contribution to observed market volatility

Although there was a wide range of empirical scholars focus on herding measure, there is a considerable lack of empirical models measuring directly herding effect on stock market returns volatility. In this section, we employ two different tests of herding behaviour effect on market clustered and asymmetric volatility. Behavioural proponents assumed that the main incentive leading to herding was uncertain information. In particular, some authors assume that under fear of making wrong decisions, investors
blindly follow the dominant market trading trend (buying or selling) and ignore their
information and market warnings signals (Hirshleifer and Teoh, 2009; Bénabou, 2013).
In the same line, Taffler and Tuckett (2005), Eshraghi and Taffler (2012), Schmeling
(2009) assert that investor decision is driven by emotions, unconscious needs, fantasies,
and fears. Hirshleifer and Teoh (2009), Scharfstein and Stein (1990) highlighted that
managers under the fear to lose their reputation they often behave irrationally and imitate
the market’s general trend. In particular, Schmeling (2009) investigated the influence of
investor sentiment on market stock return on sample of 18 industrialised countries. The
author found a significant influence of investor sentiment on market return in countries
that are prone to herd and overreact. Zhang and Yang (2009) confirm that excessive
volatility in Chinese stock markets is influenced by investor sentiment.

The most robust measure of investor sentiment are reported by Chicago Board
Options Exchange’s (CBOE) volatility index (Baker and Wurgler, 2006; Giot, 2005;
Low, 2004; Whaley, 2009). In our case we use the VXO and VXD volatilities indices as
market sentiment index for the S&P100 and VXD the DJIA stocks markets, respectively.
Market sentiment index – VXO (VXD) (or the fear gauge) is determined by all available
stock bid and ask prices of S&P100 (DJIA) index options. Therefore, similar to previous
studies (Chiang and Zheng, 2010; Yao et al., 2014; Philippas et al., 2013) we expect if
market sentiment affects herding tendency, there should be a negative correlation
between market return dispersion and investor squared sentiment. Formally, we estimate
the following model:

\[ CSAD_t = \alpha + \gamma_1 R_{VXO_t} + \gamma_2 R_{VXD_t} + \gamma_3 R_{CSAD_t} + \varepsilon_t \]  

(8)

where \( R_{VXO_t} \) is the percentage return of the VXO and VXD index for day (month) \( t \). The
empirical estimations are reported in Table 7. We expect if herding contributes to
increasing market implied volatility this would be indicated by the negative and
statistically significant coefficient of \( \gamma_4 \).

Moreover, several authors assert explicitly that herd behaviour fuels investor’s
irrational exuberance and amplified volatility (Topol, 1991; Christie and Huang, 1995;
Shiller, 2000). They add that because of random lucky strikes of positive news, investors
will trade on specific stock followed by other investors who will imitate them and trade
on the same stock creating abnormal transaction volume on the specific stock and
generating high variability in the stock price. There is a positive and significant
correlation between herding and asymmetric volatility (Chiang and Zheng, 2010).
Therefore, in order to determine the impact of herding on market asymmetric volatility
we use a dummy variable that captures herding behaviour during days (months) of
abnormal high and low volatility. Formally, we apply the following model:

\[ CSAD_t = \alpha + \gamma_1 D^{High}_{VXO_t} R_{VXO_t} + \gamma_2 (1-D^{High}_{VXO_t}) R_{VXO_t} + \gamma_3 D^{High}_{VXD_t} R_{VXD_t} + \gamma_4 (1-D^{High}_{VXD_t}) R_{VXD_t} + \varepsilon_t \]  

(9)

where \( D^{High}_{VXO_t} \) variable takes the value of unity during days (months) with unusual high
market volatility and 0 otherwise. Market return variance is estimated using the previous
30 days (12 months). The dummy variable of market conditional volatility is considered
as high if it is larger than the past 30 days (12 months) and low if it is lower than the past
30 days (12 months).
4 Results

4.1 Descriptive results

In this section we will first provide an insight into herding behaviour distribution on the US S&P100 and US DJIA markets then we will propose a summary of the statistical results. Descriptive series in Figures 1 and 2 display daily and monthly time series distribution of the real prices, stock returns and their corresponding market return dispersion respectively for the US S&P100 and US DJIA markets from January 2000 to July 2012.

**Figure 1** Times series plots of real price, $R_m$, and $CSAD$. This figure plots the path of daily and monthly real market prices, the cross sectional absolute deviations ($CSAD$) and the equally weighted market return ($R_m$) for the US S&P100 markets over the period of January 2000 to July 2012.

The observed path of both market stock returns and market return dispersion displayed in Figures 1 and 2 indicate that these series seem to be stationary and fluctuate around their means. However, we notice that the variation in stock real prices is clustered and volatile since it seems to be too close and extremely acute during the 2007–2009 crisis period (period of subprime crisis). This extreme variation is more observable for the S&P100 real price than for DJIA real price. This can be explained by the composition of the market index and the characteristics (size, innovation, investment, cost debt, etc.) of the...
firms listed on the S&P100 index. Both S&P100 and DJIA time series reached their lowest value on October, 2008 which corresponds to the explosion of the Global correlated crash (Authors, 2010). Regarding market return dispersion (CSAD) for both DJIA and S&P100 markets, we notice that it is more thick at the start (2000–2000) which corresponds to the event of the bankruptcy of the Long-Term Capital Management and the big Dot-com bubble burst.

Figure 2  Times series plots of real price, $R_{m}$ and $CSAD_t$. This figure plots the path of daily and monthly real market prices, the cross sectional absolute deviations ($CSAD_t$) and the equally weighted market return ($R_{m}$) for the US DJIA market index over the period of January 2000 to July 2012.

These crisis events made market stock price instable with a high abnormal stock volatility. Therefore, we can predict the prevailing role of herding behaviour in stimulating internet bubble. The 2004–2007 period is characterised by a perpetual increase in stock real price and a low stable distribution in CSAD time series. This can be explained by the introduction of a new asset class known as commodities in 2004 that boosted the increase in market price value and stimulated herd movement that fuelled the credit bubble that erupted in July 2007. The descriptive analysis show clearly that the abnormal increase in real stock price (abnormal increase in stock volatility) coincided with low return distribution (high herd). This provides evidence that herding represents an important stimulating factor of subsequent bubble and contributes to the abnormal increase in stock return volatility in US financial markets. Moreover summary statistics
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of market cross-sectional absolute deviation, market return, market trading volume and market implied volatility are reported in the following Table 1, at both daily and monthly basis.

Table 1
Summary statistics

<table>
<thead>
<tr>
<th>Period</th>
<th>Markets/ Variables</th>
<th>Mean</th>
<th>Std.dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque-Bera</th>
<th>ADF</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P100 Daily</td>
<td>$R_{m,t}$</td>
<td>-7.29E-05</td>
<td>0.0136</td>
<td>-0.1011</td>
<td>9.7360</td>
<td>5973.927</td>
<td>(-44.350)**</td>
</tr>
<tr>
<td></td>
<td>$Vol_{m,t}$</td>
<td>0.00045</td>
<td>0.2395</td>
<td>0.2173</td>
<td>27.737</td>
<td>80518.01</td>
<td>(-20.259)**</td>
</tr>
<tr>
<td></td>
<td>$RVXD_{t}$</td>
<td>22.896</td>
<td>10.265</td>
<td>1.6743</td>
<td>7.2839</td>
<td>4426.225</td>
<td>(-3.325)**</td>
</tr>
<tr>
<td></td>
<td>CSAD</td>
<td>0.0211</td>
<td>0.0186</td>
<td>1.9081</td>
<td>7.7365</td>
<td>4329.77</td>
<td>(-5.047)**</td>
</tr>
<tr>
<td>S&amp;P100 Monthly</td>
<td>$R_{m,t}$</td>
<td>-0.0012</td>
<td>0.0472</td>
<td>-0.5035</td>
<td>3.4520</td>
<td>7.6171</td>
<td>(-10.902)**</td>
</tr>
<tr>
<td></td>
<td>$Vol_{m,t}$</td>
<td>0.0076</td>
<td>0.1464</td>
<td>0.2817</td>
<td>4.3233</td>
<td>12.9288</td>
<td>(-13.756)**</td>
</tr>
<tr>
<td></td>
<td>$RVXD_{t}$</td>
<td>22.721</td>
<td>9.6068</td>
<td>1.7297</td>
<td>5.2782</td>
<td>73.3870</td>
<td>(-3.296)**</td>
</tr>
<tr>
<td></td>
<td>CSAD</td>
<td>0.0586</td>
<td>0.0225</td>
<td>1.2281</td>
<td>3.8621</td>
<td>42.3519</td>
<td>(-2.699)**</td>
</tr>
<tr>
<td>DJIA Daily</td>
<td>$R_{m,t}$</td>
<td>3.84E-05</td>
<td>0.0127</td>
<td>-0.043</td>
<td>10.196</td>
<td>6814.37</td>
<td>(-43.724)**</td>
</tr>
<tr>
<td></td>
<td>$Vol_{m,t}$</td>
<td>6.86E-05</td>
<td>0.272</td>
<td>0.002</td>
<td>15.397</td>
<td>20218.74</td>
<td>(-26.972)**</td>
</tr>
<tr>
<td></td>
<td>$RVXD_{t}$</td>
<td>20.665</td>
<td>8.608</td>
<td>1.7268</td>
<td>7.843</td>
<td>4654.67</td>
<td>(-3.655)**</td>
</tr>
<tr>
<td></td>
<td>CSAD</td>
<td>0.0227</td>
<td>0.034</td>
<td>2.668</td>
<td>9.954</td>
<td>10108.9</td>
<td>(-10.572)**</td>
</tr>
<tr>
<td>DJIA Monthly</td>
<td>$R_{m,t}$</td>
<td>0.0008</td>
<td>0.0392</td>
<td>-1.2344</td>
<td>6.5503</td>
<td>116.878</td>
<td>(-10.176)**</td>
</tr>
<tr>
<td></td>
<td>$Vol_{m,t}$</td>
<td>-0.0029</td>
<td>0.2183</td>
<td>0.3041</td>
<td>6.7971</td>
<td>92.4281</td>
<td>(-13.482)**</td>
</tr>
<tr>
<td></td>
<td>$RVXD_{t}$</td>
<td>20.572</td>
<td>8.1025</td>
<td>1.4001</td>
<td>5.8319</td>
<td>99.1321</td>
<td>(-3.406)**</td>
</tr>
<tr>
<td></td>
<td>CSAD</td>
<td>0.0563</td>
<td>0.0254</td>
<td>1.6576</td>
<td>6.3171</td>
<td>137.4642</td>
<td>(-4.961)**</td>
</tr>
</tbody>
</table>

Notes: This table reports the summary statistics for the daily mean, standard deviation, skewness, kurtosis, Normality test (Jarque-Bera) and stationarity test (Augmented Dickey-Fuller; ADF) of market return ($R_{m,t}$), market trading volume ($Vol_{m,t}$), market volatility index ($RVXD_{t}$) and the cross-sectional absolute deviation (CSAD) over the sample period for the US S&P100 index and the US Dow Jones Industrial Average (DJIA) stocks markets. Data are obtained from the CRSP database and cover January 2000 until July 2012.

*** denote statistical significance at 1% level.

The statistics analysis presented in Table 1 indicates that the average (the mean of market return) of monthly market return ($R_{m,t}$) and market return dispersion (CSAD) is higher than that of daily frequency with higher degree of standard deviation for both the S&P100 and DJIA markets. This implies that market return dispersion tends to increase with an increase in data frequency which provides a prior insight that if herding exists, it would be more prevailing at daily frequency rather than at monthly frequency. Moreover, the statistical estimation of the S&P100 market recorded a positive mean in its trading volume and a negative mean in its stock return at daily and monthly frequency. This suggests an abnormal high trading volume with negative and unprofitable returns.

Therefore, we can predict that the S&P100 market exhibits excessive volatility. Moreover, S&P100 return dispersion exhibits a lower standard deviation than that of the DJIA market at both daily and monthly basis, which suggests that investors on S&P100 are more likely to react to new information and diverse stocks. The normality test shows that all variables of market – return, trading volume, implied volatility and market return
dispersion (CSAD) – are not normally and symmetrically distributed since their skewness is different from 0 and their kurtosis largely exceeds 3. Thus, if herding behaviour is detected in the US S&P100 and US DJIA markets, it would be an asymmetric herd behaviour. The Dickey Fuller statistic (ADF) is highly meaningful at the 1% level implying the rejection of the null hypothesis of presence of unit roots and thus all variables are stationary.

4.2 Regression results

The regression results of herding behaviour under the CKK approach are reported in Table 2. Estimation results of daily herding behaviour presented in Table 2 Panel A indicates the presence of herding across the US S&P100 and DJIA markets with $\gamma_2$ highly significant and negative at the 1% level. The coefficient term of $\gamma_1$ on the variable $|R_{mt}|$ is positive and highly significant at the 1% level indicating the violation of the linear relationship between sectional absolute deviation CSAD and absolute market return $|R_{mt}|$. Furthermore, herding behaviour appears to be more pronounced for the S&P100 market with $\gamma_2$ ranging from $-3.5221$ for S&P100 to $-4.5032$ for DJIA.

**Table 2** Estimates of daily and monthly herding behaviour in US S&P100 and Dow Jones Industrial Average markets

<table>
<thead>
<tr>
<th>Markets</th>
<th>S&amp;P100</th>
<th>DJIA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Regression results under CKK’s model-daily data</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.0158*** (30.373)</td>
<td>0.0176*** (17.731)</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>0.6445*** (10.255)</td>
<td>0.6768*** (5.4029)</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>$-3.5221$*** $(-3.065)$</td>
<td>$-4.5032$** $( -1.895)$</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.0687</td>
<td>0.0175</td>
</tr>
<tr>
<td><strong>Panel B: Regression results under CKK’s model-monthly data</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.0467*** (15.377)</td>
<td>0.0518*** (13.9296)</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>0.201 (1.414)</td>
<td>0.0314 (0.1956)</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>2.1064** $(1.694)$</td>
<td>2.288** $(1.9306)$</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.3538</td>
<td>0.1232</td>
</tr>
</tbody>
</table>

Notes: This table reports the estimated coefficient and adjusted $R^2$ for the US S&P100 index and the Dow Jones Industrial Index (DJIA) equation (2): $CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \epsilon_t$. $CSAD_t$ is the equally-weighted cross-sectional absolute deviation, $R_{m,t}$ is the equally weighted market portfolio return at time $t$. The sample period covers 03/01/2000 to 20/07/2012, a total of 3158 daily observations and a total of 151 monthly observations. Numbers in parentheses are $t$-statistics based on Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

The stronger evidence on herding in the S&P100 compared to DJIA markets may be attributed to segmentation and information asymmetry between S&P100 and DJIA stock markets. Indeed the S&P100 stock market includes the largest and most established 100
companies listed on the S&P 500 that are traded on NYSE, Nasdaq and AMEX compared to only 30 industrial companies listed on DJIA markets. This made the S&P100 market more diversified and offer a much broader range of sectors and industries than the DJIA stock market. Moreover, the S&P100 is known to be more followed by large institutional investors than by common public which makes it a more informed market and adjusts information faster than the DJIA market. Empirical surveys confirmed that herding is more intense among institutional investors than individuals (Li et al., 2009; Cai et al., 2012). Panel B of Table 2 reports regression results using monthly data. The estimated coefficient $\gamma_1$ is insignificantly positive, indicating no herding in the S&P100 and DJIA markets. The parameter $\gamma_2$ is significant but positive. This implies that market return dispersion actually tends to increase rather decrease under extreme market conditions. Both Panel A and B in Table 2 indicate that herding behaviour in the US S&P100 and DJIA markets is a short lived phenomena. Furthermore empirical findings in Table 2 provide evidence that herding tends to be weaker with the increase in time interval. Further analysis of herding during days (months) of extreme high and low market return are presented in Table 3.

Table 3  Estimates of daily and monthly herding behaviour in rising and declining stock market conditions

<table>
<thead>
<tr>
<th></th>
<th>$\alpha$</th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$\gamma_3$</th>
<th>$\gamma_4$</th>
<th>$\gamma_3 - \gamma_4$</th>
<th>$F$ (p-value)</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Regression results under CH model – daily data</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P100</td>
<td>0.0153***</td>
<td>0.542***</td>
<td>0.5712***</td>
<td>-2.644**</td>
<td>-2.3034</td>
<td>-0.341</td>
<td>0.223***</td>
<td>0.064</td>
</tr>
<tr>
<td></td>
<td>(30.7133)</td>
<td>(7.5018)</td>
<td>(7.8108)</td>
<td>(-1.89)</td>
<td>(-1.563)</td>
<td></td>
<td>(0.673)</td>
<td></td>
</tr>
<tr>
<td>DJIA</td>
<td>0.0176***</td>
<td>0.591***</td>
<td>0.742***</td>
<td>-4.224</td>
<td>-4.526</td>
<td>-0.302</td>
<td>0.104</td>
<td>0.0182</td>
</tr>
<tr>
<td></td>
<td>(17.728)</td>
<td>(4.075)</td>
<td>(4.715)</td>
<td>(-1.493)</td>
<td>(-1.296)</td>
<td></td>
<td>(0.709)</td>
<td></td>
</tr>
<tr>
<td>Panel B: Regression results under CH model – monthly data</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P100</td>
<td>0.047***</td>
<td>0.0177</td>
<td>0.389**</td>
<td>3.455</td>
<td>0.624</td>
<td>-2.831</td>
<td>1.145</td>
<td>0.385</td>
</tr>
<tr>
<td></td>
<td>(15.107)</td>
<td>(0.086)</td>
<td>(2.498)</td>
<td>(1.438)</td>
<td>(0.465)</td>
<td></td>
<td>(0.232)</td>
<td></td>
</tr>
<tr>
<td>DJIA</td>
<td>0.058***</td>
<td>-0.852**</td>
<td>0.187</td>
<td>12.825*</td>
<td>0.859</td>
<td>0.624</td>
<td>-11.966</td>
<td>0.479</td>
</tr>
<tr>
<td></td>
<td>(14.908)</td>
<td>(-3.063)</td>
<td>(1.118)</td>
<td>(3.369)</td>
<td>(0.724)</td>
<td></td>
<td>(0.338)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table reports asymmetric herding behaviour for the US S&P100 index and Dow Jones Industrial Index (DJIA) equation (3): $\text{CSAD}_t = \alpha + \gamma_1$ \begin{equation} (1 - D) \text{R}_{mt} + \gamma_2 D \text{R}_{mt} + \gamma_3 (1 - D) \text{D}_{mt} + \gamma_4 \text{D}_{mt} \text{R}_{mt} + \epsilon_t. \end{equation} $\text{CSAD}_t$ is the equally-weighted cross-sectional absolute deviation, $\text{R}_{mt}$ is the equally weighted market portfolio return at time $t$. $D$ is a dummy variable that took the value $D = 1$ when market returns are negative and 0 otherwise. The sample period covers 03/01/2000 to 20/07/2012, a total of 3158 daily observations and a total of 151 monthly observations. Numbers in parentheses are $t$-statistics based on Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors. 

***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

The estimation results in Table 3 are perfectly consistent with the previous findings reported in Table 2. The regression coefficient of the non-linear relationship between CSAD and market returns remains highly positive and significant for both S&P100 and DJIA markets at daily frequency. This implies that above a certain level market return
dispersion (CSAD) may decline when market returns \((R_{m,t})\) rises. Furthermore, the regression results Table 2 Panel B shows that herding is insignificant at monthly frequency when markets are both up and down.

What makes herding behaviour different during period of high (low) market return remains a challenging question. This feature has been exhaustively documented by previous literature. Christie and Huang (1995) observed in their study that the increase in market return dispersion tends to be greater in extreme upward market movement than during extreme downward market condition. Chang et al. (2000) and Demirer and Kutan (2006) reported that return dispersion exhibits a wider mean when markets are rising rather than declining. The authors attribute this finding to market ‘flight to safety’ during stress period. Table 3 report results for potential asymmetric herding, separately in rising and declining market conditions.

Interestingly, we find that herding exists and differs with respect to market return sign. In particular, our empirical estimation in Table 3 Panel A indicates that herding is only significant in up-market condition for the S&P100 market. The negative and significant statistic \(\gamma_2\) of S&P100 indicates that market return dispersion decreases when the market rises. Furthermore, for both the S&P100 and DJIA markets we applied the Wald test and we reject the null hypothesis that \(\gamma_3^{\text{up}} = \gamma_4^{\text{down}}\). This finding is consistent with previous empirical surveys that indicated that agents find difficulty during boom periods to alter and adjust their anticipation hence they tend to herd (Chang et al., 2000; Yao et al., 2014; Tan et al., 2008; Shiller, 2007). However, our results reported no evidence of asymmetric herding for DJIA at daily frequency wherein herding parameters \(\gamma_3\) and \(\gamma_4\) are highly negative but insignificant. Our results differ from Philippas et al. (2013) who reported asymmetric herding for US REIT markets in down market periods. We refer our finding to the fact that during downward period, investors exhibit disposition bias that leads them to be extremely reluctant and hold too long their own portfolios especially when disposition bias is combined with investors emotions such as affect, loss aversion, regret, etc. (Shefrin and Statman, 1985).

Furthermore, Table 4 Panel A and Panel B report the regression estimates of herding behaviour with consideration of high and low trading volume periods. Regressions results of daily data reported in Table 4 Panel A show that even after controlling for highest and lowest trading days, both \(\delta_1\) and \(\delta_2\) coefficients are positive and significant indicating a non-linear relationship between market returns dispersion and market returns. Regression estimates of dummy variables suggest that \(\delta_3\) coefficient is negative and significant which imply that herding behaviour is only observable in the US S&P100 markets during period of high trading volume. This implies that market return dispersion (herding) decreases (increase) with increased high liquid market. This finding is consistent with Chuang and Lee’s (2006) prediction that investors are prone to trade more aggressively in bull markets than in bear markets which accentuates the asymmetric character of stocks volatility in US markets.

Regarding DJIA market, \(\delta_3\) and \(\delta_4\) coefficients are negative but insignificant indicating that change in market liquidity does not affect herding trends in the US DJIA markets. Moreover, the empirical analysis reported in Table 4 Panel B indicates that asymmetric herding is not captured at monthly frequency with \(\delta_3\) (\(\delta_4\)) positive and insignificant (significant). This implies that at daily frequency investors, at least in the S&P100 markets, under lack of correct and timely information, do not trade based on a
Bayesian rule but they trade arbitrarily without paying attention to stock traits. Hence they follow the market’s general trend and trade on the same stock (Barber and Odean, 2008). However, at monthly frequency, market price gets slowly adjusted to its initial fundamental value and hence herding phenomena disappears.

Table 4 Estimates of the effect of trading volume on herding behaviour

<table>
<thead>
<tr>
<th></th>
<th>α</th>
<th>δ_1</th>
<th>δ_2</th>
<th>δ_3</th>
<th>δ_4</th>
<th>δ_3−δ_4</th>
<th>χ² (p-value)</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A : regression results under CH’s model –daily data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P100</td>
<td>0.0153***</td>
<td>0.539***</td>
<td>0.582***</td>
<td>−2.465**</td>
<td>−2.409</td>
<td>0.056</td>
<td>1.296*** (0.286)</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>(30.682)</td>
<td>(7.952)</td>
<td>(7.597)</td>
<td>(−1.843)</td>
<td>(−1.608)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DJIA</td>
<td>0.017***</td>
<td>0.600***</td>
<td>0.668***</td>
<td>−3.238</td>
<td>−4.531</td>
<td>−0.302</td>
<td>0.103 (0.708)</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(17.823)</td>
<td>(4.272)</td>
<td>(4.261)</td>
<td>(−1.102)</td>
<td>(−1.420)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel B : Regression results under CH’s model –monthly data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P100</td>
<td>0.045***</td>
<td>0.215</td>
<td>0.048</td>
<td>1.672</td>
<td>3.553**</td>
<td>1.881</td>
<td>1.160 (0.286)</td>
<td>0.451</td>
</tr>
<tr>
<td></td>
<td>(17.512)</td>
<td>(1.339)</td>
<td>(0.378)</td>
<td>(1.048)</td>
<td>(3.109)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DJIA</td>
<td>0.051***</td>
<td>0.083</td>
<td>−0.458</td>
<td>1.793</td>
<td>9.716**</td>
<td>−7.923</td>
<td>1.172 (0.345)</td>
<td>0.234</td>
</tr>
<tr>
<td></td>
<td>(13.148)</td>
<td>(0.483)</td>
<td>(−1.565)</td>
<td>(1.534)</td>
<td>(2.508)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table reports the asymmetric effect of trading volume on herding behaviour for the US S&P100 index and Dow Jones Industrial Index (DJIA) equation (4): $CSAD_t = \alpha + \delta_H Vol_{H,t} |R_{m,t} + \delta_L Vol_{L,t} | \delta_Vol_L | (R_{m,t}^2) + \delta V ol_L.$ $CSAD_t$ is the equally-weighted cross-sectional absolute deviation, $R_{m,t}$ is the equally weighted market portfolio return at time t. Where $V_{m,t}$ is market detrended return at time t. $\delta_H Vol_{H,t}$ and $\delta_L Vol_{L,t}$ are dummy variables that respectively capture unusual high and Low trading volume periods. The χ² test statistic with one degree of freedom is used to examine the null hypothesis $H_0: \gamma_1 = \gamma_2.$ The p-value is the probability of the Chi-square terms. The sample period covers 03/01/2000 to 20/07/2012, a total of 3158 daily observations and a total of 151 monthly observations. Numbers in parentheses are t-statistics based on Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 5 reports the estimation of VAR and causality regression of herding (CSAD) – market return. In Table 5 Panel A and Panel B, we notice that estimated coefficient of herding (CSADt) is significantly depended to its previous value as well as to market two- days lagged returns. However market returns are not significantly correlated to lag herding (CSADt) values. Therefore, we assume that the herding variable is only influenced by past market return value which confirms our previous finding that past high return is the main incentive for investor to embark into a transient collective herding regime.

The results reported in the granger causality regression represented by the Wald statistics test reject the null hypothesis that $R_m$ does not granger cause CSAD since p-value =0.066 <10%; F-statistic = 2.399. The Granger test was valid in one direction $R_m\rightarrow CSAD,$ therefore according to VAR and granger models we conclude that contemporaneous as well as some lagged market return can generate herding and not vice versa.
Table 5  Regression results of Vector Autoregressive Regression (VAR) and Granger Causality models

<table>
<thead>
<tr>
<th>Panel A: VAR estimation for S&amp;P100 market</th>
<th>Panel B: VAR estimation for DJIA market</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSAD&lt;sub&gt;_t&lt;/sub&gt;</td>
<td>R&lt;sub&gt;_m,t&lt;/sub&gt;</td>
</tr>
<tr>
<td>CSAD&lt;sub&gt;_t-1&lt;/sub&gt;</td>
<td>0.825***</td>
</tr>
<tr>
<td></td>
<td>(47.545)</td>
</tr>
<tr>
<td>CSAD&lt;sub&gt;_t-2&lt;/sub&gt;</td>
<td>0.255</td>
</tr>
<tr>
<td></td>
<td>(11.319)</td>
</tr>
<tr>
<td>R&lt;sub&gt;_m,t-1&lt;/sub&gt;</td>
<td>–0.002</td>
</tr>
<tr>
<td></td>
<td>(–0.131)</td>
</tr>
<tr>
<td>R&lt;sub&gt;_m,t-2&lt;/sub&gt;</td>
<td>3.27E-05</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>Adjusted R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.439</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>580.886</td>
</tr>
</tbody>
</table>

Panel C: Granger Causality Tests for S&P100 market

Null Hypothesis | F-Statistic | p-Value | F-Statistic | p-Value |
----------------|-------------|---------|-------------|---------|
R<sub>_m,t</sub> does not Granger Cause CSAD<sub>_t</sub> | 2.399** | 0.066 | 1.080 | 0.356 |
CSAD<sub>_t</sub> does not Granger Cause R<sub>_m,t</sub> | 0.647 | 0.584 | 1.833 | 0.138 |
VXi<sub>_t</sub> does not Granger Cause CSAD<sub>_t</sub> | 17.882** | 2E-11 | 6.018*** | 0.000 |
CSAD<sub>_t</sub> does not Granger Cause VXi<sub>_t</sub> | 0.261 | 0.854 | 0.829 | 0.477 |

Notes: This table reports the relationship between market return and herding behaviour of the regression equations (5a), (5b), (6a) and (6b) for the S&P100 and Dow Jones Industrial Average markets. CSADt is the equally-weighted cross-sectional standard deviation, Rm,t is the equally-weighted market return, at time t for the market. VXi,t is market implied volatility ‘investor sentiment’ with i = VXO for the S&P100 market and i = VXD for the DJIA markets. The sample period is 03/01/2000 to 20/07/2012. Numbers in parentheses are t-statistics based on Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

This finding is consistent with behaviour prediction which assumes that at a first stage under emotional and psychological pitfalls such as fantasy, optimism or overconfidence, housing investment seems to investors as a fantastic object, extremely desirable and valuable object (euphoria period). Therefore, agents fall ‘in love’ with this infallible object and herding or ‘social contagion of boom thinking’ impedes these investors from correcting their biased beliefs. These investors rush into investing in housing-stocks and fuelling the housing bubble.

At a second stage, when we conducted the granger causality test between S&P100 (DJIA) volatility index noted ‘VXO’ (VXD) and herding behaviour ‘CSAD’ variable. We found that this causality is significant in one direction from VXO \( \rightarrow \) CSAD. Granger causality regression in Table 6 reject the null hypothesis that VXO does not granger
cause CSAD ($p$-value=1.E-17 <5%$; F-statistic = 39.589). This finding implies that herding fuels the housing bubble for a certain time until investors are hit by the truth and release the real high risk then they panic. Under fear, these investors rush to sell this stock triggering another herding behaviour therefore the bubble bursts and the stock price dramatically decreases. Absence of causality from CSADT (lagged herding) to market return ($Rm$) dismisses the possibility of positive feedback on the US financial market. The low correlation ($R^2 = 0.01$) between market returns and herding could be in part explain by the high frequency of either buying or of selling. When purchasing is as excessive as selling, their effect can be neutralised because one cancels the other effect.

Furthermore, regression results of equation (7) reported in Table 6 confirm VAR and granger causality test results. Indeed after adding the dummy variable $D_t$, we notice that all the coefficients such as $\gamma_1$, $\gamma_2$, and $\gamma_3$ remain highly significant at 1% level and consistent with their value in equation (2), which suggests the prevailing influence of market disturbance on herding movement.

The estimated results of herding behaviour during the 2007–2009 global crisis are reported in Table 6. We use the dummy variable to capture the effect of the subprime crisis on the US S&P100 and DJIA markets. Two out of the four crisis periods (07/07–12/08 and 09/08–10/08) show a strong evidence of herding behaviour in both S&P100 and DJIA markets ($\gamma_2$ is negative and highly significant at the 1% level). The control variable that captures the financial crisis effect ‘$\gamma_3$’ is highly and negatively significant at the 1% and 5% levels indicating that during the subprime crisis market return dispersion (herding) tend to decrease (increase). Therefore, we can assert that herding is more intensified during crisis period which accentuated market stock price deviation from its fundamental value. The analysis of herding behaviour across crisis sub-periods shows that investors behave differently in the start and in the end of the crisis. The first sub-period (07/07–12/08) corresponding to the explosion of the housing bubble, the herding coefficient ‘$\gamma_2$’ are insignificant. However during the second sub-period following the ‘Lehman Brothers bankruptcy’ herding parameter ‘$\gamma_2$’ shifts to be highly significant and negative. This result is perfectly consistent with the theoretical prediction that under high risk, fear and panic investors spontaneously abandon their position and their strategy to blindly copy others’ strategy which leads the market to disaster (Orléan, 2007). We notice across the three crisis sub-periods both significance and magnitude of herding tendency (captured by ‘$\gamma_2$’ coefficient) tend to decrease along the crisis phases to disappears completely at the end of the crisis.

Surprisingly, investors seem not to exhibit herding behaviour during the recession period (third sub-period December 2007–June 2009) with $\gamma_2$ and $\gamma_3$ parameters are negative and insignificant. The absence of herding during the recession period (the after crisis period) can be explained by the emotional financial theory of Tuckett and Taffler (2008). The authors claim that as a consequence of the crisis investors are hit by reality and exhibit a combination of conscious emotions of anger, regret and blame sentiment. As a consequence, they drop their strategy and do not follow the market trend anymore.

For deeper surveys of the change of investors’ imitative behaviour in US stock market during period of market disturbance, we add market sentiment index into herding estimation equation (see equation (6)). In particular, we estimate the relationship between implied volatility index and market return dispersion (herding behaviour). The empirical results are reported in Table 7.
### Table 6
Regression results of daily herding behaviour during the 2007–2009 global crisis

<table>
<thead>
<tr>
<th>Periods</th>
<th>$\alpha$</th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>Adj. $R^2$</th>
<th>Periods</th>
<th>$\alpha$</th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>Adj. $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P100</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>D JIA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>07/07-06/09</td>
<td>0.015***</td>
<td>0.499***</td>
<td>0.504</td>
<td>-2.592*</td>
<td>0.018***</td>
<td>0.477***</td>
<td>0.608</td>
<td>-9.786***</td>
<td>20.86%</td>
</tr>
<tr>
<td></td>
<td>(30.32)</td>
<td>(7.14)</td>
<td>(0.25)</td>
<td>(-1.73)</td>
<td>(18.06)</td>
<td>(3.43)</td>
<td>(1.52)</td>
<td>(-3.27)</td>
<td></td>
</tr>
<tr>
<td>07/07-12/08</td>
<td>0.015***</td>
<td>0.611***</td>
<td>-2.999***</td>
<td>-10.632***</td>
<td>0.017****</td>
<td>0.763***</td>
<td>-5.411***</td>
<td>-19.928**</td>
<td>20.47%</td>
</tr>
<tr>
<td></td>
<td>(30.24)</td>
<td>(9.80)</td>
<td>(-2.72)</td>
<td>(-3.54)</td>
<td>(17.36)</td>
<td>(5.92)</td>
<td>(-2.26)</td>
<td>(-2.84)</td>
<td></td>
</tr>
<tr>
<td>09/08-10/08</td>
<td>0.015***</td>
<td>0.560***</td>
<td>-2.535**</td>
<td>0.228</td>
<td>0.017***</td>
<td>0.675***</td>
<td>-4.215**</td>
<td>-5.314</td>
<td>17.82%</td>
</tr>
<tr>
<td></td>
<td>(30.07)</td>
<td>(9.17)</td>
<td>(-2.24)</td>
<td>(0.12)</td>
<td>(17.71)</td>
<td>(5.59)</td>
<td>(-1.76)</td>
<td>(-0.98)</td>
<td></td>
</tr>
<tr>
<td>09/07-06/09</td>
<td>0.015***</td>
<td>0.526***</td>
<td>-0.933</td>
<td>-1.331</td>
<td>0.018***</td>
<td>0.488***</td>
<td>5.088</td>
<td>-8.75**</td>
<td>20.14%</td>
</tr>
<tr>
<td></td>
<td>(30.01)</td>
<td>(7.38)</td>
<td>(-0.44)</td>
<td>(-0.87)</td>
<td>(17.97)</td>
<td>(3.46)</td>
<td>(1.25)</td>
<td>(-2.90)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table reports the estimated coefficient and adjusted $R^2$ for the US S&P100 index and Dow Jones Industrial Index (D JIA) of the regression equation (7):

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 D_{crisis,t} R_{m,t} + \epsilon.$$  

$CSAD_t$ is the equally-weighed cross-sectional absolute deviation, $R_{m,t}$ is the equally weighted market portfolio return at time $t$. $D_{crisis,t}$ is a dummy variable that take the value of 1 during the period of financial crisis and 0 otherwise. The sample period is from 03/01/2000 to 20/07/2012. The entire crisis period is 07/07–06/09 with three alternative sub-periods. The first sub-period is 07/07–12/08. The second sub-period is 09/08–10/08 (Lehman Brothers collapse). The third sub-period is 09/07–06/09 the recession period. Numbers in parentheses are $t$-statistics based on Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.

***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.
Table 7 Regression results of herding behaviour effect on market implied volatility

<table>
<thead>
<tr>
<th>Panel A: Regression results for S&amp;P100</th>
<th>Panel B: Regression results for DJIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>( \alpha )</td>
</tr>
<tr>
<td>0.003**</td>
<td>-0.006***</td>
</tr>
<tr>
<td>(2.771)</td>
<td>(-1.945)</td>
</tr>
<tr>
<td>( \gamma_1 )</td>
<td>( \gamma_1 )</td>
</tr>
<tr>
<td>0.235***</td>
<td>0.258**</td>
</tr>
<tr>
<td>(43.687)</td>
<td>(1.951)</td>
</tr>
<tr>
<td>( \gamma_2 )</td>
<td>( \gamma_2 )</td>
</tr>
<tr>
<td>-0.832**</td>
<td>-0.589**</td>
</tr>
<tr>
<td>(-0.745)</td>
<td>(-0.243)</td>
</tr>
<tr>
<td>( \gamma_3 )</td>
<td>( \gamma_3 )</td>
</tr>
<tr>
<td>0.001***</td>
<td>0.001***</td>
</tr>
<tr>
<td>(7.731)</td>
<td>(5.270)</td>
</tr>
<tr>
<td>( \gamma_4 )</td>
<td>( \gamma_4 )</td>
</tr>
<tr>
<td>-5.49E-06**</td>
<td>-2.66E-05***</td>
</tr>
<tr>
<td>(-3.649)</td>
<td>(-6.171)</td>
</tr>
</tbody>
</table>

Adj. R² 0.115  Adj. R² 0.037

Notes: This table reports the estimated coefficients and adjusted R² of the regression in equation (8): 

\[
CSAD_t = \alpha + \gamma_1 R_{vxo} + \gamma_2 R_{vxo}^2 + \gamma_3 + \gamma_4 R_{vxo} + \epsilon_t.
\]

Wherein the dependent variable is the CSAD for both market indices, RVXi,t is the percentage return of implied volatility for the S&P100 ‘VXO’ and DJIA ‘VXD’ markets index at day t. The sample period is from 03/01/2000 to 20/07/2012. Numbers in parentheses are t-statistics based on Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.

***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 7 Panel A and Panel B report respectively all estimated coefficients for the S&P100 and DJIA markets. The regression results in Table 7 are similar to those reported in Table 2 where herding coefficient ‘\( \gamma_2 \)’ is negative and highly significant at the 1% level which support the presence of herding phenomena for the US S&P100 and DJIA markets across days.

The estimated coefficient of absolute market implied volatility ‘\( \gamma_3 \)’ is positive and highly significant at the 1% level suggesting that actual market return dispersion tend to increase with the increase in contemporaneous market implied volatility index. However, this increase tends to be in low speed as indicated by the significant and negative sign of ‘\( \gamma_4 \)’ variable. Furthermore, the highly significant and negative sign of ‘\( \gamma_4 \)’ coefficient indicates that there is a negative correlation between market return dispersion and market implied volatility squared for both S&P100 and DJIA stock markets. This implies that herding behaviour is dictated by investor sentiment and herd behaviour tends to increase during period of fear sentiment.

Moreover, several studies (Black, 1976; Nelson, 1991; Chang et al., 2000) indicate that stocks volatility reacts differently to shock depending on the sign of these innovation shocks. Indeed, a negative innovation shock generates a lower return and higher volatility than a positive shock. This phenomenon is known as asymmetric volatility. Behavioural scholars assert that herding plays a prevailing role in increasing market asymmetric volatility (Chang et al., 2000; Park and Hamid, 2008; Yamamoto, 2010). Hence we examine whether herding behaviour affect US market asymmetric volatility. Table 8 reports the regression results of herding behaviour response to change in market volatility using a dummy variable that captures extreme high and low volatility returns across days.
Table 8  Estimates of the asymmetric effect of trading volume on herding behaviour

<table>
<thead>
<tr>
<th></th>
<th>α</th>
<th>γ₁</th>
<th>γ₂</th>
<th>γ₃</th>
<th>γ₄</th>
<th>γ₃ – γ₄</th>
<th>χ² (p-value)</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Regression results of herding model – daily data for S&amp;P100 market</td>
<td>0.0150***</td>
<td>0.519***</td>
<td>0.635***</td>
<td>–1.226</td>
<td>–5.261**</td>
<td>4.035</td>
<td>1.131***</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>(30.290)</td>
<td>(7.661)</td>
<td>(8.183)</td>
<td>(–0.984)</td>
<td>(–3.014)</td>
<td>(0.3242)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Regression results of herding model – daily data for DJIA market

<table>
<thead>
<tr>
<th></th>
<th>α</th>
<th>γ₁</th>
<th>γ₂</th>
<th>γ₃</th>
<th>γ₄</th>
<th>γ₃ – γ₄</th>
<th>χ² (p-value)</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.015***</td>
<td>0.536***</td>
<td>0.649***</td>
<td>–1.706</td>
<td>–6.883**</td>
<td>5.177</td>
<td>1.3134</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>(29.675)</td>
<td>(7.693)</td>
<td>(6.627)</td>
<td>(–1.365)</td>
<td>(–2.380)</td>
<td>(0.6372)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table reports the asymmetric effect of market volatility on herding behaviour for the US S&P100 index and Dow Jones Industrial Index (DJIA) equation (9):

\[
\text{CSAD}_t = \alpha + \gamma_1 \text{DVHigh}_t + \gamma_2 (1-\text{DVHigh}_t) + \gamma_3 \text{DVHigh}_t \text{DVHigh}_t + \gamma_4 R_{m,t}.
\]

CSADₜ is the equally-weighted cross-sectional absolute deviation, Rₘₜ is the equally weighted market portfolio return at time t. DVHigh and (1–DVHigh) are dummy variables that take the value of unity during days with unusual high market volatility and 0 otherwise. The χ² test statistic with one degree of freedom is used to examine the null hypothesis H₀: \( \gamma_3 = \gamma_4 \). The p-value is the probability of the Chi-square terms. The sample period is from 03/01/2000 to 20/07/2012, a total of 3158 daily observations. Numbers in parentheses are t-statistics based on Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors.

***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

The findings reported in Table 8 suggest that estimation of herding separately during days with abnormal high and low conditional volatility provides robust evidence on the contribution of herding to asymmetric volatility for both the S&P100 and DJIA stock markets. The significant and positive sign of \( \gamma_1 \) and \( \gamma_2 \) coefficients indicate that contemporaneous market return dispersion increases with both negative and positive contemporaneous conditional volatility. However, this increase is larger during days of negative shocks (e.g., for S&P100 market \( \gamma_2 = 0.635 > \gamma_1 = 0.519 \)). In particular, herding parameter ‘\( \gamma_4 \)’ is only significant and negative for days with low volatility. This latter implies that investors herd differently and more intensively during days with positive returns. This finding supports Tan et al. (2008) who found that herding tends to be stronger in bull market and it is a key feature of high trading volume and high market volatility. Finally, we use the Wald Test to examine the null hypothesis H₀: \( \gamma_3 = \gamma_4 \). The regression results show that the Chi-squared \( \chi^2 \)-test statistics are inferior to 5% therefore we reject the null hypothesis that herding is equally presented in days of high and low volatility.

5 Conclusion

This paper examined investment behaviour of market participants in the US S&P100 and DJIA stock markets. In particular, we investigated investor tendency to act according to market consensus known as market-wide herding behaviour at both daily and monthly frequency. This study provides a comprehensive survey of herding phenomenon in US S&P 100 and DJIA markets at both daily and monthly frequency from 4 January 2000 to
20 July 2012. The methodology was mainly based on Chang et al. (2000, CCK) model. Our empirical results show that herding is prevailing in US S&P100 and DJIA at only daily frequency and tends to be weaker with increased time lapse. Moreover, herding is found to be more observed for S&P100 rather DJIA stock markets. We also found that herd behaviour is stronger during upward market periods (period of rising markets) with days of positive market returns. Empirical results indicate that herding is influenced by change in market liquidity. Evidence of asymmetric herding in regards to trading volume is captured for daily S&P100 stock markets where investors exhibits herding in days with abnormal high trading volume.

Additionally, we conduct a series of novel tests in order to apprehend the way in which herding behaviour affects asset-price features such as fat tail behaviour, volatility clustering and bubbles in the US stock markets. In particular, we provide empirical evidence indicating that herding behaviour is dictated by past stock market returns and market sentiment index. Deeper analysis of herding during sub-periods of the subprime crisis indicates that herding was the main driving forces of the speculative housing bubble and it was strongly significant at the beginning of the crisis and tends to diminish over time. Empirical results indicate a positive and significant correlation between herding and US market conditional volatility wherein herding behaviour contributes to increase market volatility. Finally, we find that herd behaviour reacts asymmetrically to market volatility and is only significant during days with low volatility.

References


Herding behaviour and market dynamic volatility


Notes

1 S&P100 is a sub-set for the S&P500 market that includes the largest and most established firms listed on the S&P500. Moreover, the S&P100 market is about 57% of S&P500’ market capitalisation and reflects almost the half of the US market capitalisation (45% of the entire US capitalisation) in the financial market (CBOE report).

2 Actually, negative market returns generate investors’ fear from an additional market decline and positive returns will create exuberance in investors’ feelings and expect a future potential rise in markets. As a consequence, the variation in the implied volatility index ‘VXO’ will reflect market sentiment.

3 Based on the finding of Chow breakpoints test which indicates that the start of the subprime crisis corresponds exactly to 2 July 2007 (F-statistic=514.525, prob = 0.000).

4 S&P100 recorded its greatest and unprecedented fall in stock value during the 2009–2007 global crisis. In March 2009 S&P100 real market price lost its value by about 18% (undervalued) then at the end of the year its value increased 20 times bigger than its intrinsic value and continued to increase until the end of the period (2012).

5 Attention anomalies correspond to investors who are seduced by stocks with abnormally high return volume or stocks with new announcement and extreme high returns; believing that these stocks contain more information and achieve faster high returns Barberis and Odean, 2008).