A Dynamic Measure of Intentional Herd Behavior in Financial Markets

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1 October 2017

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Abstract

This paper suggests a dynamic measure of intentional herding, causing the excess volatility or even systemic risk in financial markets, which is based on a new concept of cumulative returns in the same direction as well as the collective behavior of all investors towards the market consensus. Differing from existing measures, the measure allows us to directly detect time-varying and market-wide intentional herding using the model of Dynamic Conditional Correlation (DCC) (Engle, 2002) between the financial market and its components that is partially free of spurious herding due to the inclusion of the variables of the number of economic news announcements as a proxy of market information. Strong evidence in favor of the dynamic measure over the other measures is based on empirical application in the U.S. markets (DJIA and S&P100), supporting the tendency to exhibit time-varying intentional herding. Much more important is a finding that the impact of intentional herding on market volatility tends to be stronger during the periods of turbulent markets like the degradation of U.S. sovereign credit rating by S&P, and be more significant in S&P 100 than DJIA.

Keywords: Intentional herd behavior, Dynamic conditional correlation, News announcements, Dynamic measure, Herding tests, Volatility, Quantile regression

JEL classification: G40, G10, C10

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* This work was supported by the National Research Foundation of Korea Grant funded by the Korea Government (NRF-2015S1A3A2046715) and conducted by the research fund of Dankook University in 2017.

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Ⅰ. Introduction

In financial markets herd behavior is the process that market participants are imitating each other's action and base their decisions upon the decisions or actions of others (Avery and Zemsky, 1998; Nofsinger and Sias, 1999). Bikhchandani and Sharma (2000) classify herding into spurious herding and intentional herding. When investors react with the same well known public information and make the same investment decisions, it can be regarded as a spurious herding. Whereas, if investors have an intention to follow the behavior of others, it can be regarded as an intentional herding. Although it is not easy to precisely distinguish intentional herding from spurious herding, it is a meaningful challenge because the distinction seems to be so essential to prevent erroneous analyses (Walter and Weber, 2006) and more crucially intentional herding might lead to systematic risk, bubble phenomenon, and asymmetric volatility in financial markets (Bikhchandani et al., 1992; Kodres and Pristsker, 1998; Park, 2011).

Although there are abundant measures for detecting herd behavior (Lakonishok et al., 1992; Christie and Huang, 1995; Chang et al., 2000; Sias, 2004; Patterson and Sharma, 2005), most of the empirical studies do not investigate whether their results are attributes to spurious or intentional herding. Only a few of the literatures tried to distinguish intentional from spurious herding. Hwang and Salmon (2004) and Blasco and Ferreruela (2008) tried to distinguish between spurious and intentional herding based on the ideas of the cross-sectional variance of beta and comparison of the cross-sectional standard deviation (CSSD) of returns in markets with it in the artificially created market, respectively. However, these two methods do not control for price movements induced from public information, so that it is hard to tell whether herding towards the market consensus is intentional.

In sharp contrast to prior herding research, we propose a methodological approach for dynamically detecting the intentional herding towards the market consensus, which has substantial improvement in three dimensions: Firstly, we share the same intuition as in Nofsinger and Sias (1999) that herding appears to result in return momentum. In this vein, to capture the herding intensity intrinsically, we introduce cumulative returns in the same direction, instead of returns, that is likely to be related to persistency and intensity of return autocorrelation due to herd behavior (feedback trading or momentum). Secondly, we collect the number of economic news announcements as a proxy of market information that is likely to induce agents react together, and like the assertion of Bikhchandani and Sharma (2000), consider it as spurious herding in response to new market information. Especially, we employ the method of Mitchell and Mulherin (1992) to collect the number of news announcement. The intuition underlying this method is that greater number of news announcements relates primarily to more information faced by market participants. Unlike earlier studies, our method can directly control information driven (spurious) herd behavior by using information proxy. Thirdly, herd behavior might be detected by evaluating co-movement of stock returns with the measure of conditional correlations in returns volatilities (Boyer et al., 2006) in that herding tendency of uninformed investors towards the market consensus leads to co-movement of stock returns. Having this intuition[1], we propose a new and time-varying measure for intentional herd behavior using the estimation of the Dynamic Conditional Correlation (DCC) multivariate GARCH model (Engle, 2002). That is, given the variables of cumulative returns in the same direction and the number of economic news announcements, we specify the model of DCC between the financial market and its components, and estimate DCC as the intensity of intentional herding toward the market, which is closely related to co-movement of the components under the control for the impact of economic news[2]. Based on the measure of time-varying intentional herding, we suggest the test statistic of intentional herding at time t under the null hypothesis of no intentional herding.

To investigate the reliability of our methodology for detecting market-wide intentional herding, we apply it to the two main U.S. stock market indices: Dow Jones Industrial Average (DJIA) and Standard and Poor’s 100(S&P 100), and estimate the effect of dynamic intentional herding on market volatility by quantile regression estimation (Koenker, 2005) that is a valid alternative to OLS estimation for reflecting how the effect of intentional herding on market volatility changes across different market conditions.

The rest of this study is organized as follows. Section 2 explains the methodological details, Section 3 presents the data description such as U.S. market indices (DJIA, S&P 100), and their components, sample periods, number of U.S. economic news and their sources. In Section 4, we construct the models to estimate new herding measure and implement tests for intentional herding, and show empirical evidence on dynamics of intentional herding. Finally, in Section 5 we summarize key contributions of this study and interpret the empirical results.

Ⅱ. Framework and Methodology

[1] In addition, this intuition is consistent with Devenow and Welch (1996) who consider herding as behavior patterns being correlated across investors in markets.

[2] Intuitively, even if intentional herding toward market index must give rise to co-movement in the stock returns of the components, the reverse might not be necessarily true due to the effect of spurious herding. In our model, however the increase of DCC estimates is directly linked to intentional herding because the effect of spurious herding can be largely removed by the variables of the number of economic news announcements. Furthermore, King et al. (1994) and Karolyi and Stulz (1996) insist that, contrary to volatility, conditional correlations tend to be insensitive to macroeconomic news.

1. Cumulative returns in the same direction

In this study, cumulative returns in the same direction is the first considerable factor of herd behavior. It reflects the persistency and intensity of return autocorrelation toward the same direction as a source of herd behavior. Chen (2013) argues that herd behavior can be described as an investment strategy to follow the market consensus. Nofsinger and Sias (1999) also insist that herd behavior is a phenomenon that group of participant trade to the same direction during the same time. Therefore, if market participants trade to the same direction with market consensus during same periods, autocorrelation of market index returns will be positively stronger with the direction of trading and it will also be lasted same direction for a fairly long time.

Several studies have focused on the relationship between return autocorrelation and trading behavior, especially positive feedback trading strategy as a special case of herding. Positive feedback traders base their decision on the price movement positively. That is, "Buy High, Sell Low". Thus, it makes positive return autocorrelation with respect to the previous price and it makes potential for mispricing and excess volatility (Sentana and Wadhwani, 1992; Campbell et al., 1993; Barclay and Warner, 1993; Sias and Starks, 1997; Cooper, 1999; Koutmos and Saidi, 2001). However, simple return autocorrelation cannot represent exactly the herd behavior because return autocorrelation may be occurred not only herd behavior but also sequential information arrival.

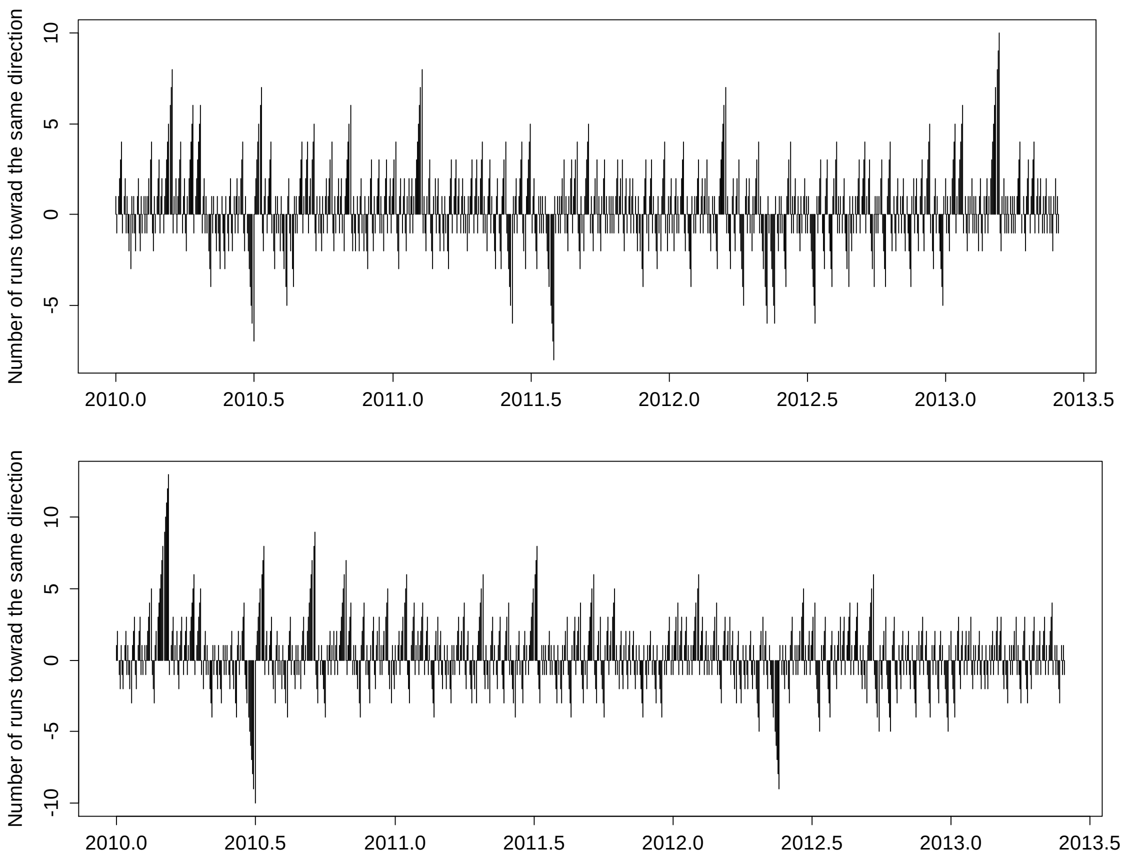
In this viewpoint, Patterson and Sharma (2005) propose the PS measure for intraday level data using bootstrapped runs test which is based on the information cascade models of Bikhchandani et al. (1992). They classify that if the current trade price is higher than previous trade price(up-tick), it is ‘buyer-initiated’ and if current trade price is lower than previous trade price(down-tick), it is ‘seller-initiated’ and, if there is no change, it is ‘zero-tick’. The key idea is that if investors herd, real number of buyer-initiated and seller-initiated sequences will be lower than expected number of sequences (1/3 each) on day *t*.

We propose a new concept to capture the persistency and intensity of return autocorrelation toward the same direction as a significant source of herd behavior. We call it ‘cumulative returns in the same direction (*crs*)’, which is obtained by the following two steps: in first step, we set the number of runs toward the same direction $T_{i,t}$ as a persistency of return autocorrelation in the same direction.

$$\begin{cases} \text{if} \quad r_{i,1} \neq 0, & T_{i,1} = 1 \\ \quad \text{if} \quad r_{i,t} > 0 \begin{cases} \text{and} \quad r_{i,t-1} \leq 0, & T_{i,t} = 1 \\ \text{and} \quad r_{i,t-1} > 0, & T_{i,t} = T_{i,t-1} + 1 \end{cases} \\ \quad \text{if} \quad r_{i,t} < 0 \begin{cases} \text{and} \quad r_{i,t-1} \geq 0, & T_{i,t} = -1 \\ \text{and} \quad r_{i,t-1} < 0, & T_{i,t} = T_{i,t-1} - 1 \end{cases} \\ \text{if} \quad r_{i,t} = 0, & T_{i,t} = 0 \end{cases} \qquad \text{(Eq. 1)}$$

where, $r_{i,t}$ is observed returns on stock *i* at time t [3]. Thus, $T_{i,t}$ denotes how long the autocorrelation toward the same direction is lasted in stock *i*. For example, if $T_{i,t}$= 2, all of the observed returns are greater than zero during 2 days, on the other hand, if $T_{i,t}$= -10, all of the observed returns are lower than zero during 10 days. Therefore, if $|T_{i,t}|$ is relatively high, it means the greater probability of herd behavior. [Figure 1] shows the calculated $T_{i,t}$ in DJIA and S&P 100 returns from January 4th, 2010 to May 31st, 2013.

[Figure 1] $T_{i,t}$ of DJIA (upper) and S&P 100(lower)



In second step, to catch both the intensity and persistency of return autocorrelation, we should

[3] Let $p_{i,t}$ be the price of stock *i* at time *t* and $r_{i,t} = \ln(p_{i,t}/p_{i,t-1})$.

combine the ideas of cumulative returns and $T_{i,t}$ simultaneously. If the return sequences lasted toward the same direction for a long time, cumulative returns in the same direction ($crs_{i,t}$) at time *t* gets rather bigger than observed returns at time *t*. Hence, it is defined as follows:

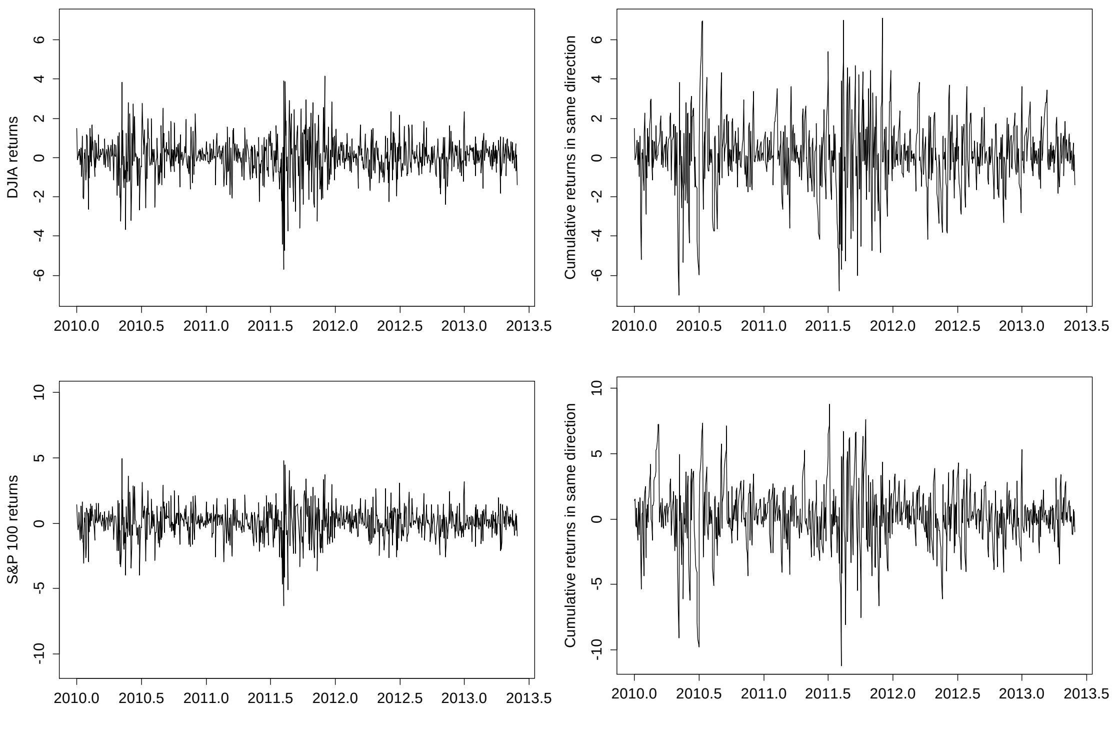
$$crs_{i,t} = I(T_{i,t} \neq 0)sgn(T_{i,t})\left[\prod_{j=1}^{|T_{i,t}|}(1 + |r_{i,t-j+1}|) - 1\right] + I(T_{i,t} = 0)r_{i,t} \quad \text{(Eq. 2)}$$

where $I(\cdot)$ is an indicator function and $sgn(\cdot)$ is a sign function. For example, in [Table 1], if we observe 5% returns during 4 days each, cumulative return at last forth day is 21.55% because $(1.05)^4 - 1 = 0.2155$. Cumulative returns toward the same direction are only calculated in the range of sequence of $T_{i,t}$ is in the same direction.

[Table 1] Key idea of cumulative returns in same direction (*crs*)

	Day 1	Day 2	Day 3	Day 4
Observed returns	0.05	0.05	0.05	0.05
Cumulative returns	0.05	0.1025	0.1576	0.2155

[Figure 2] Returns and cumulative returns in same direction of DJIA (upper) and S&P 100(lower) (Unit: percent)



Therefore, the persistency and intensity of return autocorrelation toward the same direction as a result of herd behavior can cause bubble phenomenon. The left panels of [Figure 2] show the returns of DJIA and S&P 100 and the right panels of [Figure 2] show the cumulative returns in same direction of DJIA and S&P100. In [Figure 2], the movements of the cumulative return series support the view that, as expected, the cumulative return series are more highly dynamic and include the more extreme values compared with the return series. On the nature of the cumulative return series, this additional volatility should be attributed to the herding caused by the momentum strategy for investment. Moreover, the cumulative return series also tend to be clustered together over time and this might be related to a repeating pattern in which herding is concentrated at an irregular point in time and disappears immediately afterwards.

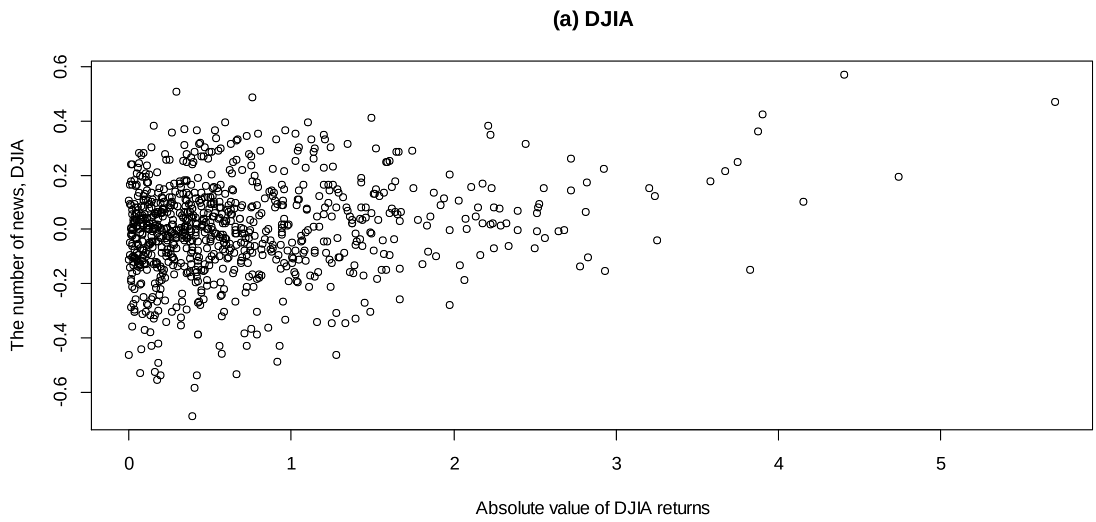
2. The Number of Economic News as a Proxy of Market Information

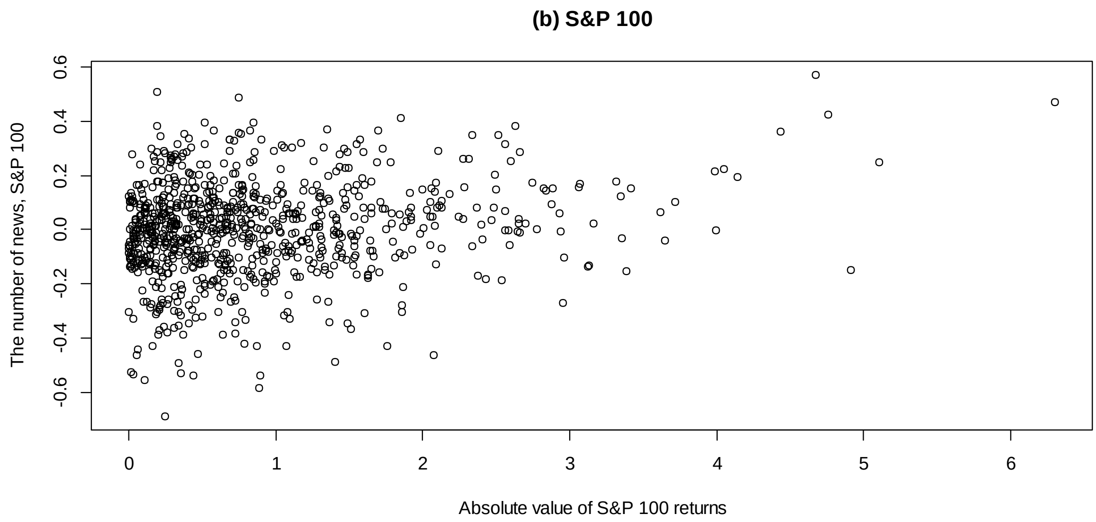
According to Bikhchandani and Sharma (2000), if investors react with the same well known public information and make the same investment decisions, it can be regarded as spurious herding. In contrast, if investors have an intention to follow the others' behavior, it can be regarded as intentional herding. That is, intentional herding is purely imitative actions with neglecting their own private information.

Since any type of herding is not observable directly, there is no apparent criterion that distinguishes intentional herding from spurious herding and only a few studies made an attempt to do it. Especially, both Hwang and Salmon (2004) and Blasco and Ferreruela (2008) tried to distinguish them using the ideas of cross-sectional variance of beta and comparison between CSSD and artificially created CSSD, respectively. However, these two methodologies have limitation in classifying the intentional herd behavior because they do not directly control the impact of public information. Thus, there is the question of how to control it. In this context, we use the number of economic news announcement as a proxy of market information to account for the information driven herding (i.e. spurious herding) and can more accurately classify intentional herding.

Several empirical studies have reported that New York Times front-page headlines, the number of daily Dow Jones or the Wall Street Journal stories and dividend announcements are closely related to regularities in financial markets or market activities (Penman, 1987; Thompson et al., 1987; Atkins and Basu, 1991; Berry and Howe, 1994; Mitchell and Mulherin, 1994). We collected the number of economic news announcements by Dow Jones Institutional News and The Wall Street Journal using Dow Jones FACTIVA news repository service. Unlike previous studies, we consider only well categorized economic news such as Commodity/Financial Market News, Corporate/Industrial News, Economic News. [Figure 3] shows the positive relationship between |DJIA returns| and the number of news, which is log-transformed and linearly detrended. This visual impression can also be confirmed by the estimation of the correlation. Pearson's correlation test results indicate that the correlation coefficient between |DJIA returns| and the number of news is 0.1965(p-value=0) and it increases to 0.5336(p-value=0.0604) when the |DJIA returns| is greater than 3%. Similarly, the correlation coefficient between |S&P 100 returns| and the number of news is 0.1891(p-value=0) and it increases to 0.5903(p-value=0.0030) when the |S&P 100 returns| is greater than 3%. This implies that the positive relationship is nonlinearly significant.

[Figure 3] Relationship between absolute value of returns and the number of news

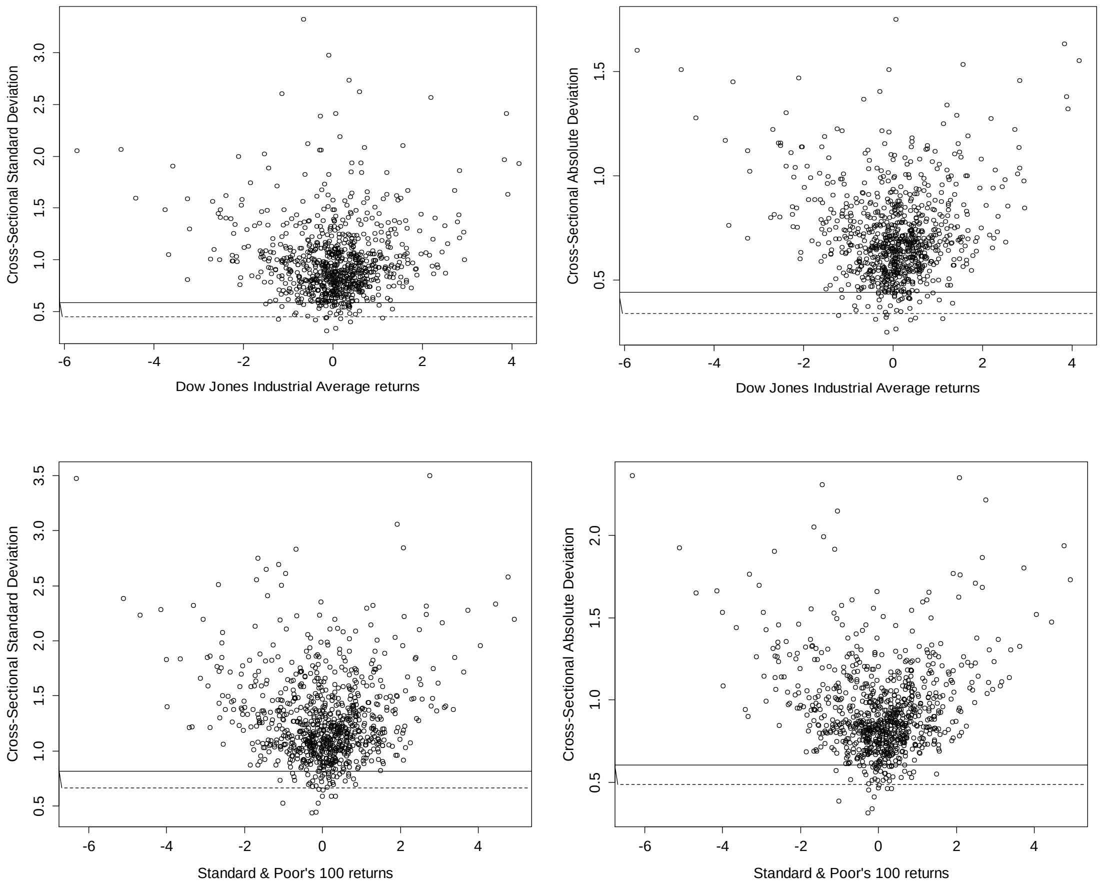




3. Cross-sectional DCC between market and its components

Literature on herd behavior in market index has mainly focused on two streams. The first stream is nearly linked to the existence of herd behavior by monitoring the stock returns dispersions between market index price and its components. The most commonly used empirical methodologies are suggested by Christie and Huang (1995) for CSSD and Chang, et al. (2000) for CSAD (henceforth referred as CH and CCK respectively). They argue that if market participants herd, returns in index components won't deviate far from the market index returns and thus return dispersions should be relatively low. Many of the studies have employed CSSD and CSAD method to capture the herd behavior in the U.S. market as well as international markets (Demirer and Kutan, 2006 and Tan *et al*., 2008 for Chinese stock market; Chiang *et al*., 2010 for global markets; Enonomou *et al*., 2011 for south European markets).

[Figure 4] Relationship between CSSD/CSAD and DJIA/S&P 100 returns



However, the initial results for daily and monthly U.S. data are not consistent with the presence of herd behavior during periods of large price movements (Christie and Huang, 1995). Especially, Chang *et al*. (2000) find no evidence of herding for the U.S. and Hong Kong, partial evidence of herding in Japan, and the significant evidence of herding for South Korea and Taiwan.

[Figure 4] shows the relationship between CSSD (left side) / CSAD (right side) and daily DJIA returns(upper) and S&P 100 returns(lower) during sample period. Horizontal full line denotes 5% quantile of CSSD / CSAD and dotted line denotes 1% quantile of CSSD / CSAD. According to CH and CCK, herd behavior occurs during periods of extreme fluctuation of asset returns and the presence of herd behavior in the financial market should make CSSD and CSAD relatively low. In [Figure 4], however, the relation between CSSD/CSAD and returns is opposite to the intuition, implying that CSSD and CSAD measure may not play a role in explaining the herd behavior during extreme fluctuation of asset returns. This failure is partially linked to some limitations of CH and CCK methods. First, Hwang and Salmon (2004) point out that simple cross-sectional dispersion of individual stock returns is not independent of time series volatility, but we find CH measure hard to capture herding dynamics in stock returns or market index returns. Second, CH essentially employs one fraction of the total return to capture herding toward the market consensus. In other words, it tests for one specific form of herding and ignores herding in other contexts. Third, Bohl, et. al. (2017) argue that their methods are particularly prone to be biased against finding evidence for herding and lead us to misinterpretation on herd behavior in markets.

The second stream is nearly linked to the degree of co-movement. Dhaene, et. al. (2012) explain that the volatility of a stock market is determined by the higher positive interdependence in markets. Therefore, the stronger positive interdependence is a sign of less diversification and may cause extreme volatility of market index. Sylliganakis and Kouretas (2011) consider cross-sectional DCC as the degree of co-movement. They examine the financial contagion effect on seven emerging stock markets of Central and Eastern Europe. They explain that during the period of the 2007-2009 stock crash, strong positive DCC coefficients are observed and it is an exact evidence of contagion effect due to herd behavior (see also Bekaert and Harvey, 2000; Corsetti, Pericoli, and Sbracia, 2005; Boyer et al., 2006; Chiang et al., 2007; Jeon and Moffett, 2010).

In this vein, we emphasize that cross-sectional DCC can more directly and intuitively explain the interdependence structure in a financial market resulting from herding toward the market (i.e., convergence of investors' behaviors), implying that a high degree of herd behavior toward the market gives rise to strong conditional correlation between market index and its components as well as high market volatility. Consequently, we propose a new and dynamic measure for intentional herd behavior using the estimation of cross-sectional DCC model with the variables of the number of economic news announcements as a proxy of market information.

4. New dynamic measure and test for intentional herding

As mentioned earlier, we derive the new intentional herding measure from combination of three methodologies: (1) To capture the market-wide herd behavior and its intensity in market index, we calculate the cumulative returns in the same direction which reflects the persistency and intensity of return autocorrelation caused by the momentum strategy. (2) We consider the number of economic news announcements by Dow Jones Institutional News and The Wall Street Journal as a proxy of market information to distinguish intentional herd behavior from spurious one. (3) Using the cumulative returns in the same direction and the number of economic news announcements, we estimate the cross-sectional DCC model across the market and extract an intensity of intentional herding in the market. In order to estimate cross-sectional DCC, we consider the ARMA (1,1)-DCC (1,1) multivariate GARCH (1,1) model. Mean equations can be defined as:

$$\begin{aligned}
crs_{m,t} &= \mu_m + \delta_{m,1} DN^G_{m,t} + \delta_{m,2} DN^B_{m,t} + \theta_{m,1} crs_{m,t-1} + \theta_{m,2} \varepsilon_{m,t-1} + \varepsilon_{m,t} \\
crs_{1,t} &= \mu_1 + \theta_{1,1} crs_{1,t-1} + \theta_{1,2} \varepsilon_{1,t-1} + \varepsilon_{1,t} \\
&\vdots \\
crs_{i,t} &= \mu_1 + \theta_{i,1} crs_{i,t-1} + \theta_{i,2} \varepsilon_{i,t-1} + \varepsilon_{i,t} \\
&\vdots \\
crs_{n,t} &= \mu_n + \theta_{n,1} crs_{n,t-1} + \theta_{n,2} \varepsilon_{n,t-1} + \varepsilon_{n,t} \qquad \text{(Eq. 3)}
\end{aligned}$$

In (Eq. 3), $crs_{m,t}$ is cumulative returns in the same direction of the market index (i.e., *m*=DJIA or S&P 100 index in this paper) and $crs_{i,t}$ is that of the ith component (stock) of market index (*i*=1, …, 30 for DJIA or *i*=1, …, 100 for S&P 100 index). $DN^G_{m,t}(DN^B_{m,t})$ is a dummy variable which takes value of 1, if $crs_{m,t} > 0(crs_{m,t} < 0)$ and the number of economic news announcements is greater than average number of news at time *t*. $\theta_{m,1}$(or $\theta_{i,1}$) and $\theta_{m,2}$(or $\theta_{i,2}$) are AR(1) and MA(1) coefficient respectively.

Then, variance equations can be also defined as:

$$\begin{aligned}
h_{m,t} &= \gamma_m + \alpha_m \varepsilon^2_{m,t-1} + \beta_m h_{m,t-1} \\
h_{1,t} &= \gamma_1 + \alpha_1 \varepsilon^2_{1,t-1} + \beta_1 h_{1,t-1} \\
&\vdots \\
h_{i,t} &= \gamma_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i h_{i,t-1} \\
&\vdots \\
h_{n,t} &= \gamma_n + \alpha_n \varepsilon^2_{n,t-1} + \beta_n h_{n,t-1} \qquad \text{(Eq. 4)}
\end{aligned}$$

In (Eq. 4), $h_{m,t}$ is conditional variance of market cumulative returns in the same direction, $h_{i,t}$ is that of the i th component of market index, $\varepsilon_t = H_t^{1/2} v_t$, $v_t \sim iid\ \ N(0, \sigma^2)$ is residuals of the process, and $H_t^{1/2}$ is $(1+N) \times (1+N)$ positive define matrix at time *t*. Conditional covariance matrix H_t can be decomposed in DCC model (Engle, 2002) such that:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \qquad \text{(Eq. 5)}$$

where $D_t^{1/2}$ is diagonal matrix of conditional standard deviation and R_t is the positive define time-varying correlation matrix. That is,

$$D_t = \begin{bmatrix} h_{1,t} & 0 & \cdots & 0 \\ 0 & h_{2,t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & h_{n+1,t} \end{bmatrix}, \ R_t = \begin{bmatrix} 1 & \rho_{1,2,t} & \cdots & \rho_{1,n+1,t} \\ \rho_{1,2,t} & 1 & \cdots & \rho_{2,n+1,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1,n+1,t} & \rho_{2,n+1,t} & \cdots & 1 \end{bmatrix}$$

With the estimates of parameters in the DCC models, our measure of time-varying intentional herd behavior in a financial market is defined as:

$$DH_{m,t} = \sum_{i=1}^{n} \omega_{i,t} \rho_{m,i,t}, \qquad \omega_{i,t} = \frac{p_{i,t} s_{i,t}}{\sum_{i=1}^{n} p_{i,t} s_{i,t}} \qquad \text{(Eq. 6)}$$

where $DH_{m,t}$ is dynamic herding measure, $\rho_{m,i,t}$ is DCC coefficient between market index *m* and the i^{th} component at time t, *i=1, 2, ..., n*, *n* is the total number of components, and $\omega_{i,t}$ is weight of the i^{th} component at time *t*. $p_{i,t}$ and $s_{i,t}$ are close price and outstanding shares of the i^{th} component stock at time *t*, respectively.

Some studies (King et al., 1994; Karolyi and Stulz, 1996) show that conditional correlations tend to be insensitive to macroeconomic news and, as mentioned earlier, the impact of market information is directly controlled by the number of news announcement in the DCC model. That is, conditional correlations among cumulative returns of component stocks are primarily driven by intentional herding and change over time. Consequently, it is reasonable to expect that the measure captures market-wide intentional herding substantially as a function of conditional correlations and is time-varying by nature.

According to the definition of the herding measure, $DH_{m,t}$ ranges from 0 to 1 and its mean is 0.5. Hence, the intensity of intentional herding in markets varies in degree based on the value of the herding measure. For example, high values indicate existence of significant intentional herding at time t, whereas low values indicate existence of insignificant intentional herding at time t. Standardizing the intentional herding measure, eventually, we can derive the following test statistic of intentional herding at time t under the null hypothesis of no intentional herding.

$$Z_{DH_{m,t}} = \frac{DH_{m,t} - 0.5}{\hat{\sigma}_{DH_m}} \qquad \text{(Eq. 7)}$$

where the test statistic $Z_{DH_{m,t}}$ follows standard normal distribution and $\hat{\sigma}_{DH_m}$ is the estimated standard deviation of $DH_{m,t}$ in the market. Following standard hypothesis test procedures, we perform the test for intentional herding with the null and alternative hypotheses:

Null hypothesis $H_0 : DH_{m,t} \leq 0.5$

Alternative hypothesis $H_1 : DH_{m,t} > 0.5$

and determine whether the null hypothesis of no intentional herding at time t is rejected.

Ⅲ. Data Description

1. U.S. market index and its components

We consider the two main U.S. stock market indices: Dow Jones Industrial Average (DJIA) and Standard and Poor's 100 (S&P 100) to investigate whether there has been significant herd behavior in U.S. stock markets. The sample period is from January 4th, 2010 to May 31st, 2013 and it contains 858 trading days. DJIA index contains thirty U.S. companies and one of them was replaced during sample periods. [4] Meanwhile, S&P 100 index contains one hundred U.S. companies and twelve of them were replaced during sample periods. [5] Therefore, these changes are reflected in the stock return time series of index components.

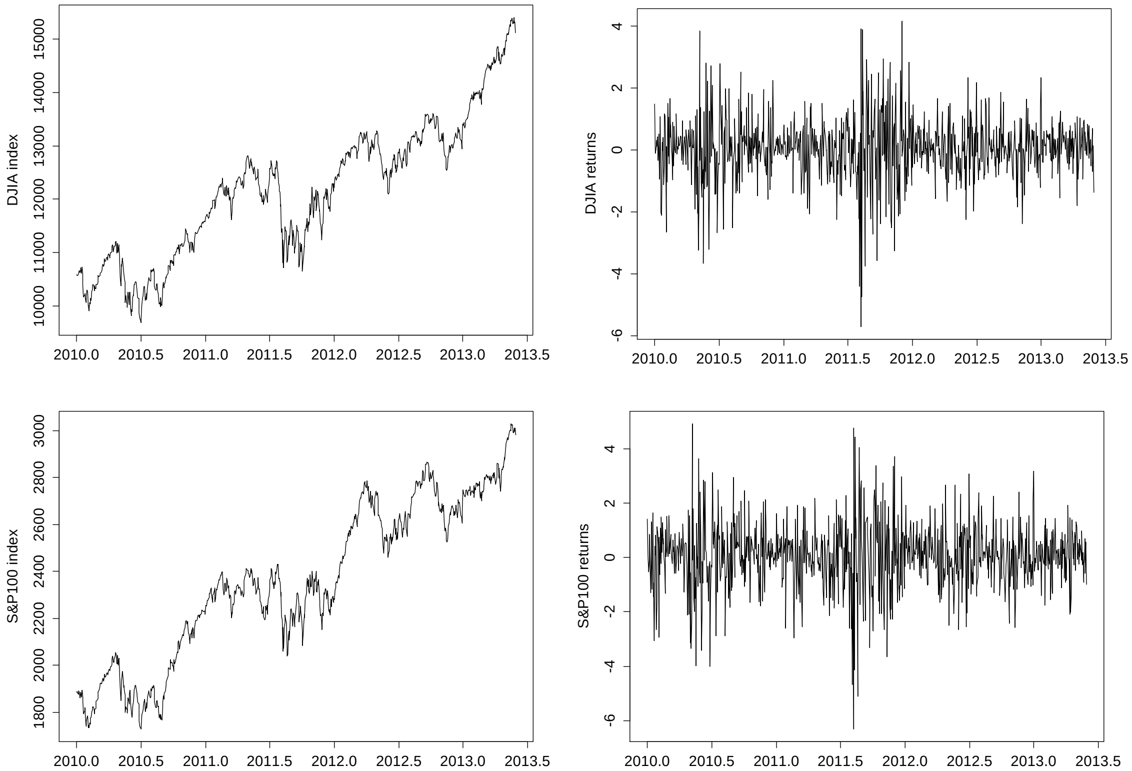
DJIA index is calculated by the arithmetic sum of the prices of all 30 individual stocks and divided by the divisor. That is, $\text{DJIA index} = \sum_{i=1}^{N} p_i / d$. Where, p_i is the price of stock i and

[4] On September 24, 2012, Kraft Foods (KFT) was replaced by United Health Group (UNH) by following Kraft Foods spinning off its snacks business into new Mondelez International Inc. (MDLZ).

[5] On February 13, 2010, Burlington Northern Railroad (BNI) was replaced by Berkshire Hathaway Inc. Class B (BRK.B). On March 31, 2011, Campbell Soup (CPB), NYSE Euronext (NYX), Regions Financial Corp. (RF) and Hillshire Brands Co. (HSH) were replaced by Apache Crop. (APA), Emerson Electric Co. (EMR), Union Pacific Co. (UNP), Visa Inc.(V). On March 30, 2012, Alcoa Inc. (AA), Avon Products Inc. (AVP), Entergy Corp. (ETR), Spring Nextel Corp. (S), Weyerhaeuser Co. (WY), Xerox Corp. (XRX) were replaced by Anadarko Petroleum Corp. (APC), Accenture Plc. (ACN), EBAY Inc. (EBAY), Eli Lilly and Co. (LLY), Starbucks Corp. (SBUX), Simon Property Group Inc. (SPG). On January 31, 2013, Dell Inc. (DELL) was replaced by AbbVie Inc. (ABBV).

d is Dow Divisor, N is total number of index components, thus N=30. So, DJIA index is only depends on its price of index components. Unlike DJIA, S&P 100 index follows the method of capitalization weighted. That is, $S\&P\ \ 100\ \ index = \sum_{i=1}^{N}(p_i q_i)/d,$ where p_i is the price of stock i, q_i is outstanding shares and d is divisor, N is total number of index components, here N=100. For reflecting the weights of index components with respect to S&P 100 index, we collected the shares outstanding data on iShares S&P 100 ETF website.[6] [Figure 5] shows the DJIA index price (upper left), DJIA index returns (upper right), S&P 100 index price (lower left) and S&P 100 index returns (lower right) during sample periods.

[Figure 5] Close price and returns, DJIA and S&P 100



2. Economic News Announcements

In order to collect the number of economic news announcements by Dow Jones Institutional News and The Wall Street Journal, we use Dow Jones FACTIVA news repository service.[7] Dow Jones FACTIVA provides 48 major news and business publications in United States such as ABC,

[6] Source: www.ishares.com/us/products/239723/ishares-sp-100-etf

[7] Source: https://global.factiva.com

Barron's, and The Washington Post. We consider all the companies and industries to consider market wide news. We choose three main subject options: Commodity and Financial Market news, Corporate and Industrial news, and Economic news. [Table 2] shows sources and subjects of the collected news.

[Table 2] News summary: sources and subjects

Source	Dow Jones Institutional News, The Wall Street Journal
Company	All Companies
Industry	All Industries [8]
Subject	Commodity/ Financial Market, Corporate/Industrial, Economic news
Region	United States

[Table 3] Top 30 subjects of news announcements for January 04, 2010

	Subject		Subject
1	Derivative Securities	16	National Gov. Debt/Bond Markets
2	Routine Market/Financial News	17	Treasury Bond Prices/Commentary
3	Energy Prices	18	Foreign Exchange News
4	Crude Oil Markets	19	Tables
5	Crude Spot Market Commentary	20	Corporate Debt Instruments
6	Commodity/Financial Market News	21	Debt/Bond Markets
7	Commodity Markets	22	Central Bank Intervention
8	Energy Markets	23	Acquisitions/Mergers/Takeovers
9	Commentaries/Opinions	24	Regulation/Government Policy
10	Interest Rates	25	Selection of Top Stories/Trends
11	Economic News	26	Equity Markets
12	Money Markets	27	Cash Commodities Commentaries
13	Energy Commentary	28	Page-One Stories
14	Crude Oil/Natural Gas Product	29	Industry Profile
15	Analyst Comments/Recommendations	30	Equity Derivatives

[8] Dow Jones FACTIVA news archive provides 17 sub-categories for industry type: (1) Agriculture, (2) Automotive, (3) Basic Materials/Resources, (4) Business/Consumer Services, (5) Consumer Goods, (6) Energy, (7) Financial Services, (8) Health Care/Life Sciences, (9) Industrial Goods, (10) Leisure/Arts/Hospitality, (11) Media/Entertainment, (12) Real Estate/Construction, (13) Retail/Wholesale, (14) Technology, (15) Telecommunications, (16) Transportation/Shipping, (17) Utilities.

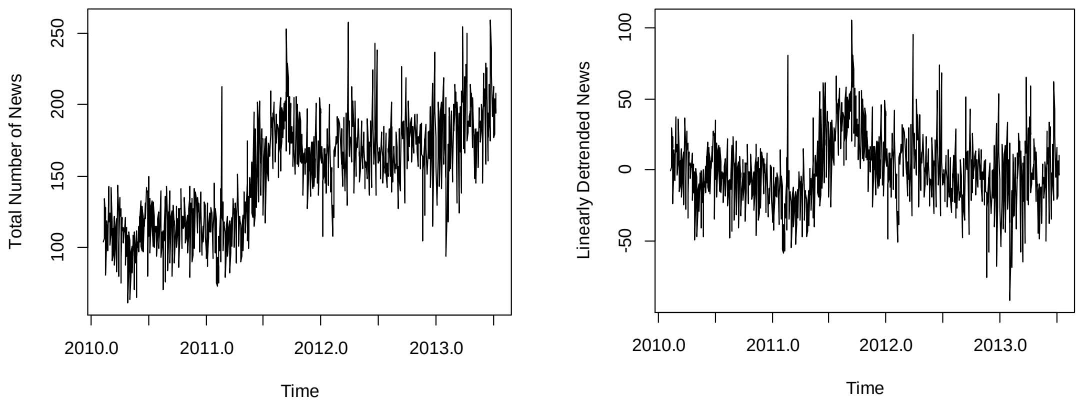
[Table 3] reports top 30 subjects of Dow Jones Institutional News and The Wall Street Journal News announcements for a sample day, January 4th, 2010. Total 123 news announcements were reported on this day and classified total 100 subjects. Top 30 subjects have 65% of news announcements in this sample day. [Table 4] shows the standard summary statistics for the number of news announcements. It is interesting to note that the number of Dow Jones Institutional News is on average lower than the number of the Wall Street Journal, but the standard deviation of Dow Jones Institutional News is greater than the Wall Street Journal.

[Table 4] Summary statistic: The number of news (2010. 01. 04 ~ 2013. 05. 31)

	Mean	Std. Dev.	Skewness
Dow Jones Institutional News	66.0105	32.7505	0.1693
The Wall Street Journal	84.9138	12.2853	-0.3073
Total Number of News	150.9242	36.9273	0.0253

The left side of [Figure 6] shows the total number of news announcements by Dow Jones Institutional News and The Wall Street Journal, and the right side shows linearly detrended total number of news.

[Figure 6] Total number of news, linearly detrended



Ⅳ. Empirical Evidence

1. Estimating Intentional Herding and its Dynamics

We provide the estimation results of the ARMA (1,1)-DCC (1,1) multivariate GARCH (1,1) model (Eq.s 3 and 4) that are reported in [Table 5]. Parameters μ, θ_1, and θ_2 are intercept, AR (1), and MA (1) parameters of (Eq. 3) respectively. δ_1 and δ_2 are parameters of dummy variables in mean equation of market index. Thus, positive (negative) and significant $\delta_1(\delta_2)$

means much public good (bad) information has a positive (negative) effect on the market cumulative returns in the same direction significantly. The estimation results show that both $\delta_{DJIA,1}$ and $\delta_{S\&p100,1}$ ($\delta_{DJIA,2}$ and $\delta_{S\&p100,2}$) are significantly positive (negative).

[Table 5] Estimation results of DCC models: using cumulative returns crs_t in mean equations

(a) Market cumulative returns: DJIA and S&P 100

	Parameter							
	μ	θ_1	θ_2	δ_1	δ_2	γ	α	β
DJIA	0.2147 (0.0003)	0.2415 (0.0050)	0.2054 (0.0151)	0.6922 (0.0000)	-0.9003 (0.0000)	0.1314 (0.1048)	0.3789 (0.0007)	0.5774 (0.0000)
S&P 100	0.2340 (0.0051)	0.3154 (0.0000)	0.1109 (0.0446)	0.9067 (0.0000)	-1.1068 (0.0000)	0.4615 (0.1395)	0.4769 (0.0048)	0.4057 (0.0991)

(b) Cumulative returns of DJIA components

Ticker symbol	Parameter					
	μ	θ_1	θ_2	γ	α	β
MMM	0.1821(0.00)	0.4187(0.00)	-0.1072(0.13)	0.9485(0.00)	0.6691(0.00)	0.1892(0.03)
AXP	0.1656(0.05)	0.4000(0.00)	-0.0832(0.19)	1.7088(0.00)	0.7309(0.00)	0.1371(0.19)
T	0.0681(0.23)	0.2802(0.00)	0.0275(0.67)	0.9254(0.00)	0.7800(0.00)	0.0000(1.00)
BA	0.1519(0.09)	0.2878(0.00)	0.0784(0.22)	1.6810(0.00)	0.6406(0.00)	0.1872(0.22)
CAT	0.1056(0.34)	0.3510(0.00)	0.0259(0.84)	2.5015(0.09)	0.7188(0.00)	0.1250(0.65)
CVX	0.2347(0.00)	0.4090(0.00)	-0.0285(0.64)	0.7046(0.00)	0.5788(0.00)	0.3422(0.00)
CSCO	0.1432(0.36)	0.3856(0.00)	0.0227(0.82)	1.4922(0.02)	0.3952(0.00)	0.4938(0.00)
DD	0.0751(0.37)	0.3728(0.00)	0.0174(0.77)	0.6578(0.02)	0.5908(0.00)	0.3726(0.00)
XOM	0.1343(0.02)	0.2506(0.00)	0.0544(0.49)	0.7771(0.00)	0.7274(0.00)	0.1466(0.19)
GE	0.0650(0.48)	0.4131(0.00)	-0.0376(0.64)	1.3798(0.00)	0.6842(0.00)	0.1850(0.14)
GS	0.1326(0.28)	0.3937(0.00)	-0.0920(0.09)	3.4266(0.00)	0.7162(0.00)	0.0112(0.92)
HD	0.1871(0.01)	0.3924(0.00)	-0.0416(0.50)	1.1693(0.00)	0.7941(0.00)	0.0885(0.22)
INTC	0.0398(0.66)	0.3393(0.01)	-0.0112(0.92)	1.9959(0.00)	0.8037(0.00)	0.0092(0.92)
IBM	0.0807(0.33)	0.3948(0.00)	-0.0371(0.42)	1.1104(0.00)	0.7516(0.00)	0.0763(0.48)
JNJ	0.0457(0.28)	0.3629(0.00)	-0.0608(0.51)	0.4487(0.00)	0.8413(0.00)	0.0291(0.72)
JPM	0.0475(0.69)	0.3058(0.00)	0.0061(0.95)	2.0643(0.00)	0.6641(0.00)	0.2029(0.18)
MCD	0.1934(0.00)	0.3529(0.00)	-0.0676(0.50)	1.0322(0.00)	0.6323(0.00)	0.0000(1.00)
MRK	0.0048(0.97)	0.3780(0.01)	-0.0713(0.28)	1.4803(0.21)	0.7109(0.02)	0.0000(1.00)
MSFT	0.1867(0.03)	0.3395(0.00)	-0.0562(0.37)	1.8757(0.00)	0.7172(0.00)	0.0000(1.00)
NKE	0.1249(0.63)	0.3216(0.15)	-0.0118(0.96)	2.3502(0.18)	0.6877(0.02)	0.0000(1.00)
PFE	-0.0144(0.86)	0.2987(0.00)	0.0020(0.98)	1.4144(0.00)	0.7093(0.00)	0.0151(0.93)
PG	0.0245(0.67)	0.2571(0.01)	0.0480(0.59)	0.7547(0.00)	0.7618(0.00)	0.0000(1.00)
KO	0.0540(0.39)	0.3153(0.00)	0.0035(0.94)	0.8979(0.01)	0.7428(0.00)	0.0000(1.00)
TRV	0.0400(0.55)	0.3538(0.00)	-0.0703(0.35)	1.1076(0.00)	0.7776(0.00)	0.0283(0.69)
UTX	0.1601(0.04)	0.3188(0.00)	0.0206(0.74)	1.2632(0.00)	0.7469(0.00)	0.1043(0.38)
UNH	0.0910(0.28)	0.3270(0.00)	-0.0269(0.76)	2.0935(0.00)	0.7294(0.00)	0.0697(0.41)
VZ	-0.0045(0.95)	0.3783(0.00)	-0.0404(0.58)	1.0661(0.00)	0.7990(0.00)	0.0038(0.96)
V	0.0884(0.40)	0.3085(0.00)	-0.0520(0.44)	2.3105(0.00)	0.8376(0.00)	0.0000(1.00)
WMT	0.1020(0.03)	0.0953(0.63)	0.1687(0.23)	0.8491(0.00)	0.7402(0.00)	0.0000(1.00)
DIS	0.2001(0.01)	0.3351(0.00)	-0.0018(0.97)	1.4950(0.00)	0.6768(0.00)	0.1357(0.45)

(c) Cumulative returns of S&P 100 components

Ticker symbol	Parameter					
	μ	θ_1	θ_2	γ	α	β
AAPL	0.1873(0.31)	0.3418(0.00)	0.0059(0.94)	2.8982(0.01)	0.8114(0.00)	0.0000(1.00)
APC	0.0188(0.88)	0.3614(0.00)	-0.0685(0.27)	4.3699(0.00)	0.7541(0.00)	0.0205(0.80)
ABBV	-0.1222(0.59)	0.5328(0.00)	-0.2233(0.13)	4.9192(0.00)	0.6590(0.00)	0.0000(1.00)
ABT	0.0623(0.25)	0.3006(0.00)	0.0036(0.95)	0.8957(0.00)	0.7750(0.00)	0.0000(1.00)
ACN	0.0325(0.77)	0.4151(0.00)	-0.0782(0.52)	1.5304(0.02)	0.8162(0.00)	0.1422(0.44)
AXP	0.1656(0.05)	0.4000(0.00)	-0.0832(0.19)	1.7087(0.00)	0.7309(0.00)	0.1372(0.19)
AEP	0.0943(0.09)	0.3163(0.00)	0.0268(0.74)	0.7361(0.00)	0.6521(0.00)	0.1514(0.14)
HON	0.1595(0.05)	0.3369(0.00)	0.0077(0.91)	0.9567(0.00)	0.6086(0.00)	0.3059(0.02)
ALL	0.2160(0.01)	0.4079(0.00)	-0.1141(0.12)	1.4824(0.00)	0.6459(0.00)	0.1691(0.11)
AMGN	-0.0203(0.80)	0.4263(0.00)	-0.1257(0.09)	1.4149(0.00)	0.7150(0.00)	0.0858(0.41)
⋮	⋮	⋮	⋮	⋮	⋮	⋮
UPS	0.0943(0.14)	0.3604(0.00)	-0.0348(0.65)	0.8023(0.00)	0.7521(0.00)	0.1438(0.06)
USB	0.0846(0.26)	0.3010(0.00)	0.0050(0.95)	0.9295(0.00)	0.6665(0.00)	0.2724(0.01)
UTX	0.1602(0.04)	0.3188(0.00)	0.0207(0.74)	1.2632(0.00)	0.7468(0.00)	0.1043(0.37)
V	0.0790(0.40)	0.2666(0.00)	-0.0170(0.83)	1.7801(0.00)	0.8637(0.00)	0.0000(1.00)
VZ	-0.0045(0.95)	0.3783(0.00)	-0.0404(0.58)	1.0661(0.00)	0.7990(0.00)	0.0038(0.96)
WAG	0.0733(0.46)	0.2720(0.02)	0.0097(0.93)	2.6603(0.00)	0.7012(0.00)	0.0000(1.00)
WFC	0.0996(0.23)	0.2053(0.02)	0.0907(0.27)	1.2900(0.00)	0.7063(0.00)	0.2462(0.00)
WMB	0.2236(0.10)	0.2975(0.00)	0.0969(0.42)	1.5216(0.19)	0.4804(0.02)	0.4358(0.12)
WMT	0.1020(0.03)	0.0953(0.64)	0.1687(0.24)	0.8491(0.00)	0.7402(0.00)	0.0000(1.00)
XOM	0.1343(0.02)	0.2506(0.00)	0.0545(0.49)	0.7772(0.00)	0.7275(0.00)	0.1466(0.19)

* Notes: (1) Value in parentheses denotes p-value of t-test.

(2) DJIA and S&P 100 indices consist of 30 and 100 components respectively. In particular, we report only first 10 and last 10 components of S&P 100 index to save space[9].

(3) All of the ticker symbols are extended in Appendix.

[Figure 7] shows the conditional volatility of DJIA and S&P 100 index returns (upper left and lower left) and intensity of intentional herd behavior in DJIA and S&P 100 markets (upper right and lower right). It highlights that the conditional volatility of DJIA and S&P 100 index returns increased sharply at two periods and intentional herding also was exacerbated significantly in the same periods. The first period is 'European sovereign debt crisis' that is from end of 2009 to end of 2010, and the second period is 'degradation of U.S. sovereign credit rating by Standard & Poor's' that is about half year since August 6th, 2011. It is worthwhile to note that negative events in markets, such as crisis, cause investors to have strong market-wide herding[10] and increase the conditional volatility considerably. That is, dynamic intentional herding can be regarded as a potential explanatory factor that drives the market volatility. This relationship is further analyzed formally in next sections.

[Table 5] reports simple summary statistics of: (1) DJIA and S&P 100 index returns ($r_{DJIA,t}, r_{S\&P100,t}$), (2) cumulative returns in the same direction of DJIA and S&P 100 index

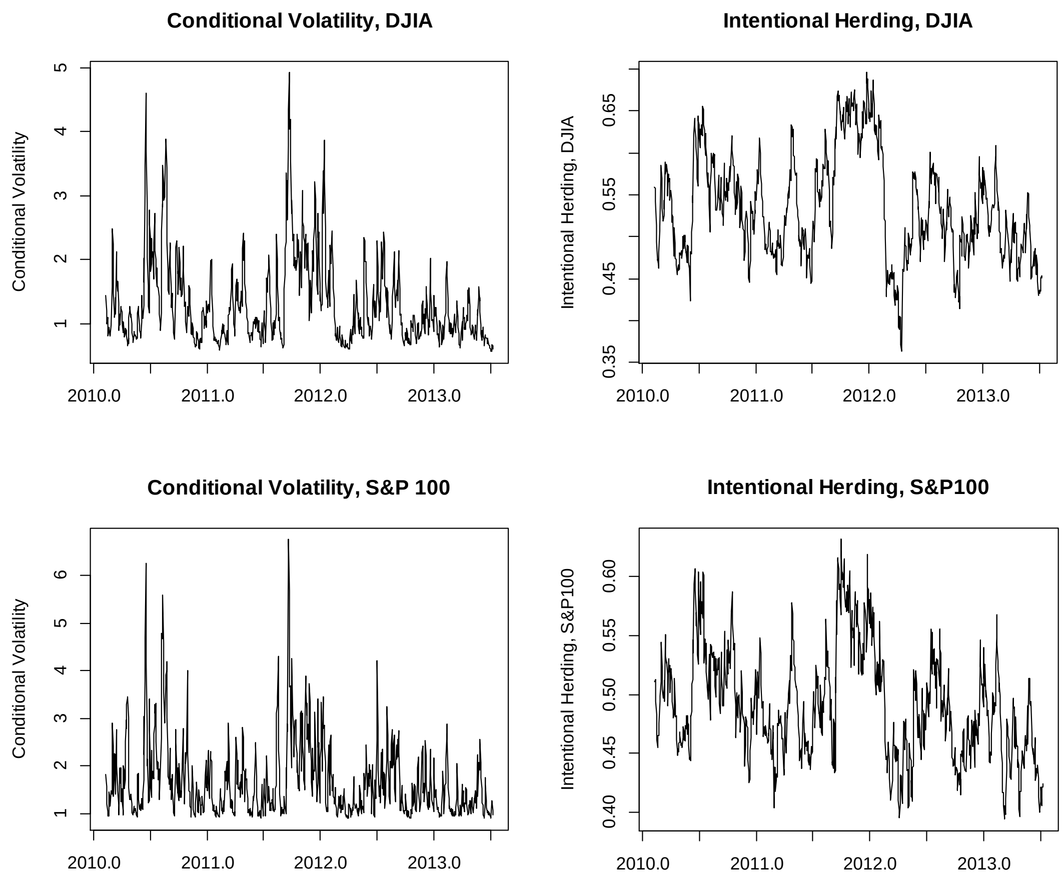
[9] The additional estimation results of other components are available from the author upon request.

[10] This is consistent with the argument of Christie and Huang (1995) and Chang et al. (2000) and others.

($crs_{DJIA,t}, crs_{S\&P100,t}$), (3) intensity of intentional herding in DJIA and S&P 100 markets ($DH_{DJIA,t}, DH_{S\&P100,t}$), and presents the correlation coefficient between $DH_{m,t}$ and conditional variance $h_{m,t}$. It should be noted that the range of $crs_{m,t}$ is greater than $r_{m,t}$ (*m*=DJIA and S&P 100) and autocorrelation of $crs_{m,t}$ is much greater than $r_{m,t}$ as a result of Ljung-Box Q test (at lag=5 and 10).

We also turn to the joint test of autocorrelation in the herding series, $DH_{DJIA,t}, DH_{S\&P100,t}$. The Ljung-Box Q statistics indicate an exceptionally high autocorrelation in the herding series and support that traders follow positive feedback trading strategy as a main factor of herd behavior, which should be serially correlated over time.

[Figure 7] Conditional volatility ($h_{m,t}^{1/2}$) and intentional herding



[Table 5] Summary statistic

	$r_{DJIA,t}$	$r_{S\&P100,t}$	$crs_{DJIA,t}$	$crs_{S\&P100,t}$	$DH_{DJIA,t}$	$DH_{S\&P100,t}$
Min	-5.7060	-6.3050	-6.9970	-11.2000	0.3513	0.3943
1st Qu.	-0.3925	-0.5182	-0.6802	-0.8437	0.4860	0.4567
Median	0.0564	0.0952	0.1479	0.2212	0.5256	0.4846
Mean	0.0433	0.0549	0.1654	0.2787	0.5335	0.4905
3rd Qu.	0.5334	0.6882	1.1150	1.4850	0.5764	0.5207
Max	4.1540	4.9150	7.1220	8.7720	0.6951	0.6310
Std. Dev	1.0127	1.2085	1.8569	2.4425	0.0626	0.0462
Skewness	-0.4333	-0.2952	-0.2047	-0.2590	0.3305	0.4498
Kurtosis	6.7021	5.6101	4.7974	5.2512	2.5120	2.7850
Q(5)	26.41 (0.0000)	13.65 (0.0179)	170.36 (0.0000)	245.27 (0.0000)	3321.50 (0.0000)	2935.90 (0.0000)
Q(10)	31.10 (0.0006)	17.75 (0.0593)	174.87 (0.0000)	248.28 (0.0000)	5465.30 (0.0000)	4633.70 (0.0000)
Cor($DH_{DJIA,t}$, $h_{DJIA,t}$)		0.7382(0.0000)				
Cor($DH_{S\&P100,t}$, $h_{S\&P100,t}$)		0.6524(0.0000)				

* Notes: Value in parentheses denotes p-value of in Ljung-Box Q(d.f.) test and Pearson's correlation test

2. Empirical Test for Intentional Herding

In this section we implement the tests for market-wide intentional herding that address evidence for its dynamics and compare them with other tests such as CH and CCK that are pioneering works on this field. [Table 5] reports the means of $DH_{DJIA,t}$ and $DH_{S\&P100,t}$ are 0.5335 and 0.4905 respectively, and their standard deviations are 0.0626 and 0.0462 respectively. From (Eq. 4), the test statistics $Z_{DH_{DJIA}}$ and $Z_{DH_{S\&P100}}$ under the null hypothesis of no intentional herding in markets are computed. Since the estimates are 0.5351 and -0.2056 by using the mean values of $DH_{DJIA,t}$ and $DH_{S\&P100,t}$, the null hypothesis of no intentional herding in both market indices is not rejected at the significant level of 5 percent.

While the test results do not suggest statistical evidence of intentional herding over the period investigated, [Figure 7] depicts the fact that the values of $DH_{DJIA,t}$and $DH_{S\&P100,t}$ in the periods of market stress exceed 0.5 obviously, which means the existence of intentional herd behavior. From the visual impression, it can be inferred that although there is no significant intentional herding in the whole period, intentional herding can significantly occur during the periods of market stress. To verify this, it is necessary to run the tests at every time t. P-value of the test at the significant level of 5 percent is 0.6029 in terms of $DH_{DJIA,t}$ and 0.5028 in terms of $DH_{S\&P100,t}$. According to the test results, interestingly we find that in both market indices the null hypothesis of no intentional herding is rejected on most of days included in the periods of market stress like European sovereign debt crisis and the degradation of U.S. sovereign credit rating by S&P, namely intentional herd behavior is expected to take place under extreme market conditions. This phenomenon is also confirmed by some previous studies such as Avramov et al. (2006). In addition, intentional herd behavior is more frequent in S&P 100 than DJIA, which is supported by the fact that significant intentional herd behavior has occurred for 138 days out of 858 days in DJIA but for 364 days out of 858 days in S&P 100.

We now turn to perform the tests of CH and CCK. CH employed the following regression model to investigate whether the dispersion of returns (Cross-Sectional Standard Deviation, CSSD) is decreased significantly by during periods of extreme market movements:

$$CSSD_t = \alpha + \beta^L {D_t}^L + \beta^U {D_t}^U + \varepsilon_t \qquad \text{(Eq. 8)}$$

Christie and Huang (1995) suggest that in (Eq. 8), ${D_t}^L({D_t}^U)$ is a dummy variable which takes the value of 1 if the market returns at time *t* is positioned in the extreme lower(upper) tail of the distribution and the value of 0 otherwise, and α is an intercept term. Thus, dummy variables can capture the differences between investor's behavior in extreme market condition and normal market condition.

Chang *et al*. (2000) argue that if market participants tend to follow market consensus during periods of large market price fluctuation, increasing and linear relation between individual stock return dispersions and market returns will become non-linearly increasing or even decreasing. On this intuition, they suggest the following regressions to examine whether the degree of herd behavior is asymmetric in rising (UP) and falling (DN) markets:

$$CSAD_t{}^{UP} = \alpha + \gamma_1{}^{UP}\left|R_{m,t}{}^{UP}\right| + \gamma_2{}^{UP}(R_{m,t}{}^{UP})^2 + \varepsilon_t \qquad \text{(Eq. 9)}$$

$$CSAD_t{}^{DN} = \alpha + \gamma_1{}^{DN}\left|R_{m,t}{}^{DN}\right| + \gamma_2{}^{DN}(R_{m,t}{}^{DN})^2 + \varepsilon_t \qquad \text{(Eq. 10)}$$

In (Eq.s 9 and 10), $\left|R_{m,t}{}^{UP}\right|(\left|R_{m,t}{}^{DN}\right|)$ is the absolute value of returns of all available securities on day *t* when the market is up(down). According to CCK, if during periods of extreme market conditions investors tend to herd toward the market, a negative non-linear relation between CSAD and the average market return should exist and be captured by the coefficient on the non-linear term. We implement the tests using DJIA and S&P 100 returns and the test results are reported in [Table 6].

According to CSSD, statistically significant and negative coefficients may suggest that investors herd during extreme market conditions. By contrast, β^L and β^U are positive coefficient and statistically significant at 5% and 10% dummy criteria in DJIA and S&P 100 indices. Furthermore, although negative γ^{UP} and γ^{DN} indicate herd behavior in CSAD, γ^{UP} and γ^{DN} are positive in real market indices. It means, high return volatility has little effect on the intensity of herd behavior and its non-linear relationship cannot also be explained. Therefore, according to the results of [Table 6], there is not significant herd behavior in U.S. stock markets.[11]

[Table 6] Simple regression test results: CSSD and CSAD

			CSSD			CSAD	
			Estimate			Estimate	
DJIA	5%	α	0.9559	***	α^{UP}	0.6513	***
		β^L	0.3295	***	${\gamma_1}^{UP}$	0.0348	
		β^U	0.2866	***	${\gamma_2}^{UP}$	0.0397	***
	10%	α	0.9428	***	α^{DN}	0.6306	***
		β^L	0.2260	***	${\gamma_1}^{DN}$	0.0843	***
		β^U	0.2126	***	${\gamma_2}^{DN}$	0.0170	**
S&P 100	5%	α	1.2357	***	α^{UP}	0.7824	***
		β^L	0.4538	***	${\gamma_1}^{UP}$	0.1505	***
		β^U	0.5117	***	${\gamma_2}^{UP}$	0.0099	
	10%	α	1.2222	***	α^{DN}	0.8241	***
		β^L	0.3388	***	${\gamma_1}^{DN}$	0.1147	***
		β^U	0.2782	***	${\gamma_2}^{DN}$	0.0161	*

*Significant Codes: ' *** ' for 0.01, ' ** ' for 0.05, ' * ' for 0.1.

In view of the earlier arguments concerning the drawbacks of CH and CCK, we should be cautious about interpreting the test results. Comparing them with our test results, in particular, we find that if it is failed to take into account the dynamic nature of herd behavior (i.e., the intensity of herd behavior varies over time significantly), we might draw a wrong evidence and tend to misinterpret it as not market-wide herding even during the periods of market stress.

[11] The results are consistent with those documented by Christie and Huang (1995) and Chang et al. (2000). Especially, Chang et al. (2000) found the equity return dispersions tend to increase rather than decrease for the U.S., Hong Kong, and Japan during extreme price movements. They only found the herd behavior in South Korea and Taiwan during both extreme up and down price movement days.

3. The Effect of Intentional Herding on Volatility

The question of whether herd behavior prevalent in financial markets drives markets fluctuated remarkably has been widely investigated in recent years. To substantiate this central issue[12], therefore, we estimate the (Eq. 14) regression model using quantile regression method that is a semiparametric approach (Koenker, 2005) and observe the effect of intentional herd behavior $DH_{m,t}$ on a conditional volatility of market index returns from (Eq. 4) over the entire distribution[13]. Indeed, the quantile regression method is ideal for examining the influence of intentional herding on volatility under different market conditions.

In a simple regression model,

$$y_i = x_i'\beta + \varepsilon_i \qquad \text{(Eq. 11)}$$

τ^{th} conditional quantile function of y given x can be determined as:

$$Q_y(\tau|x) = x'\beta_\tau \qquad \text{(Eq. 12)}$$

Quantile regression estimator $\hat{\beta}_\tau$ can be solved from minimization problem of τ^{th} sample quantile.

$$\hat{\beta}_\tau = argmin_{\beta \in R^p} \sum_{i=1}^{p} \rho_\tau(y_i - x_i'\beta) \qquad \text{(Eq. 13)}$$

where $\rho_\tau(\mathrm{a}) = \mathrm{a}(\tau - \mathrm{I}(\mathrm{a} < 0))$ is check function, $\tau \in (0,1)$, and $\mathrm{I}(\cdot)$ is an indicator function which takes value of 1 if $\mathrm{a} < 0$, and 0 otherwise.

The quantile regression of an absolute value of market index returns is

$$h_{m,t}^{1/2}(\tau|x) = \omega_m + \theta_m DH_{m,t}(\tau) + \varepsilon_{m,t} \qquad \text{(Eq. 14)}$$

where $h_{m,t}^{1/2}$ is a conditional volatility of market index return on day *t* as a simple estimate of volatility and $DH_{m,t}$ is our dynamic measure of intentional herd behavior. The estimation results for quantile regression are reported in [Table 7].

Extreme returns are located at the upper tail of the distribution of conditional volatility of market returns. Thus, somewhat similar in spirit to Chang et al. (2000), the influence of intentional herding on volatility during market stress periods can be naturally investigated by inspecting high quantiles such as $\tau = 0.90$ and 0.95. According to the results in [Table 7], all estimates of the

[12] Generally, given some motivations for herding such as informational cascades, we can expect that the intensity of intentional herding might affect the level of volatility.

[13] According to Christie and Huang (1995) and Chang et al. (2000), we might observe herding during market stress and intuitively the quantile regression method is considerably valid in analyzing extreme quantiles of absolute returns and nonlinearity in the effect of herding.

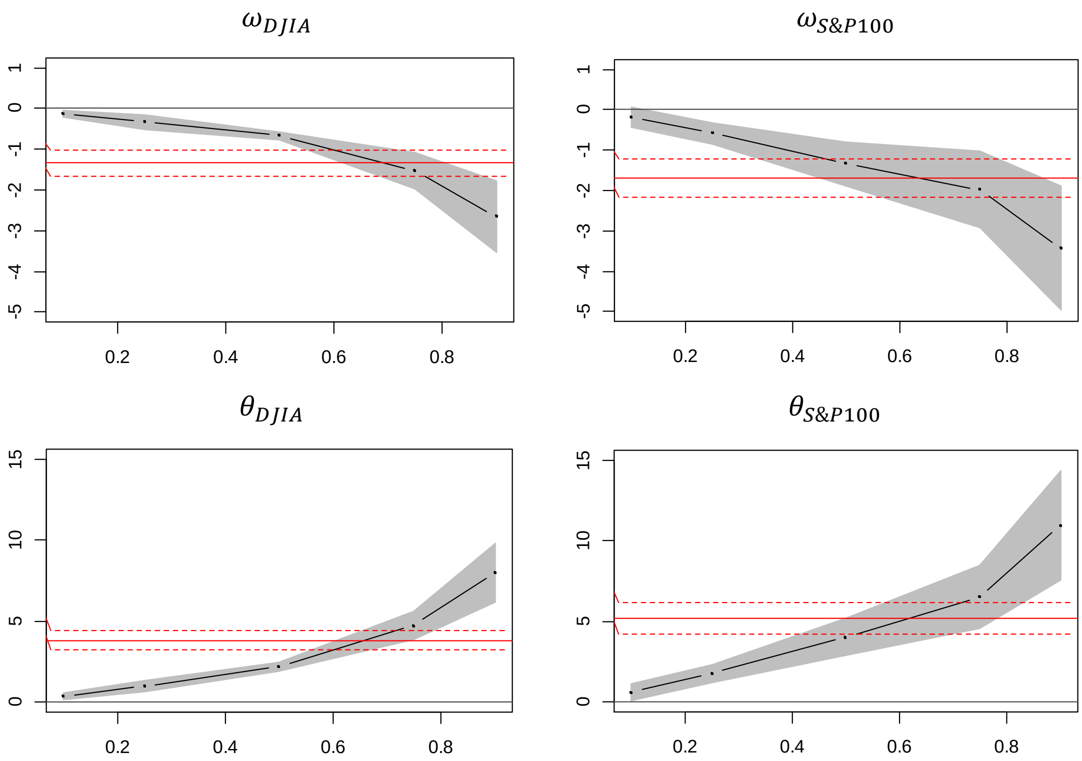
θ are positive and statistically significant for DJIA and S&P 100 indices. Moreover, as the value of τ increases from 0.1 to 0.9, the value of θ also increases. It means, as markets become more turbulent, the level of positive relationship between intensity of intentional herding and market return volatility is also higher. Furthermore, in [Figure 8], all estimates of the θ for S&P 100 are always greater than DJIA. Thus, we document the higher level of the effect of intentional herd behavior on return volatility in S&P 100 index than DJIA index.

[Table 7] Estimation results for quantile regression

Market	τ	Parameter	Estimate	Std. Dev.	Pr. (> | t |)	
DJIA	0.05	ω_{DJIA}	-1.1573	0.0740	0.0000	
		θ_{DJIA}	3.7031	0.1595	0.0000	
	0.10	ω_{DJIA}	-1.1919	0.0860	0.0000	**
		θ_{DJIA}	3.8787	0.1745	0.0000	***
	0.25	ω_{DJIA}	-1.6533	0.0747	0.0000	***
		θ_{DJIA}	5.0150	0.1616	0.0000	***
	0.50	ω_{DJIA}	-2.2715	0.0669	0.0000	***
		θ_{DJIA}	6.5555	0.1475	0.0000	***
	0.75	ω_{DJIA}	-2.4319	0.1765	0.0000	***
		θ_{DJIA}	7.3594	0.3558	0.0000	***
	0.90	ω_{DJIA}	-2.9876	0.3338	0.0000	***
		θ_{DJIA}	9.0705	0.6726	0.0000	***
	0.95	ω_{DJIA}	-3.7022	0.5761	0.0000	***
		θ_{DJIA}	11.0177	1.1416	0.0000	***
S&P 100	0.05	$\omega_{S\&P100}$	-0.8109	0.0957	0.0000	***
		$\theta_{S\&P100}$	3.8173	0.2178	0.0000	***
	0.10	$\omega_{S\&P100}$	-1.1597	0.1396	0.0000	***
		$\theta_{S\&P100}$	4.6514	0.3128	0.0000	***
	0.25	$\omega_{S\&P100}$	-2.0570	0.1042	0.0000	***
		$\theta_{S\&P100}$	6.8099	0.2503	0.0000	***
	0.50	$\omega_{S\&P100}$	-3.0051	0.2111	0.0000	***
		$\theta_{S\&P100}$	9.2521	0.4567	0.0000	***
	0.75	$\omega_{S\&P100}$	-3.6457	0.3325	0.0000	***
		$\theta_{S\&P100}$	11.3630	0.7019	0.0000	***
	0.90	$\omega_{S\&P100}$	-4.9614	0.5730	0.0000	***
		$\theta_{S\&P100}$	15.0055	1.2420	0.0000	***
	0.95	$\omega_{S\&P100}$	-6.3495	0.7742	0.0000	***
		$\theta_{S\&P100}$	18.7126	1.8175	0.0000	***

* Significant Codes: ‘ *** ’ for 0.01, ‘ ** ’ for 0.05, ‘ * ’ for 0.1.

[Figure 8] Coefficients of quantile regression



Ⅴ. Concluding Remarks

Most previous studies for detecting herd behavior have not distinguished intentional from spurious herding, but such distinction is a great challenge, as we can significantly distort the empirical results of herd behavior if we do not distinguish between them. This paper therefore suggests a new measure which accounts for market-wide intentional herding and additionally dynamic property. Our measure is derived from the DCC multivariate GARCH model of the cumulative returns in the same direction with the variable for the number of economic news announcements as a proxy of market information. Further, under the null hypothesis of no intentional herding we propose the test statistic of intentional herding at time t which follows standard normal distribution.

We estimate the model by employing daily data from January 4th, 2010 to May 31st, 2013 for the main U.S. stock market indices (DJIA and S&P 100) and the stock prices of companies belonging to each index, and apply our measure to check its reliability and to investigate the existence of intentional herding in U.S. stock markets. The test results with respect to the CSSD and CSAD show the positive coefficients that are statistically significant by 5% and 10% dummy criteria in DJIA and S&P 100 indices. Thus, both CSSD and CSAD cannot explain exactly the relationship between herd behavior and extreme market movements and suggest cannot reject the hypothesis of no intentional herding. Meanwhile, our empirical results provide clear evidence that intentional herding is more prevalent in the stress periods in which markets are highly volatile than the normal periods. This implies that the intensity of intentional herding varies with market conditions.

We need to pay attention to the period of European sovereign debt crisis in which even though the news inflows are not so many, the markets are turbulent and the estimates of intentional herd behavior $DH_{m,t}$ are remarkably high because investor might follow others to suppress psychological stress induced by the crisis, especially this turbulence is more pronounced in terms of the cumulative returns. This interesting finding can provide insight into exactly why we frequently observe high volatility in financial markets even in the absence of any significant information or news including macroeconomic announcements and strongly supports that intentional herding causes high volatility[14].

In addition, we estimate the quantile regression model using the dynamic herding measure to investigate whether intentional herd behavior makes extreme market fluctuation. According to the estimation results, the effect of intentional herding on market volatility tends to be stronger during the periods of turbulent markets like the degradation of U.S. sovereign credit rating by S&P and European sovereign debt crisis. Overall, since intentional herding is a crucial source of high volatility and increases the fragility of the financial system, this study demonstrates that dynamic intentional herding should be measured and considered seriously during the periods of market stress.

[14] This is theoretically argued in the existing literature that is based on asset pricing models with heterogeneous beliefs (e.g., Brock and Hommes, 1998; Park, 2014).

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Appendix.

Ticker symbols for Dow Jones Industrial Average and Standard & Poor's 100 Index

AA	Alcoa Incorporated
AAPL	Apple Incorporated
APC	Anadarko Petroleum Corporation
ABBV	AbbVie Incorporated
ABT	Abbott Laboratories
ACN	Accenture Plc.
AXP	American Express Company
AEP	American Electric Power Company Incorporated
AVP	Avon Products Incorporated
HON	Honeywell International Incorporated
ALL	Allstate Corporation
AMGN	Amgen Incorporated
AMZN	Amazon.com Incorporated
APA	Apache Corporation
BA	Boeing Corporation
BAC	Bank of America Corporation
BAX	Baxter International Incorporated
BHI	Baker Hughes Incorporated
BK	Bank of New York Mellon Corporation
BMY	Bristol-Myers Squibb Corporation
BNI	Burlington Northern Railroad
BRK.B	Berkshire Hathaway Incorporated
C	Citigroup Incorporated
CAT	Caterpillar Incorporated
CL	Colgate-Palmolive Company
CMCSA	Comcast Corporation
COF	Capital One Financial Corporation
COP	ConocoPhillips
COST	Costco Wholesale Corporation
BPB	Campbell Soup Company
CSCO	Cisco Systems Incorporated
CVS	CVS Health Corporation
CVX	Chevron Corporation
DD	E I Du Pont De Nemours And Company
DELL	Dell Incorporated
DIS	Walt Disney Company
DOW	Dow Chemical Company
DVN	Devon Energy Corporation
EBAY	eBay Incorporated
EMC	EMC Corporation
EMR	Emerson Electric Company
ETR	Entergy Corporation
EXC	Exelon Corporation
F	Ford Motor Company
FCX	Freeport-McMoRan Incorporated
FDX	FedEx Corporation

GD	General Dynamics Corporation
GE	General Electric Company
GILD	Gilead Sciences Incorporated
GOOGL	Google Incorporated
GS	Goldman Sachs Group Incorporated
HAL	Halliburton Company
HD	Home Depot Incorporated
HNZ	H.J. Heinz Company
HPQ	Hewlett-Packard Company
HSH	Hillshire Brands Company
IBM	International Business Machines Corporation
INTC	Intel Corporation
JNJ	Johnson & Johnson
JPM	JPMorgan Chase & Company
KFT	Kraft Foods Incorporated
KO	The Coca-Cola Company
MDLZ	Mondelez international Incorporated
LLY	Eli Lilly and Company
LMT	Lockheed Martin Corporation
LOW	Lowe’s Companies Incorporated
MA	Mastercard Incorporated
MCD	McDonald’s Corporation
MDT	Medtronic Incorporated
MMM	3M Company
MO	Altria Group Incorporated
MON	Monsanto Company
MRK	Merck & Company Incorporated
MS	Morgan Stanley
MSFT	Microsoft Corporation
MET	Metlife Incorporated
NWSA	News Corporation
NKE	Nike Incorporated
NOV	National-Oilwell Varco, Incorporated
NSC	Norfolk Southern Corporation
NYX	New York Stock Exchange Euronext
ORCL	Oracle Corporation
OXY	Occidental Petroleum Corporation
PEP	PepsiCo Incorporated
PFE	Pfizer Incorporated
PG	Procter & Gamble Company
PM	Philip Morris International Incorporated
QCOM	QUALCOMM Incorporated
RF	Regions Financial Corporation
RTN	Raytheon Company
S	Spring Nextel Corporation
SBUX	Starbucks Corporation
SLB	Schlumberger Limited
SO	Southern Company
SPG	Simon Property Group Incorporated
T	AT&T Incorporated
TGT	Target Corporation

TRV	Travelers Companies Incorporated
TWX	Time Warner Incorporated
TXN	Texas Instruments Incorporated
UNH	UnitedHealth Group Incorporated
UNP	Union Pacific Corporation
UPS	United Parcel Service Incorporated
USB	U.S. Bancorp
UTX	United Technologies Corporation
V	Visa Incorporated
VZ	Verizon Communications Incorporated
WAG	Walgreen Company
WFC	Wells Fargo & Company
WMB	Williams Companies Incorporated
WMT	Wal-Mart Stores Incorporated
WY	Weyerhaeuser Company
XOM	Exxon Mobil Corporation
XRX	Xerox Corporation