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重大事件、從眾行為與投資人情緒的日內關係

Intraday Evidence on Relationships among Great Events, Herding Behavior, and Investors' Sentiments

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摘要：本研究旨在探討 2005-2008 期間內三項重大事件發生時投資人交易行為與情緒的日內從眾傾向。相較於早期相關文獻，本研究至少具有下列四點特色：首先，本研究分別採用 1 分鐘、5 分鐘與 10 分鐘的日內資料來深入地調查投資人的日內從眾現象。其次，本研究探討 2005-2008 期間內三項重大事件對投資人交易行為與情緒之日內從眾傾向的影響。再者，本研究檢查投資人交易行為、投資人情緒與股票報酬的日內領先落後關係。最後，為了強化研究結果的正確性，我們分別使用絕對與相對的委買（賣）量來做為投資

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人交易行為的代理變數。三種頻率日內資料與兩種投資人交易行為代理變數的實證結果均指出「投資人情緒」領先「投資人交易行為」；而且當研究模式納入重大事件的虛擬變數時，投資人情緒與投資人交易行為都具有明顯的從眾傾向。另外，重大事件也顯著地影響投資人情緒的條件波動性。
關鍵詞：日內資料；投資人情緒；重大事件；從眾行為；領先落後關係

Abstract: This study investigates the intraday herding tendency of investors' trading behavior and sentiments around the three great events that happened during 2005-2008. In comparison with previous literature, this study contains at least four important aspects. First, this study applies 1-minute, 5-minute, and 10-minute intraday data to closely examine the intraday herding of investors. Second, the influence of the three great events that happened during 2005-2008 on the herding tendency of investors' trading behavior and sentiments is explored in this study. Third, we look further into the intraday lead-lag relationships among investors' trading behavior, investors' sentiments, and stock returns. Finally, in order to improve the robustness of empirical findings, both the absolute and relative bid/ask volumes are adopted by this study as proxies of investors' trading behavior. The empirical results of the three-frequency intraday data and those of the two investor trading behavior proxies both show that investors' sentiments lead investors' trading behavior, and both of them exhibit pronounced herding tendency for the models with dummy variables of great events. In addition, the three great events have a significant impact on the conditional volatility of investors' sentiments.
Keywords: Intraday data; Investors' sentiments; Great events; Herding behavior; Lead-Lag relationships

1. Introduction

During 2005-2008, the stock market in Taiwan faced dramatic price fluctuations exerted by domestic events such as the second regime change as well as a run on the Chinese Bank. Internationally, examples of events include the subprime crisis caused by Fannie Mae and Freddie Mac and the global financial tsunami. In addition to the change of fundamentals caused by the great events mentioned above, one of the reasons for the dramatic variation in share prices was the herding behavior demonstrated by investors due to the failure to respond properly to great events. Behavioral finance based on cognitive dissonance, as suggested by Festinger (1957), contests that investors fail to respond to information shocks with correct cognition and that this leads to overreaction or underreaction. Hence, when the information of one great event is released into the market for the first time, only informed traders are able to respond in a timely manner, but when relevant information of this great event is continuously sent to the market, the majority of investors have already responded to it and it is more likely for noise traders to overreact due to herding behavior. This implies that when there is bad news, individual investors not only fail to respond to it but also act together with the majority due to panic. The above described behavior is the same investment strategy adopted by the majority of investors during the same period of time and presents the pronounced herding behavior in the stock market.

Although evidence of cognitive dissonance shows that herding behavior is more likely to be demonstrated by less sophisticated investors, previous literature revealed the existence of herding behavior among sophisticated mutual fund managers (Kraus and Stoll, 1972; Klemkosky, 1977), hedge fund managers (Ennis and Sebastian, 2003; Boyson, 2010), and foreign institutional investors (Choe, Kho, and Stulz, 1999; Chen, Wang, and Lin, 2008). In addition, previous literature indicated the observation of herding behavior in financial markets at different sophisticated levels. Choe, Kho, and Stulz (1999) and Chen, Wang, and Lin (2008) respectively found significant herding behavior of foreign institutional investors in the stock markets of Taiwan and South Korea, while Voronkova and Bohl (2005), Walter and Weber (2006), and Carpenter and Wang (2007) observed investor behavior highly similar to herding among managers of Polish pension funds, German mutual funds, and Australian non-bank financial institutions (hedge funds and mutual funds). In addition to the investigation of herding behavior, recent studies have begun to explore how to avoid herding behavior. Among them, Dass, Massa, and Patgiri (2008) suggested the use of implicit incentives in an entrust contract to avoid the herding behavior of mutual fund managers, while Boyson (2010) pointed out that implicit incentives significantly dominate the herding tendency of hedge fund managers. In short, earlier studies comprehensively investigated herding behavior but the majority of them used daily or monthly data for empirical analysis. The occurrence of herding behavior of investors involves quick response, so the use of daily or monthly data may fail to obtain a complete picture of herding behavior. Moreover, Gleason, Mathur, and Peterson (2004) and Henker, Henker, and Mitsios (2006) proposed the demonstration of herding tendency of investors within a very short period of time and low frequency data (daily or monthly data) make it difficult to detect herding behavior. As a result, there is a need to adopt higher frequency intraday data for empirical analysis.

Psychological factors should be one of the causes of investors' herding behavior, and the influence is particularly on investors' sentiments. Previous literature revealed the influence of investors' sentiments on the procurement willingness of stocks. Siegel (1992) showed that during a panic in the market, there has been high correlation between investors' sentiments and market index returns. Baker and Wurgler (2006) found the help of investors' sentiments for predicting the returns on stocks difficult to arbitrage. Kumar and Lee (2006) revealed that investors' sentiments have an impact on investment decision and stock returns. Kaustia and Knupfer (2008) indicated the significant influence and domination of investors' sentiments on trading behavior and demand for initial public offerings (IPOs), while Liao, Huang, and Wu (2011) presented the important role of investors' sentiments on the herding behavior explanation of mutual fund managers. Hence, in-depth investigation on the issues of investor sentiment herds, the relationship among herding behavior, stock returns and herding inclination of investors' sentiments shall be conducted.

In terms of the influence of psychological factors on investors' trading behavior, traditional finance and behavioral finance express different perspectives. Among which, traditional finance assumes the existence of rational investors and an efficient market. Even if there are irrational investors in the market, traditional finance believes that the random occurrence of irrational behavior demonstrated by individuals, not by groups, allows the stock market to retain its efficiency. Traditional finance fails to rationally explain anomalies shown in some studies (*e.g.*, Banz, 1981; Bernard and Thomas, 1990) and behavioral finance, which focuses on changes in psychological status accordingly, tries to describe the causes of anomalies as irrational behavior and long-time inefficiency. According to behavioral finance, humans are prone to group mistakes and the behavior demonstrated does not match with the assumption of rationality (Shiller, 1984). Due to the irrationality of herding behavior, it is feasible to conduct a study based on cognitive dissonance proposed by behavioral finance to address the behavioral model of investors as well as the reasons behind it.

For the impact of information shocks on investors' psychology, the occurrence of great events may change the psychological status and investment strategies of investors. In particular, during 2005-2008 both domestic and international great events significantly affected investors' sentiments and trading activities. They not only had huge impacts on investors' confidence but also inevitably triggered the herding inclination of investors' sentiments and trading behavior. Previous literature, such as the study of Tetlock (2007), indicated a surge of stock trading pushed by recent bad news; while Chiang and Zheng (2010) pointed out significant herding behavior in the stock market instigated by great events. Since a great event is the possible cause of herding behavior, this study investigates the influence of great events on herding behavior and inclination of investors' sentiments toward herding in order to more comprehensively understand herding behavior.

The purpose of this study is to investigate the influence of the three great events that happened during 2005-2008 on herding behavior and investors' sentiments. Compared to previous literature, this study has five features: First, this study conducts an empirical study with high frequency intraday data at 1-minute, 5-minute, and 10-minute intervals, which is different from the daily or monthly data used by earlier studies, in order to examine the intraday herding tendency of investors' sentiments and trading behavior. Second, we apply two measures of investors' trading behavior to avoid the contamination of the bull-bear market cycle. Third, although previous literature pointed out the influence of herding behavior and investors' sentiments on share price performance, they rarely addressed the interdependence among investors' sentiments, herding behavior, and share price performance. Thus, in order to further understand the above interdependence, this study explores the lead-lag relationship among trading behavior, investors' sentiments, and share price performance. Fourth, in lieu of the impact exerted by recent domestic and international great events on the stock market, this study examines the influence of great events on the herding tendency and lead-lag relationship. Finally, cognitive dissonance is used by this study to explain the demonstration of herding tendency of trading behavior and investors' sentiments as well as the influential factors of significant lead-lag effect.

The contributions of this study are proposed as follows: First, according to the results of the GARCH(1,1) model without a dummy variable of a great event, we compared the differences in empirical findings arising from different frequency data. Among them, like the findings in previous literature of using low frequency daily or monthly data (Kraus and Stoll, 1972; Klemkosky, 1977; Choe, Kho, and Stulz, 1999; Ennis and Sebastian, 2003; Voronkova and Bohl, 2005; Walter and Weber, 2006; Chen, Wang, and Lin, 2008; Boyson, 2010; Demirer, Kutan, and Chen, 2010), our empirical results, with the use of high frequency data, also indicate the significant herding inclination of investors' trading behavior. However, unlike previous literature (Lakonishok, Shleifer, and Vishny, 1992; Keim and Madhavan, 1995; Wermers, 1999; Venezia, Nashikkar, and Shapira, 2011), this study found the failure of previous stock returns to predict current trading behavior. Second, in terms of the influence of great events, we found that before and after the three great events conditional volatility of investors' trading behavior did not generate significant changes but conditional volatility of investors' sentiments changed significantly. In the end, in terms of the lead-lag relationship, our results present that investors' sentiments lead their trading behavior, so good use of investor sentiment variation is beneficial to the understanding of investors' trading behavior and the prediction of herding tendency.

The structure of this study is as follows: The introduction of great events encountered by Taiwan's stock market as well as literature review on the "impact of great events," "herding behavior," and "investors' sentiments," is found in the next section. Section 3 describes the methodologies and data adopted by this study, while Section 4 presents the empirical results of this study. The robust analyses with the use of 5-minute and 10-minute intraday data, as well as relative bid and ask volumes, are conducted in Section 5. The final section is the conclusion and suggestions of this study.

2. Great Events and Literature Review

2.1. Great Events during 2005-2008 and Literature Review on the Impact of Great Events

Along with rapid dissemination of information and flow of international capital, the interdependence of stock markets in each country has also increased. This high interdependence reacts to changes in the share price in each market and also results in the herding behavior of investors in various countries. Due to the significant impact of great events on investors' sentiments and stock price volatility, these events may also influence the correlation of share price changes in each market as well as investors' herding tendency. In a review of the great events that happened during 2005-2008, we identify the most influential ones as, "the plea for a takeover by the Financial Supervisory Commission (FSC) of the Chinese Bank due to a bank run on January 6, 2007," "the supportive effort of the US Fed to fill in funds to save its banks from the subprime mortgage crisis on August 11, 2007 (this event later triggered the global financial turmoil)," and "the second regime change in Taiwan on March 22, 2008." On the first business day after the Chinese Bank event (on January 8, 2007), contrary to the previous soaring trend, the Taiwan Stock Exchange Capitalization Weighed Index (TAIEX) saw a drop and closed down 98.86 points. This was led by a decrease in financial stocks' prices due to the loss of investors' confidence. The US subprime mortgage crisis on August 11, 2007 resulted in a drop of the TAIEX by about 300 points, while on the first business day after the supportive effort made by the Fed significant sell-off pressure was still observed due to the influences of the US subprime mortgage crisis and systematic risks of the global stock market. Fortunately, funds used to stabilize the stock market worked to increase stock prices and the TAIEX closed at the same level as the previous business day. Due to the election result corresponding to the general prediction, there was a significantly optimistic inclination of investors' attitude toward the second regime change in Taiwan on March 22, 2008 that boosted stock prices. The TAIEX, on the next business day, soared 340.36 points and the increase percentage of the day reached to 3.99%.

In lieu of the possible influence of great events on stock price and investors' behavior, previous literature addressed the influence of great events on stock price. Among which, some indicated the significant impact of great events on the stock market. For example, Niederhoffer (1971) investigated the headlines of the New York Times and found dramatic variation in stock prices on the great event day and the following day while Tetlock (2007) presented the significant influence of bad news of a recent great event on trading volume. Chiang and Zheng (2010) pointed out the result of herding behavior in countries experiencing a financial crisis. But Choe, Kho, and Stulz (1999) and Bowe and Domuta (2004) came to a different conclusion and suggested that the great event (the Asian financial crisis) did not trigger herding tendency among investors. Although the previous literature already focused on the influence of great events, different attributes (such as economic and political) of great events result in different types of impact to the stock market. The discussion on the influence of both economic events (subprime mortgage crisis and bank run) as well as political events (regime change) on stock returns, trading behavior, and investors' sentiments shall be able to expand the research scope of existing literature.

2.2. Literature Review on Herding Behavior

The practical observation of the financial market indicated that an investor often gave up his/her original investment strategies and chose to follow strategies adopted by the majority investors and held identical or similar financial assets as the majority did to demonstrate herding behavior. Herding behavior has been demonstrated due to the common decision making and investment direction adopted by the majority investors during a certain period of time, and this herding inclination results in dramatic price volatility of the financial market. In order to deeply understand the impact of herding behavior on trading activities in the financial market, since the 1970s, a couple of scholars began to study herding behavior of fund managers. Kraus and Stoll (1972), as well as Klemkosky (1977), in their empirical studies surveyed the US mutual fund industry and found herding behavior of followers for stock buying while Wermers (1999) found that the herding behavior of the US mutual fund managers accelerate the price adjustment process. After the identification of herding behavior among fund managers, earlier studies also attributed this herding behavior to positive feedback trading. Lakonishok, Shleifer, and Vishny (1992) pointed out the observation of herding behavior and positive feedback trading only among small stocks in the US market and that they do not increase volatility of stock prices. Kim and Wei (2002) indicated positive feedback trading and significant herding behavior of foreign investors before an Asian financial crisis, but weakened herding behavior and disappearance of positive feedback trading during an Asian financial crisis.

As presented in the review of literature on herding behavior, previous studies mainly examined the US financial market. However, in recent years, some studies (Bowe and Domuta, 2004; Voronkova and Bohl, 2005; Li and Laih, 2005; Walter and Weber, 2006; Lu and Li, 2008; Chen, Wang, and Lin, 2008; Zhou and Lai, 2009) have become concerned with the influence of herding behavior on the different levels of market sophistication and have focused on herding behavior other than in the US financial market. Chang, Cheng, and Khorana (2000) investigated the herding tendency in markets with different levels of sophistication and identified non-herding behavior in the US and Hong Kong stock markets, partial herding behavior in Japan, and significant herding behavior in emerging markets including South Korea and Taiwan. Huang and Chiang (2003) showed the asymmetry of herding tendency between bull markets and bear markets in both developed and emerging countries. Demirer, Kutan, and Chen (2010) found the existence of herding behavior in emerging countries and a more significant herding effect in bear markets. In addition to the focus on herding behavior in less sophisticated markets, positive feedback trading and the process of price adjustment has become the concern of both academia and the industry and there is concern about how to reduce the negative influence of herding behavior. Therefore, recent studies also began to explore how to avoid herding behavior of mutual fund managers. Dass, Massa, and Patgiri (2008) and Boyson (2010) revealed the reduction of herding behavior of fund managers with incentives in trust contracts and the avoidance of overburdened risks of fund holders due to the herding behavior of fund managers.

To sum up, we conclude: First, although the majority of earlier studies found evidence of significant herding behavior among mutual funds, foreign institutional investors, or aggregate investors, they mainly adopted low frequency daily or monthly data for empirical analysis and the use of higher frequency intraday data would benefit the identification of herding behavior within the shorter period of time. Second, previous literature focused more on the herding tendency of investors' trading behavior, but the herding attitude of investors is the reflection of their psychological status, and the investigation of the inclination of investors' sentiments toward herding would help to improve research contributions.

2.3. Literature Review on Investors' Sentiments

Herding behavior is irrational and investors demonstrate their irrational attitude in trading activities as well as sentiments. Unlike the suggestion of market efficiency and rationality hypothesis proposed in traditional finance, behavioral finance holds different perspectives and assumes the domination of investor behavior by psychological pitfalls and the evidence of irrationality among investors from historical examples. Among which, practical examples of the investors' herding tendency include the rush of investors toward high tech stocks between 1970-1980, the favor over internet stocks between 1990-2000, and a preference of biotechnology and alternative energy stocks in recent years that are against the proposed efficient market hypothesis. Investors continuously demonstrate herding behavior toward certain stocks resulting in stock market bubbles. For the cause of herding behavior, positive feedback trading plays a key role in the development of herding behavior among investors and it helps to explain the fever of irrational investors that drives unbelievable soaring prices of certain stocks. Positive feedback trading, that is to say, implies the domination of investors' trading behavior by their psychological factors (*e.g.*, investors' sentiments) that is reflected in excessive optimistic or pessimistic attitudes for certain stocks and the sufficient power of investors' sentiments to influence stock prices.

Several earlier studies indicated the high interdependence between investors' sentiments and stock returns or trading activities. For example, Keim and Madhavan (1995) investigated the trading behavior of 21 institutional investors and indicated a significant correlation between trading decision and previous returns. Brown and Cliff (2005) found the influence of investors' sentiments on financial asset valuation as well as negative (positive) correlation between investors' sentiments and returns within the previous several years (errors of valuation model). Chou, Chang, and Lin (2007) pointed out that when a turnover rate is used as the proxy of investors' sentiments, there is a feedback relationship between investors' sentiments and stock returns. While Luo and Li (2008) concluded that when investors demonstrate optimistic sentiment, foreign investors sell stocks, but when investors demonstrate pessimistic sentiment, foreign investors buy stocks. Furthermore, Baker and Stein (2004), Baker and Wurgler (2006), and Kaustia and Knupfer (2008) showed the significant prediction ability of investors' sentiments for stock returns or investors' trading behavior. In recent years, some scholars have been devoted to the exploration of the relationship between investors' sentiments and herding behavior. Chiang, Tsai, and Lee (2011) revealed a push in the herding behavior of foreign institutional investors for soaring prices of construction stocks in Taiwan and the high correlation between bubbles of construction stock prices and sentiments of foreign institutional investors. Liao, Huang, and Wu (2011) found evidence to explain the herding behavior of mutual fund managers toward selling from investors' sentiments.

As shown in the literature review on investors' sentiments, investigations on the relationship between investors' sentiments and herding behavior has become a popular focus of research in recent years, but most studies used low frequency data to examine the issue and there has been a lack of discussions on the herding tendency of investors' sentiments. As a result, this study explores the intraday relationship among great events, investors' sentiments, and herding behavior with high-frequency 1-minute based data to further understand the interdependence between investors' psychological status and trading activities.

3. Data and Methodologies

3.1. Source of Data and Sample Processing

This study adopts 1-minute ask volume, 1-minute bid volume, the 1-minute TAIEX returns, and the 1-minute buy-sell imbalance (BSI) as research variables to explore the influence of great events on investors' herding behavior, herding tendency of investors' sentiments, and lead-lag relationships. Among them, the BSI is introduced as a proxy of investors' sentiments. It is acquired from the calculation of bid and ask volumes. In detail, this study first obtains the intraday data for bid volume, ask volume, and TAIEX "per minute" (for example, data at 9:00, 9:01, 9:02...) from the Taiwan Stock Exchange Corporation (TWSE) and data bank of the Taiwan Economic Journal. Then, we calculate the TAIEX returns and BSI per minute using the above data. That means this study adopts 1-minute intraday data during the normal business hours of the TWSE for the empirical study. The research period was from 9:00 am on January 2, 2005 to 1:30 pm on December 31, 2008 (at the interval, January 1, 2005 was a non-business day, and the interval lasted for four years). However, due to the one time record for trading between 1:25 pm and 1:30 pm in the TWSE, there is only one observation for each variable. In total, there have been 266 observations for each variable within one business day resulting in 263,606 observations for each variable during the research period.

The high frequency intraday data adopted by this study uses 1- minute bid volume, 1-minute ask volume, 1-minute TAIEX returns, and 1-minute BSI as an observation; among which, bid volume and ask volume are presented as proxy of investors' trading behavior (the willingness to buy/sell stocks) while BSI serves as that for investors' sentiments. We refer to the suggestion of Clarke and Statman

(1998) and Kumar and Lee (2006) for the selection of BSI as a proxy for investors' sentiments. The calculation of BSI is shown below:

$$BSI_t = \frac{\mathrm{Bid}_t - Ask_t}{\mathrm{Bid}_t + Ask_t}, \tag{1}$$

where, BSI_t is BSI for minute t, Bid_t is bid volume for minute t, and Ask_t is ask volume for minute t.

3.2. Selection of Great Events

During the research period between 9:00 am on January 2, 2005 and 1:30 pm on December 31, 2008, some great events that influenced normal trading activities occurred, but due to the use of high frequency intraday data for the empirical analysis in this study, exact times needed to be known (such as when did this great event occur?). Definitely, it is not easy to acquire the exact time rather than date of the great event. In order to solve the issue and determine the importance of each great event during the research period, three great events occurring during weekends Taiwan time are selected as the research subjects. Weekends are non-business days for the Taiwanese stock market and as a result, this study defines the occurrence of great events at the opening time (at 9:00 am) of the next business day after the day when the great events occurred. The great events selected by this study are introduced as below:

(1) On January 6, 2007 (Saturday), the Financial Supervisory Commission officially took over the Chinese Bank. Because January 6^{th} and 7^{th} are non-business days for the Taiwanese stock market, as stated earlier, this study defined the occurrence time of the Chinese Bank event as 9:00 am on January 8, 2007 (the opening time of the next business day after the day when the great event occurred).

(2) On August 11, 2007 (Saturday), the US subprime mortgage crisis unfolded and central banks around the world injected over US$326.2 billion to rescue stock markets and the US Fed allocated a total capital of US$ 38 billion to banks in order to stabilize its stock market. Because the rescues occurred on a non-business day for the Taiwanese

stock market, this study defined the occurrence time as 9:00 am on August 13, 2007. Undoubtedly, it is not easy to "accurately" define the unfolding time of the US subprime mortgage crisis, and there has been a lack of consensus on "the exact occurrence time" of the subprime mortgage crisis from the academic and industry perspectives. Although it is not easy to overcome the challenge of the occurrence time, official rescues (from the US Fed) exhibits the most obvious influence of the subprime mortgage crisis on the US stock market. Hence, this study regards, "the allocation of US$38 billion by the Fed to banks due to the subprime mortgage crisis," as the event day of the "subprime mortgage crisis."

(3) On March 22, 2008 (Saturday), the presidential candidate of the Kuomintang (KMT) was elected as the 12th ROC President. This marked the second regime change in the political history of Taiwan. Because the presidential election day was a non-business day for the Taiwanese stock market, the opening time of the next business day after the presidential election day is considered to be the occurrence time of the second regime change event (*i.e.*, 9:00 am on March 24, 2008).

3.3. Unit Root Test

In order to avoid the spurious regression results caused by non-stationary time series data, this study needs to examine four entries of time series data, 1-minute bid volume, 1-minute ask volume, 1-minute TAIEX returns, and 1-minute BSI for stationary patterns before conducting econometrics analysis. As proposed by Said and Dickey (1984) an Augmented Dickey-Fuller (ADF) unit root test and Schwarz's (1978) Criterion (SC) that determine the optimal lag length are used to examine the stationary pattern of above time series data. If the result of the ADF unit root test indicates the above time series data as non-stationary, then time series data need to begin difference processing until stationary data structure is presented. ADF unit root test adopted by this study including, "model without drift term and trend," "model with drift term and without trend," and "model with drift term and trend," is described as bellow:

$$\Delta S_{m,t} = \omega_a S_{m,t} + \sum_{j=1}^{h} \nu_{a,j} \Delta S_{m,t-j} + \xi_{a,t}, \quad m = 1,2,3,4 \tag{2}$$

$$\Delta S_{m,t} = \mu_b + \omega_b S_{m,t} + \sum_{j=1}^{h} \nu_{b,j} \Delta S_{m,t-j} + \xi_{b,t}, \quad m = 1,2,3,4 \tag{3}$$

$$\Delta S_{m,t} = \mu_c + \chi \mathrm{T} + \omega_c S_{m,t} + \sum_{j=1}^{h} \nu_{c,j} \Delta S_{m,t-j} + \xi_{c,t}, \quad m = 1,2,3,4 \tag{4}$$

where, the null hypothesis of Equation (2) to (4) is assumed as the existence of a unit root for $S_{m,t}$ (that is, $\omega_a = 0$, $\omega_b = 0$ and $\omega_c = 0$). Δ is the symbol of difference processing. h is the optimal lag length determined by SC. T refers to trend. μ_b and μ_c are drift terms. ω_a, ω_b, ω_c, $\nu_{a,j}$, $\nu_{b,j}$, $\nu_{c,j}$, and χ are regression coefficients. $\xi_{a,t}$, $\xi_{b,t}$, and $\xi_{c,t}$ are innovations (residuals). $S_{1,t}$ is bid volume for minute t. $S_{2,t}$ is ask volume for minute t. $S_{3,t}$ is BSI for minute t. $S_{4,t}$ is the TAIEX returns for minute t.

3.4. GARCH(1,1) Model

There are three major purposes of this study: The first purpose is to examine the herding tendency of investors' behavior and sentiments; the second is to investigate the influence of great events on herding behavior and investors' sentiments; and the last is to explore the lead-lag relationship among investors' behavior, investors' sentiments, and stock returns. Previous studies (Kuo and Tsai, 2003; Tan *et al.*, 2008; Venezia, Nashikkar, and Shapira, 2011) have been conducted using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model proposed by Bollersler (1986) for the inspection of herding behavior. The GARCH model has been known for its advantage over the description of clustering volatility and fat tails of financial asset returns, as well as the acquisition of more accurate results (Bollersler, 1986). Therefore, this study adopts the GARCH(1,1) model of Kuo and Tsai (2003) provided below for, "the examination on the herding inclination of investors' behavior and sentiments," and "the investigation on the influence of a great event on herding behavior and investors' sentiments:"

$$S_{m,t} = \beta_0 + \beta_1 S_{m,t-1} + \beta_2 S_{4,t-1} + \varepsilon_t, \quad m = 1,2,3 \tag{5}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2, \tag{6}$$

where, $S_{m,t}$ refers to bid volume, ask volume, and BSI for minute t, respectively (m=1, 2, 3). $S_{m,t-1}$ refers to bid volume, ask volume, and BSI for minute t-1, respectively (Since the one-period lag partial autocorrelation coefficients of the 1-minute bid volume, 1-minute ask volume, and 1-minute BSI are significantly different from zero and the result of the ADF unit root test in Table 1 indicates that the optimal lag length of most models is 1, this study only includes $S_{m,t-1}$ in the GARCH model). $S_{4,t-1}$ is the TAIEX returns for minute t-1. ε_t is an error term for minute t. α_1, β_1 and β_2 are regression coefficients. α_0 and β_0 are drift terms. σ_t^2 and σ_{t-1}^2 are, respectively, the conditional variances of ε_t and ε_{t-1}.

Based on the above GARCH(1,1) model, we examine the herding tendency of bid volume, ask volume, and BSI for the current minute (minute t) and the previous minute (minute t-1) under the allowed autoregressive conditional heteroskedasticity and the inclusion of the previous TAIEX returns. From Equations (5) and (6), a significant positive β_1 indicates the herding tendency of investors' trading behavior or investors' sentiments. That is to say, if there is a larger bid volume, ask volume, or BSI for minute t-1, then the bid volume, ask volume, or BSI for minute t increases. Notably, BSI is a proxy for investors' sentiments and accordingly a significant positive β_1 also indicates the more exciting (or optimistic) attitudes of investors for minute t-1, the more exciting (or optimistic) attitudes they demonstrate for minute t.

This study also utilizes a dummy variable to investigate the influence of great events on the herding tendency of trading behavior and investors' sentiments. We modify Equations (5) and (6) as below:

$$S_{m,t} = b_0 + b_1 S_{m,t-1} + b_2 S_{4,t-1} + e_t, \tag{7}$$

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \sigma_{t-1}^2 + a_3 D_t, \tag{8}$$

where, D_t is a dummy variable and this study assumes that before great events, $D_t = 0$ and after great events, $D_t = 1$. e_t is a residual term for minute t. b_0, b_1, b_2, a_0, a_1, a_2 and a_3 are regression coefficients and among them a_3 measures the influence of a great event on conditional heteroscedastic volatility. When a_3 is a statistically significant positive value, conditional heteroscedastic volatility of bid volume, ask volume, or BSI after a great event is significantly higher than that before a great event.

3.5. Investigation on the Lead-Lag Relationship

Earlier studies (Malliaris and Urrutia, 1992; Parhizgari, Dandapani, and Bhattacharya, 1994; Kavussanos and Visvikis, 2004; Yang, Balyeat, and Leatham, 2005; Chou, Chang, and Lin, 2007; Kavussanos, Visvikis, and Alexakis, 2008; Goyenko and Ukhov, 2009) mostly adopted Granger causality as suggested by Granger (1969) to explore the lead-lag relationship between two time series data (two financial asset return data). Granger causality uses observed return series for empirical analysis and determines the causal relationship of two time series data from the perspective of prediction. In other words, Granger (1969) proposes the use of mutual prediction between two observed series to explain the lead-lag relationship. However, Stoll and Whaley (1990) found that the serial correlation of financial asset returns comes mainly from the infrequent trading and bid-ask spread. The serial correlation caused by infrequent trading and bid-ask spread decreases the accuracy of the result of econometrics analysis. Thus, if the observed return series with autocorrelation and Granger causality are used for empirical analysis, they both may contaminate the finding of the lead-lag relationship. As presented in previous literature (Stoll and Whaley, 1990; Chan, 1992; Shyy, Vijayraghavan, and Scott-Quinn, 1996), the research model of the lead-lag relationship shall consider the autocorrelation of observed return series. Chan (1992) suggested the use of a proxy without autocorrelation to replace the observed return series for the lead-lag relationship investigation.

Although Stoll and Whaley (1990) pointed out the presentation of infrequent trading and bid-ask spread effect in the format of ARMA(p,q), Chan (1992) found that MA(q) representing bid-ask spread is insignificant and close to 0, so MA(q) shall be excluded and only the infrequent trading effect shown as AR(p) shall be used. Meanwhile, residual term (innovation) should be used as the proxy for financial asset returns. Through the AR(p) of the proxy, infrequent trading effect can be modified. Chan (1992), Abhyankar (1995), Iihara, Kato, and Tokunaga (1996), Chiang and Fong (2001), Gwilym and Buckle (2001), and Chang *et al.* (2011) also used similar methods to modify the infrequent trading effect.

In addition to the financial asset returns series (*e.g.*, stock returns series), the infrequent trading effect may appear in the data of bid volume, ask volume, and BSI. In order to decline the serial correlated faced in the investigation of lead-lag relationship, this study referred to Chan (1992), Chiang and Fong (2001), and Chang *et al.* (2011) to extract AR(p) representing infrequent trading effect from time series and uses the innovation as the proxy of observed return series for the investigation of lead-lag relationship. The description is presented in Equation (9):

$$S_{m,t} = A_0 + \sum_{l=1}^{p} \mathrm{B}_l S_{m,t-l} + s_{m,t} \;, \quad m = 1,2,3,4 \tag{9}$$

where, A_0 and B_l are regression coefficients. $s_{m,t}$ is the proxy of $S_{m,t}$ (innovation of regression model). p is the optimal lag length determined by the SC.

After the resolution of issues regarding the influence of infrequent trading and serial correlation, this study applies the methods of Stoll and Whaley (1990) and Chang *et al.* (2011) to construct a lead-lag relationship model of investors' sentiments, investors' trading behavior, and stock returns. Furthermore, this study also refers to Chiang and Fong (2001) and Chang *et al.* (2011) to assume three periods of the lead-lag length where if the regression coefficients of these three periods are all significantly different from zero, this study will add the number of periods until any coefficient is insignificantly different from zero. The model of the lead-lag relationship between investors' sentiments, investors' trading behavior, and stock returns is shown as in Equation (10) to (12):

$$s_{3,t} = C1_0 + \sum_{k=-3}^{3} D1_k s_{1,t+k} + \tau 1_t \tag{10}$$

$$s_{3,t} = C2_0 + \sum_{k=-3}^{3} D2_k s_{2,t+k} + \tau 2_t \tag{11}$$

$$s_{3,t} = C3_0 + \sum_{k=-3}^{3} D3_k s_{4,t+k} + \tau 3_t \tag{12}$$

where, $C1_0$, $C2_0$, $C3_0$, $D1_k$, $D2_k$ and $D3_k$ are regression coefficients and $\tau 1_t$, $\tau 2_t$ and $\tau 3_t$ are innovations. In addition, when $k = 1, 2, 3$ and $D1_k$, $D2_k$, or $D3_k$ are significantly different from zero, investors' sentiments lead investors' trading behavior (or stock returns) by k periods while on the contrary, when $k = -1, -2, -3$ and $D1_k$, $D2_k$ or $D3_k$ are significantly different from zero, investors' sentiments lag investors' trading behavior (or stock returns) by k periods.

4. Empirical Results

4.1. Results of the Unit Root Test

In order to ensure the accuracy of econometrics analysis and to avoid spurious regression, this study uses the ADF unit root test on, "model without drift term and trend," "model with drift term and without trend," and "model with drift term and trend," to examine the stationary pattern of the four time series data including bid volume, ask volume, TAIEX returns, and BSI. In addition to ADF unit root test, we use the DF unit root test (Dickey and Fuller, 1979) to investigate whether the four time series data are stationary. If the results of DF and ADF unit root tests indicate that the level value of bid volume, ask volume, TAIEX returns, and BSI are all stationary, this study then uses the level value of the four time series data for econometrics analysis; on the contrary, if any of the level value of the four time series data is indicated as non-stationary, the first order difference will be acquired from the level value of non-stationary data. We examine the stationary pattern of the first order difference data and repeat the above steps until the four time series data are all indicated as stationary. Table 1 shows the results of the DF and ADF unit root tests.

From the results of the DF unit root test indicated in Table 1, for the level value of bid volume, ask volume, TAIEX returns, and BSI, the null hypothesis of having a unit root is rejected at the 1% significant level and the four time series data show stationary patterns in the three different models. Furthermore, the results of the ADF unit root test in Table 1 also showed that, as that of DF unit root test, the unit-root null hypotheses for the four time series data are all rejected at the 1% significant level and they are all stationary with the three different models. Thus, according to the results of the DF and ADF unit root tests, this study is able to directly apply the level value of the intraday data including bid volume, ask volume, TAIEX returns, and BSI to the GARCH(1,1) analysis and the investigation of a lead-lag relationship.

Table 1

The Results of DF and ADF Unit Root Tests

Models	Bid volume		Ask volume		TAIEX returns		BSI	
	DF	ADF	DF	ADF	DF	ADF	DF	ADF
Model 1	-106.45*	-56.14* (h=1)	-92.79*	-54.36* (h=1)	-195.50*	-74.56* (h=1)	-486.33*	-248.49* (h=1)
Model 2	-168.61*	-94.45* (h=1)	-167.05*	-98.14* (h=1)	-196.86*	-75.40* (h=1)	-486.33*	-248.49* (h=2)
Model 3	-175.72*	-99.60* (h=1)	-176.58*	-102.02* (h=1)	-196.91*	-76.87* (h=1)	-486.33*	-248.49* (h=2)

Note: Model 1 refers to the model without drift term and trend. Model 2 refers to the model with drift term and without trend. Model 3 refers to the model with drift term and trend. "*" refers to significant at 1% level. h is the optimal lag length determined by SC. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 263,606.

4.2. Investors' Herding Behavior and Herding Tendency of Investors' Sentiments

Although previous literature (Huang and Chiang, 2003; Li and Laih, 2005; Chen, Wang, and Lin, 2008; Lu and Li, 2008) indicated the herding behavior of investors in the Taiwanese stock market, most used low frequency daily or monthly data for empirical analysis. Adopting high frequency intraday data for empirical analysis is helpful to examine the herding tendency of investors within the short period of time. In order to explore whether the herding behavior is exhibited in high frequency data, this study uses 1-minute intraday data for the empirical investigation. In addition to the examination of investors' herding behavior, as indicated by earlier studies (Kaustia and Knupfer, 2008; Liao, Huang, and Wu, 2011), investors' sentiments influence their decision making or herding behavior. This study also examines whether investors' sentiments tend to move in herds. In detail, this study applies the GARCH(1,1) model to investigate the herding tendency of investors' trading behavior and sentiments. Table 2 shows the results of the GARCH(1,1) analysis.

Table 2 shows an insignificant positive regression coefficient of the BSI for the previous minute. This means that there is a lack of herding tendency for investors' sentiments. In addition, Table 2 presents that the regression coefficients of both bid and ask volumes for the previous minute are significantly positive. This means that both stock-buying and -selling behavior follow the herd. In other words, the bid (ask) volume for the previous minute made a significant positive contribution to the bid (ask) volume for the current minute. In the end, the insignificant regression coefficients of the TAIEX returns for the previous minute on Table 2 indicate that the TAIEX returns for the previous minute is not a significant predictor for the bid volume, ask volume, and BSI for the current minute. That is, stock price performance for the previous minute has no influence on investors' sentiments and trading behavior for the current minute.

The above results point out the significant and insignificant herding tendency for investors' trading behavior and investors' sentiments, respectively. Furthermore, the stock price performance for the previous minute does not play an important role in the stock-buying behavior, stock-selling behavior, and investors' sentiments for the current minute. Overall, Table 2 reveals the supportive evidence of investors' herding behavior corresponding to the findings of previous literature (Kraus and Stoll, 1972; Klemkosky, 1977; Choe, Kho, and Stulz, 1999; Ennis and Sebastian, 2003; Voronkova and Bohl, 2005; Walter and Weber, 2006; Chen, Wang, and Lin, 2008; Boyson, 2010; Demirer, Kutan, and Chen, 2010). However, Table 2 shows the failure of the share price performance for the previous minute to predict the stock trading behavior for the current minute contradicting, "the significant influence of the previous stock returns on current investors' decision or current herding inclination," as suggested in earlier studies (Lakonishok, Shleifer, and Vishny, 1992; Keim and Madhavan, 1995; Wermers, 1999; Venezia, Nashikkar, and Shapira, 2011). The causes of different findings between this study and previous literature may be the difference of data frequency. Because this study uses 1-minute intraday data for empirical analysis and after submitting buy/sell orders, the majority of investors spent more than one minute waiting for a transaction, the stock price performance for the previous minute cannot immediately be reflected in trading behavior and investors' sentiments. Meanwhile, the reason for insignificant herding tendency of investors' sentiments is possibly due to the influence of cognitive dissonance and high frequency data type. Relevant studies on behavioral finance (Hong and Stein, 1999; Hong, Lim, and Stein, 2000) identified the initial underreaction and subsequent overreaction

Table 2

The Herding Tendency of Bid Volume, Ask Volume, and Investors' Sentiments in Taiwan's Stock Market

Variables	Bid volume for minute t	Ask volume for minute t	BSI for minute t
Intercept (β_0)	15013.4990 (307.5323)*	9945.0862 (323.2182)*	0.0010 (0.1841)
Bid volume for minute t-1	0.0898 (72.2109)*		
Ask volume for minute t-1		0.5669 (40.6065)*	
BSI for minute t-1			0.0499 (1.3499)
TAIEX returns for minute t-1	0.0003 (0.0005)	-0.4406 (-1.1829)	-0.0001 (-0.2074)
Intercept (α_0)	1.53×10^{9} (52.0484)*	8.63×10^{8} (87.2502)*	4.08×10^{8} (152.6897)*
Unconditional variance	0.3788 (138.0765)*	0.4528 (477.9216)*	0.0002 (4.0199)*
Conditional variance	-0.0012 (-0.0632)	0.0098 (35.4426)*	-0.0005 (-0.1897)

Note: "*" refers to significant at 1% significance level. The number in parentheses is t-statistic. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 263,606.

of investors toward certain information released and thus, for 1-minute intraday data, investors' respond with "initial underreaction to certain information" as well as inconsistent perception about certain information content. Therefore, it is more likely for higher frequency data (such as intraday data) to provide evidence to support the lack of herding tendency of investors' sentiments.

4.3. Influence of Great Events on the Herding Tendency of Trading Behavior and Investors' Sentiments

Finance textbooks state that stock prices are mainly driven by various types of information shocks, including great events. That is, the information shocks, including great events, not only directly influence investors' psychological status and behavioral decision, but also indirectly determine stock prices. The concrete objectives for investors' psychological status and behavioral decisions are respectively investors' sentiments and trading activities. This study applies the GARCH(1,1) model with the dummies of great events to investigate further the influence of great events on investors' sentiments and trading activities. The results are shown in Table 3 to 5.

The influence of, "the Chinese Bank taken over by the Financial Supervisory Commission," on the tendency of bid volume, ask volume, and BSI is first addressed in Table 3, which indicates the significant positive regression coefficients of bid volume, ask volume, and BSI for the previous minute. This shows that when the GARCH(1,1) model includes the dummy variable of, "a run on the Chinese Bank after it was taken over by the Financial Supervisory Commission," the significant herding tendency of investors' behavior and sentiments are observed. Furthermore, the results of the GARCH(1,1) model with dependent variables of current bid volume, current ask volume, and current BSI (shown in Table 3), all indicate that regression coefficient of the TAIEX returns for the previous minute is insignificantly different from zero. In other words, there is no statistically significant relationship between the previous stock returns and current investors' behavior or sentiments. Finally, in Table 3, the result of the GARCH(1,1) model with dependent variables of current BSI presents that the coefficient of dummy variable of the Chinese Bank event is a significantly positive value. This means that after a run on the Chinese Bank after it was taken over by the Financial Supervisory Commission, conditional volatility of BSI significantly increased, as did investors' sentiments.

Table 3
The Influence of the Chinese Bank Taken Over by the Financial Supervisory Commission on the Herding Tendency of Bid Volume, Ask Volume, and BSI

Variables	Bid volume for minute *t*	Ask volume for minute *t*	BSI for minute *t*
Intercept (b_0)	7734.6745 (549.4526)*	15018.1681 (318.4811)*	0.0012 (0.1989)
Bid volume for minute *t*-1	0.4541 (364.8873)*		
Ask volume for minute *t*-1		0.1168 (91.4603)*	
BSI for minute *t*-1			0.4206 (46.7730)*
TAIEX returns for minute *t*-1	-0.1952 (-0.9780)	-0.0007 (-0.0013)	-0.00002 (-0.0156)
Intercept (a_0)	1.17×10^9 (76.5783)*	1.48×10^9 (61.3601)*	4.51×10^9 (57.3116)*
Unconditional variance	0.9245 (310.3562)*	0.4912 (163.3546)*	0.0086 (16.9977)*
Conditional variance	0.2094 (206.4051)*	-0.0002 (-0.0146)	0.0515 (15.4416)*
Dummy (great events)	7949.2758 (0.1783)	-5443.1589 (-0.0195)	0.1895 (295.2756)*

Note: "*" refers to significant at 1% significance level. The number in parentheses is *t*-statistic. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 263,606.

Table 4

The Influence of the US Subprime Mortgage Crisis on the Herding Tendency of Bid Volume, Ask Volume, and BSI

Variables	Bid volume for minute t	Ask volume for minute t	BSI for minute t
Intercept (b_0)	9494.0178 (761.1549)*	14908.5050 (329.1107)*	0.0010 (0.1606)
Bid volume for minute t-1	0.2620 (285.0315)*		
Ask volume for minute t-1		0.0687 (54.4322)*	
BSI for minute t-1			0.2672 (35.7871)*
TAIEX returns for minute t-1	-0.1311 (-0.8700)	-0.0021 (-0.0055)	0.00001 (0.0059)
Intercept (a_0)	5.37×10^8 (41.0527)*	1.25×10^9 (63.0147)*	3.42×10^8 (86.9280)*
Unconditional variance	1.2346 (409.1903)*	0.2790 (581.3390)*	0.0114 (14.4851)*
Conditional variance	0.1528 (255.7239)*	0.0010 (0.0607)	-0.0057 (-0.8536)
Dummy (great events)	-33869.8477 (-1.0513)	51247.5688 (0.2813)	0.0034 (18.9963)*

Note: "*" refers to significant at 1% significance level. The number in parentheses is t-statistic. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 263,606.

In regards to the influence of "the US subprime mortgage crisis" on the herding tendency of bid volume, ask volume, and BSI, Table 4 reveals that the coefficients of previous bid volume, previous ask volume, and previous BSI are all significantly greater than zero. The above results implies that when the GARCH(1,1) model includes a dummy variable for the US subprime mortgage crisis, trading behavior and investors' sentiments for the current minute follow significantly those for the pervious minute, indicating the herding effect. Moreover, in Table 4, the results of the GARCH(1,1) models with dependent variables of current bid volume, current ask volume, and current BSI all indicate that the coefficient of the TAIEX returns for the previous minute is insignificantly different from zero. This means that the previous share price performance is not a significant predictor for current trading behavior and current investors' sentiments. In the end, the result of the GARCH(1,1) model with dependent variables of current BSI (shown in Table 4) reveals that the coefficient of dummy variable of the US subprime mortgage crisis is a significantly positive value. That is, the conditional volatility of BSI (investors' sentiments) after the US subprime mortgage crisis is significantly higher than that before the US subprime mortgage crisis.

Table 5
The Influence of the Second Regime Change on the Herding Tendency of Bid Volume, Ask Volume, and BSI

Variables	Bid volume for minute t	Ask volume for minute t	BSI for minute t
Intercept (b_0)	15018.1683 (314.4810)*	14908.5059 (329.1371)*	0.0008 (0.1214)
Bid volume for minute t-1	0.1168 (91.4928)*		
Ask volume for minute t-1		0.0686 (54.3840)*	
BSI for minute t-1			0.2691 (36.1763)*
TAIEX returns for minute t-1	-0.0009 (-0.0017)	-0.0021 (-0.0055)	-0.0003 (-0.7829)
Intercept (a_0)	1.48×10^9 (61.3614)*	1.25×10^9 (63.0354)*	8.15×10^8 (76.5189)*
Unconditional variance	0.4913 (163.5131)*	0.2788 (581.7806)*	0.0034 (13.5688)*
Conditional variance	-0.0002 (-0.0145)	0.0010 (0.0611)	-0.0350 (-4.2931)*
Dummy (great events)	-5454.4251 (-0.0195)	1570.2752 (0.0086)	-0.0244 (-85.2629)*

Note: "*" refers to significant at 1% significance level. The number in parentheses is t-statistic. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 263,606.

As for the influence of "the second regime change" on the herding tendency of bid volume, ask volume, and BSI, the coefficients of previous bid volume, previous ask volume, and previous BSI (shown in Table 5) are all a significant positive value indicating that when the GARCH(1,1) model includes a dummy variable for the second regime change, significant herding inclination of investors' behavior and sentiments are observed. In addition, as shown in Tables 3 and 4, Table 5 presents the insignificant coefficient of the previous TAIEX returns, as well as the failure of the previous share price performance to predict current bid volume, current ask volume, and current BSI. Finally, in Table 5, what deserves our attention is that the result of the GARCH(1,1) model with dependent variables of current BSI indicate a significant negative coefficient of dummy variable of the second regime change. This is very evident after the second regime change in which conditional volatility of BSI significantly decreased. In other words, the conditional volatility of investors' sentiments after the second regime change is significantly lower than that before the second regime change.

In total, Tables 3, 4, and 5 indicate that trading behavior of investors has a herding inclination as does investors' sentiments. When the GARCH(1,1) model includes a dummy variable for a great event, trading behavior and investors' sentiments for the current minute are prone to corresponding to those for the previous minute. The above results agree with the herding behavior of investors in countries suffering from the financial crisis, as suggested by Chiang and Zheng (2010). In addition, Tables 3, 4, and 5 present insignificant influence of the previous share price performance on current stock-buying and -selling behavior of investors, as well as investors' sentiments. This shows that compared to the studies of low frequency data, there is a lower correlation between stock returns and investors' behavior or sentiments in intraday studies. Furthermore, Tables 3, 4, and 5 reveal no significant change in the conditional volatility of bid and ask volumes around the three great events. This indicates that the influences of great events on investor behavior are primarily exhibited in the bid and ask volumes and do not change the original volatility trend of bid and ask volumes. This is also consistent with the findings of Choe, Kho, and Stulz (1999) and Bowe and Domuta (2004): Although investors demonstrate herding inclination, the Asian financial crisis did not result in more obvious herding behavior of investors. Finally, Tables 3, 4, and 5 show a significant change in the conditional volatility of BSI after the three great events. The above result implies that after the three great events, investors' sentiments may lead to stock-selling and -buying behavior, as well as result in a more significant variation.

4.4. The Lead-Lag Relationship among Investors' Sentiments, Investors' behavior, and Stock Returns

In order to explore the intraday interdependence among bid volume, ask volume, and BSI, this study refers to a method suggested by Chan (1992), Chiang and Fong (2001), and Chang *et al.* (2011) and uses innovations in Equation (9) for each dependent variable as proxies for observed time series, putting them into Equation (10) to (12). We then assume the lead and lag length of Equation (10) to (12) as three, respectively. In the end, the least square method is used to estimate Equation (10) to (12) and acquire the estimated regression coefficients. Table 6 presents the lead-lag relationship among investors' sentiments, investors' behavior, and the TAIEX returns.

Table 6 shows that first, coefficient $D1_0$ and $D2_0$ are respectively significant positive and negative values (8.29×10^{-6} and -7.83×10^{-6}), indicating a high concurrent correlation between "BSI and bid volume" and "BSI and ask volume." This implies that when investors demonstrate more optimistic sentiment, the bid volume and ask volume show significant increase and decrease, respectively. Secondly, because the statistical significance (the absolute value of *t*-statistic) of coefficients $D1_0$ and $D2_0$ is higher than other coefficients in the regression models, the main interdependence of "BSI and bid volume" and "BSI and ask volume" is the concurrent correlation. Third, coefficients $D1_3$, $D1_2$, $D1_1$, and $D1_{-1}$ are significant positive values. This points out that BSI leads bid volume by three periods (three minutes) but bid volume only leads BSI by one period (one minute). This implies stronger evidence that supports the argument that the, "stock-buying behavior of investors lead investors' sentiments," more than, "investors' sentiments lead stock-buying behavior of investors." Fourth, coefficients $D2_{-3}$, $D2_{-2}$, $D2_{-1}$, $D2_3$, $D2_2$, and $D2_1$ are significantly different from zero. This reveals that BSI leads ask volume by three minutes and ask volume also leads BSI by three minutes, but because the statistical significance of coefficients $D2_{-3}$, $D2_{-2}$, and $D2_{-1}$ is smaller than that of coefficients $D2_3$, $D2_2$, and $D2_1$, "the lead of ask volume by BSI" is more significant than "the lead of BSI by ask volume." In other words, the change in investors' sentiments occurred before they sold stocks.

Finally, what deserves our attention is the empirical result of lead-lag relationship between BSI and stock returns. Table 6 does not find any significant concurrent correlation or lead-lag relationship. This indicates that compared to previous literature (Baker and Wurgler, 2006; Kumar and Lee, 2006; Frazzini and Lamont, 2008) that used lower frequency data (such as daily, monthly, or quarterly data) and found, "the significant influence of investors' sentiments on stock returns," this study uses higher frequency intraday data and does not find evidence to support the prediction of BSI for stock returns. The difference in the above findings may be caused by the difference of data frequencies because this study uses 1-minute intraday data for empirical analysis. The share price changes within 1 minute are usually small and do not significantly affect the current imbalance between the bid and ask volume (*i.e.*, the current BSI). Moreover, due to the limited change of BSI within 1 minute, the TAIEX did not experience a significant variation caused by investors' sentiments within the short period of time. In other words, within a short period of time (one minute), there is low correlation between investors' sentiments and the TAIEX returns.

Table 6

The Empirical Result of Lead-Lag Relationship among Investors' Sentiments, Investors' Trading Behavior, and Stock Returns

Coefficients	BSI and bid volume		BSI and ask volume		BSI and TAIEX returns	
	Estimated value	*t*-statistic	Estimated value	*t*-statistic	Estimated value	*t*-statistic
$C1_0 \sim C3_0$	2.60×10^{-7}	7.77×10^{-5}	3.89×10^{-6}	0.0012	2.85×10^{-6}	0.0009
$D1_{-3} \sim D3_{-3}$	6.68×10^{-7}	1.3954	-1.79×10^{-6}	-3.1401*	-4.93×10^{-6}	-0.0400
$D1_{-2} \sim D3_{-2}$	4.12×10^{-7}	0.8600	-1.32×10^{-6}	-2.3129#	6.06×10^{-6}	0.0489
$D1_{-1} \sim D3_{-1}$	2.23×10^{-6}	4.6593*	-1.25×10^{-6}	-2.1948#	3.80×10^{-6}	0.0304
$D1_0 \sim D3_0$	8.29×10^{-6}	17.1845*	-7.83×10^{-6}	-13.6651*	-9.25×10^{-6}	-0.0726
$D1_1 \sim D3_1$	4.21×10^{-6}	8.7835*	-4.98×10^{-6}	-8.7507*	1.60×10^{-8}	0.0001
$D1_2 \sim D3_2$	3.59×10^{-6}	7.4817*	-4.20×10^{-6}	-7.3911*	1.01×10^{-6}	0.0082
$D1_3 \sim D3_3$	5.11×10^{-6}	10.6622*	-4.42×10^{-6}	-7.7708*	9.39×10^{-7}	0.0076

Note: "*" and "#" refer to significant at 1% and 5% significance levels, respectively. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 263,606.

Overall, Table 6 presents the lead of investors' behavior by investors' sentiments. The change of investors' sentiments helps to understand the trading behavior of investors. Surprisingly, however, this finding contradicts previous literature (Siegel, 1992; Keim and Madhavan, 1995; Baker and Stein, 2004; Brown and Cliff, 2005; Baker and Wurgler, 2006; Chou, Chang, and Lin, 2007) confirming, "the close relevance between investors' sentiments and stock returns." Table 6 shows the failure of investors' sentiments to predict stock price performance. This means that investors' sentiments help to predict the herding behavior of investors but it does not help to improve investment performance, probably for a few reasons, beginning with the influence of data frequency. Because this study uses 1-minute intraday data, and high frequency data helps to identify changes in investors' sentiments and behavior earlier, stock prices need to be determined by matched trading (stock price performance needs to be reacted after a period of time); in other words, investors' sentiments and behavior are voluntary changes and investors may immediately change their sentiments and behavior after receiving information, but stock price is the result of a voluntary change of investors, so it may not reflect the change of investors' sentiments within three minutes. In addition to data frequency, another possible reason is the initial underreaction of investors. When information is released to the stock market, investors, at the initial stage, underreact to the information shock, which results in a gradual change of investors' sentiments and behavior rather than a onetime complete reaction. Thus, stock prices respond more slowly to the influence of information shocks than the reactions of investors' sentiments and behavior, and this causes the insignificant relevance between investors' sentiments and stock prices in high frequency data.

In addition to the above two possible causes, the most likely reason is that within the short period of time investors are not willing to "buy at high prices" and "sell at low prices." When investors' sentiments turn optimistic (when good news is released to the market), although the bid volume and ask volume respectively increase and decrease, investors do not fully recognize the good news within the short period of time and they are not willing to buy at higher bid prices (the bid volume increases but they buy stocks at lower prices). Stock prices, thus, may not soar immediately. Likely, this also occurs when bad news is released to the market, although investors' sentiments turn pessimistic, yet investors are not willing to sell at lower ask prices (the ask volume increases but investors sell stocks at higher prices). This will not drive stock prices down immediately. The above situations are more obviously observed in high frequency intraday data.

5. Robust Analysis

5.1. Empirical Results of 5-minute and 10-minute Intraday Data

In the previous section, this study uses 1-minute intraday data to investigate intraday relationships between great events, herding behavior, and investors' sentiments. While earlier studies on herding behavior mostly used low frequency daily (Choe, Kho, and Stulz, 1999; Voronkova and Bohl, 2005; Chiang and Zheng, 2010; Demirer, Kutan, and Chen, 2010) or monthly (Wermers, 1999; Kim and Wei, 2002; Li and Laih, 2005; Liao, Huang, and Wu, 2011) data for empirical analysis, only a few studies have adopted high frequency intraday data (Gleason, Mathur, and Peterson, 2004; Zhou and Lai, 2009) for their investigation. Due to the inconsistent use of the frequency of intraday data in previous literature, in addition to the 1-intraday data, this study uses 5-minute and 10-minute intraday data to examine herding tendency and the lead-lag relationship in order to comprehensively understand intraday interdependence between trading behavior and investors' sentiments. Tables 7, 8, 9, and 10 present the empirical results of herding behavior and the lead-lag relationship of 5-minute and 10-minute intraday data.

As shown in Table 2, the results of Model 1 in Tables 7 and 8 also presented the coefficients for the previous bid volume and the previous ask volume to be significantly positive values. Both 5-minute and 10-minute intraday data indicate the significant herding inclination of both stock-buying and -selling behavior of investors. Furthermore, results of Model 1 in Tables 7 and 8 match with those in Table 2 where 5-minute and 10-minute intraday data show the coefficient of the previous TAIEX returns insignificantly different from zero. This indicates that the stock price performance for the previous 5-minute (10-minute) cannot affect the investors' sentiments and trading behavior for the current 5-minute (10-minute). What deserves our attention is that the coefficients of previous BSI of Model 1 in Tables 7 and 8, using 5-minute and 10-minute intraday data for empirical analysis are insignificantly different from zero and a significant positive value, respectively. This supports again the lack of herding tendency in investors' sentiments resulting from the influence of cognitive dissonance and data frequencies. Based on the cognitive dissonance of behavioral finance, when investors respond to information shocks with initial underreaction and sequential overreaction, it is less likely to find herding evidence of investors' sentiments for the higher frequency data. As a result, when intraday data reduces its frequency (from 1-minue to 10-minute), the empirical results of using 10-minute intraday data show herding evidence of investors' sentiments.

In terms of the herding influence due to great events on the bid volume and ask volume [the GARCH(1,1) models with the dependent variables of current bid volume and current ask volume], as shown in Table 3-5, Model 2-4 in Tables 7 and 8 also indicate that there is an insignificant influence of three great events on the conditional volatilities of current bid and ask volumes. Additionally, for the herding influence of great events on investors' sentiments [the GARCH(1,1) model with the dependent variable of current BSI], Model 2-4 of Tables 7 and 8 show the coefficients of great events are significantly different from zero in addition to the coefficient of Event 3 (the second regime change) in Model 4 with the dependent variable of current BSI shown in Table 8. This corresponds to the results of using 1-minute intraday data presented in Table 3-5. The results of the 5-minute and 10-minute intraday data also reveal significant change in conditional volatility of BSI after the three great events and support the lead of trading behavior by investors' sentiments.

Compared to the empirical results in Tables 6, 9, and 10, we find that first, 1-minute, 5-minute, and 10-minute intraday data indicate the high concurrent correlation of "BSI and bid volume" and "BSI and ask volume" ($D1_0$ and $D2_0$ in Tables 9 and 10 are significantly different from zero). Moreover, Table 9 shows that BSI leads bid volume and ask volume by three periods (*i.e.*, 15 minutes) but the bid volume and ask volume leads BSI by two periods (*i.e.*, 10 minutes), while Table 10 shows that BSI leads bid volume and ask volume by two periods (*i.e.*, 20 minutes) and it is insignificant for the leads of BSI by bid volume and ask volume. The above results imply that stronger evidence supports more, "stock trading behavior led by investors' sentiments," than "investors' sentiments led by stock trading behavior." In the end, although Tables 9 and 10 do not display the evidence of the significant lead-lag relationship between "BSI and the TAIEX returns" compared to Table 6, the significance of regression coefficients of Tables 9 and 10 ($D3_{-3}$ - $D3_3$) has increased. This indicates that when high frequency intraday data is used for empirical investigation, it is unlikely for the TAIEX returns to have significant variation due to insignificant change of BSI (investors' sentiments) within a short period of time. But if data frequency is prolonged (from 1-minute to 10-minute), the correlation between investors' sentiments and stock returns will be increased.

5.2. Empirical Results of Relative Bid Volume and Relative Ask Volume

In terms of the investigation on "herding behavior of investors" and "the lead-lag relationship of investors' behavior and sentiments" in the previous section, this study uses the "absolute" bid volume and the "absolute" ask volume as proxies for investors' behavior. But due to the possible influence of trading volume and the bull-bear market cycle on above "absolute" bid and ask volumes, this study adopts "relative" bid volume [*i.e.*, the bid volume/(the bid volume + the ask volume)] and "relative" ask volume [*i.e.*, the ask volume/(the bid volume + the ask volume)]" to replace "absolute" bid volume and "absolute" ask volume as well as respectively conduct the investigation on the herding inclination of investors' trading behavior, the influence of great events on the investors' herding behavior, and the lead-lag relationship of investors' behavior and sentiments. The empirical results are shown in Tables 11 and 12.

Table 11 shows that except for the coefficient of the previous relative ask volume in Model 4 with the dependent variable of current relative ask volume, the coefficients of previous relative bid volume and previous relative ask volume in

Table 7

The Impact of Great Events on the Herding Tendency of Bid Volume, Ask Volume, and Investors' Sentiments: The Empirical Results of 5-minute Intraday Data

Variables	Current bid volume				Current ask volume				Current BSI			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Intercept	15868.67	16039.84	15897.61	15868.67	9569.58	8506.94	13036.44	7955.51	0.27	0.02	-0.03	-0.05
b_0 (β_0)	(135.77)*	(128.99)*	(132.95)*	(134.26)*	(76.52)*	(210.98)*	(327.91)*	(102.92)*	(641.67)*	(253.38)*	(-42.67)*	(-70.64)*
Previous bid	0.08	0.10	0.13	0.08								
volume	(21.99)*	(23.82)*	(32.28)*	(21.61)*								
Previous ask					0.46	0.37	0.13	0.54				
volume					(57.65)*	(130.16)*	(47.35)*	(109.82)*				
Previous									0.01	-0.02	1.24	1.49
BSI									(0.52)	(-1.03)	(13.07)*	(55.69)*
Previous	-0.08	-2.65	-4.85	-0.09	7.22	-0.49	-6.25	13.89	0.09	0.42	0.56	0.78
TAIEX returns	(-0.00002)	(-0.0006)	(-0.001)	(-0.00002)	(0.0007)	(-0.0002)	(-0.004)	(0.002)	(0.29)	(0.23)	(1.56)	(1.87)
Intercept	1.74×10^9	1.84×10^9	1.38×10^9	8.90×10^8	1.99×10^8	3.87×10^8	7.62×10^8	1.36×10^9	2.29	2.04	2.48	2.00
a_0 (α_0)	(48.91)*	(9.48)*	(32.57)*	(27.53)*	(78.07)*	(220.95)*	(350.12)*	(136.57)*	(342.01)*	(39.23)*	(251.93)*	(216.44)*
Unconditional	0.23	0.23	0.32	0.22	0.83	0.66	0.87	0.56	0.001	0.0003	0.01	0.01
variance	(813.41)*	(528.15)*	(762.94)*	(797.70)*	(54.93)*	(299.98)*	(193.85)*	(91.86)*	(256.48)*	(105.95)*	(638.42)*	(439.92)*
Conditional	-0.0001	-0.004	0.001	-0.0001	0.08	0.32	0.07	0.06	0.01	0.003	0.002	0.001
variance	(-0.00006)	(-0.04)	(0.02)	(-0.00006)	(9.33)*	(147.59)*	(50.57)*	(11.52)*	(184.89)*	(590.66)*	(463.14)*	(304.43)*
Dummy of		74.40				-4877.23				5.4515		
Event 1		(0.0001)				(-0.04)				(157.66)*		
Dummy of			513.64				-12775.42				0.04	
Event 2			(0.0009)				(-0.05)				(350.58)*	
Dummy of				-10.56				-7337.27				-0.20
Event 3				(-0.00002)				(-0.01)				(-923.24)*

Note: "*" refers to significant at 1% significance level. The number in parentheses is *t*-statistic. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 53,514. Event 1 refers to the Chinese Bank Chinese Bank taken over by the Financial Supervisory Commission. Event 2 refers to the US subprime mortgage crisis. Event 3 refers to the second regime change. Model 1-4 refers to "the GARCH(1,1) model without dummy variable," "the GARCH(1,1) model with dummy variable of Event 1," "the GARCH(1,1) model with dummy variable of Event 2," and "the GARCH(1,1) model with dummy variable of Event 3," respectively.

Table 8

The Impact of Great Events on the Herding Tendency of Bid Volume, Ask Volume, and Investors' Sentiments: The Empirical Results of 10-minute Intraday Data

Variables	Current bid volume				Current ask volume				Current BSI			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Intercept b_0 (β_0)	7740.88 (68.61)*	15538.82 (86.79)*	8473.61 (90.93)*	8749.08 (46.63)*	8059.91 (51.94)*	5665.87 (68.85)*	4214.37 (28.70)*	6534.45 (79.66)*	2.08 (402.31)*	6.00 (198.42)*	0.01 (42.00)*	0.002 (2.55)#
Previous bid volume	0.53 (102.04)*	0.12 (11.87)*	0.45 (87.60)*	0.47 (52.52)*								
Previous ask volume					0.55 (69.37)*	0.62 (127.35)*	0.71 (91.21)*	0.62 (134.34)*				
Previous BSI									0.52 (84.58)*	-0.01 (-1.36)	0.18 (158.74)*	0.18 (102.41)*
Previous TAIEX returns	18.66 (0.005)	-5.19 (-0.001)	4.81 (0.002)	5.70 (0.0008)	55.75 (0.02)	33.94 (0.01)	57.24 (0.01)	48.33 (0.01)	-1.68 (-1.72)	-0.68 (-1.03)	0.79 (0.63)	1.10 (1.17)
Intercept a_0 (α_0)	8.41×10^8 (161.24)*	1.38×10^9 (70.55)*	4.93×10^8 (86.45)*	1.51×10^9 (77.31)*	9.20×10^8 (81.32)*	3.57×10^8 (98.52)*	7.89×10^8 (92.21)*	5.46×10^8 (137.52)*	4.85 (137.22)*	2.25 (289.90)*	1.66 (213.64)*	2.28 (251.82)*
Unconditional variance	0.75 (53.46)*	0.24 (26.76)*	0.54 (63.51)*	1.32 (33.77)*	0.19 (35.35)*	0.68 (79.19)*	0.59 (45.85)*	0.86 (77.20)*	0.001 (357.33)*	0.002 (273.37)*	0.005 (358.74)*	0.006 (457.54)*
Conditional variance	-0.005 (-2.10)#	-0.02 (-1.99)#	0.18 (30.04)*	-0.004 (-1.33)	-0.02 (-1.66)	0.26 (52.42)*	0.03 (5.56)*	0.09 (30.85)*	0.06 (273.30)*	0.03 (216.89)*	-0.03 (-505.75)*	0.001 (565.06)*
Dummy of Event 1		10588.48 (0.008)				16980.76 (0.07)				15.82 (546.50)*		
Dummy of Event 2			-918.08 (-0.002)				19844.44 (0.18)				0.26 (51.92)*	
Dummy of Event 3				14613.78 (0.007)				16901.14 (0.30)				0.0008 (0.59)

Note: "*" and "#" refer to significant at 1% and 5% significance levels, respectively. The number in parentheses is *t*-statistic. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 26,757. Event 1 refers to the Chinese Bank Chinese Bank taken over by the Financial Supervisory Commission. Event 2 refers to the US subprime mortgage crisis. Event 3 refers to the second regime change. Model 1-4 refers to "the GARCH(1,1) model without dummy variable," "the GARCH(1,1) model with dummy variable of Event 1," "the GARCH(1,1) model with dummy variable of Event 2," and "the GARCH(1,1) model with dummy variable of Event 3," respectively.

Table 9

The Lead-Lag Relationship among Trading Behavior, Investors' Sentiments, and Stock Returns: The Empirical Result of 5-minute Intraday Data

Coefficients	BSI and bid volume		BSI and ask volume		BSI and TAIEX returns	
	Estimated value	*t*-statistic	Estimated value	*t*-statistic	Estimated value	*t*-statistic
$C1_0$~$C3_0$	2.82×10^{-5}	0.0129	1.87×10^{-5}	0.0085	2.71×10^{-5}	0.0121
$D1_{-3}$~$D3_{-3}$	1.58×10^{-7}	0.7530	-3.71×10^{-7}	-1.8025	0.0578	0.3643
$D1_{-2}$~$D3_{-2}$	4.85×10^{-7}	2.3047#	-5.06×10^{-7}	-2.4605#	0.1013	0.6394
$D1_{-1}$~$D3_{-1}$	2.22×10^{-6}	10.5550*	-3.83×10^{-7}	-1.8596	-0.1619	-1.0220
$D1_0$~$D3_0$	7.93×10^{-6}	37.7245*	-6.63×10^{-6}	-32.2316*	0.2508	1.5835
$D1_1$~$D3_1$	1.69×10^{-6}	8.0508*	-3.02×10^{-7}	-2.4664#	-0.2822	-1.7809
$D1_2$~$D3_2$	2.40×10^{-6}	11.4005*	-2.23×10^{-6}	-10.8194*	-0.1918	-1.2104
$D1_3$~$D3_3$	1.31×10^{-6}	6.2270*	-1.58×10^{-6}	-7.6935*	-0.0578	-0.3643

Note: "*" and "#" refer to significant at 1% and 5% significance levels, respectively. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 53,514.

Table 10

The Lead-Lag Relationship among Trading Behavior, Investors' Sentiments, and Stock Returns: The Empirical Result of 10-minute Intraday Data

Coefficients	BSI and bid volume		BSI and ask volume		BSI and TAIEX returns	
	Estimated value	*t*-statistic	Estimated value	*t*-statistic	Estimated value	*t*-statistic
$C1_0$~$C3_0$	6.95×10^{-6}	0.0024	8.34×10^{-6}	0.0028	5.63×10^{-6}	0.0019
$D1_{-3}$~$D3_{-3}$	-4.04×10^{-6}	-1.3316	4.42×10^{-7}	0.9925	0.0645	0.3284
$D1_{-2}$~$D3_{-2}$	2.47×10^{-7}	0.8141	-1.02×10^{-6}	-2.2834#	-0.0038	-0.0192
$D1_{-1}$~$D3_{-1}$	3.22×10^{-7}	1.0623	-1.89×10^{-7}	-0.4241	0.0103	0.0527
$D1_0$~$D3_0$	1.29×10^{-5}	42.5090*	-1.21×10^{-5}	-27.0293*	0.2856	1.4597
$D1_1$~$D3_1$	3.85×10^{-6}	12.6988*	-9.39×10^{-6}	-21.0614*	-0.1228	-0.6274
$D1_2$~$D3_2$	1.77×10^{-6}	5.8233*	-3.69×10^{-6}	-8.2737*	-0.0745	-0.3793
$D1_3$~$D3_3$	-1.04×10^{-9}	-0.0034	7.03×10^{-7}	1.5759	-0.0610	-0.3103

Note: "*" and "#" refer to significant at 1% and 5% significance levels, respectively. The numbers of observations for the bid volume, ask volume, TAIEX returns, and BSI are all 26,757.

Table 11

The Impact of Great Events on the Herding Tendency of Relative Bid Volume and Relative Ask Volume

Variables	Current relative bid volume				Current relative ask volume			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Intercept	0.35	0.37	0.41	0.44	0.43	0.76	0.41	0.43
b_0 (β_0)	(70.14)*	(199.17)*	(62.90)*	(25.15)*	(950.35)*	(120.97)*	(218.51)*	(39.99)*
Previous relative bid	0.21	0.22	0.12	0.15				
volume	(26.40)*	(101.20)*	(18.01)*	(3.97)*				
Previous relative ask					0.23	0.55	0.09	0.01
volume					(63.14)*	(35.39)*	(85.60)*	(0.80)
Previous TAIEX	0.001	1.72	0.05	0.002	-0.23	-0.56	0.13	-0.002
returns	(1.56)	(2.33)#	(0.47)	(0.85)	(-2.09)#	(-0.52)	(0.42)	(-0.58)
Intercept	0.84	0.84	1.00	0.98	0.98	0.45	0.99	0.61
a_0 (α_0)	(252.25)*	(216.45)*	(805.79)*	(121.95)*	(675.97)*	(624.50)*	(367.11)*	(448.78)*
Unconditional	0.51	0.25	0.39	0.31	1.06	0.91	1.26	0.30
variance	(36.31)*	(769.04)*	(670.97)*	(13.22)*	(695.35)*	(78.08)*	(326.54)*	(23.30)*
Conditional	0.05	-0.004	0.001	-0.01	0.07	0.29	0.07	0.01
variance	(12.31)*	(-648.74)*	(416.92)*	(-1.46)	(229.08)*	(246.10)*	(898.71)*	(4.47)*
Dummy of		47.60				-44.55		
Event 1		(18.70)*				(-1.68)		
Dummy of			-0.20				-140.76	
Event 2			(-0.05)				(-1.78)	
Dummy of				-9.15				-8.84
Event 3				(-0.99)				(-0.15)

Note: "*" and "#" refer to significant at 1% and 5% significance levels, respectively. The number in parentheses is t-statistic. The numbers of observations for the relative bid volume, relative ask volume, TAIEX returns, and BSI are all 263,606. Event 1 refers to the Chinese Bank Chinese Bank taken over by the Financial Supervisory Commission. Event 2 refers to the US subprime mortgage crisis. Event 3 refers to the second regime change. Model 1-4 refers to "the GARCH(1,1) model without dummy variable," "the GARCH(1,1) model with dummy variable of Event 1," "the GARCH(1,1) model with dummy variable of Event 2," and "the GARCH(1,1) model with dummy variable of Event 3," respectively.

Table 12
The Lead-Lag Relationship among Investors' Sentiments, Relative Bid Volume, and Relative Ask Volume

Coefficients	BSI and relative bid volume		BSI and relative ask volume	
	Estimated Value	*t*-statistic	Estimated Value	*t*-statistic
$C1_0 \sim C2_0$	-1.81×10^{-7}	-0.0009	-1.81×10^{-7}	-0.0009
$D1_{-3} \sim D2_{-3}$	0.0003	1.1063	-0.0003	-1.1063
$D1_{-2} \sim D2_{-2}$	0.0001	0.2885	-0.0001	-0.2885
$D1_{-1} \sim D2_{-1}$	-0.0021	-0.8297	0.0021	0.8297
$D1_0 \sim D2_0$	1.9933	7791.73*	-1.9933	-7791.73*
$D1_1 \sim D2_1$	0.0062	24.0865*	-0.0062	-24.0865*
$D1_2 \sim D2_2$	0.0060	23.3608*	-0.0060	-23.3608*
$D1_3 \sim D2_3$	0.0059	22.9546*	-0.0059	-22.9546*

Note: "*" refers to significant at 1% significance level. The numbers of observations for the relative bid volume, relative ask volume, TAIEX returns, and BSI are all 263,606.

the various models are all significant positive values. This indicates that the larger the relative bid volume or the relative ask volume for the previous minute, the larger the relative bid volume or the relative ask volume for the current minute. In other words, the results in Table 11 acquire the same conclusion as Table 2 in that there is a significant herding tendency when investors buy and sell stocks. However, unlike Table 2, either the GARCH(1,1) models with dependent variable of either the current relative bid volume or the current relative ask volume, parts of the coefficients of the previous TAIEX returns are significantly different from zero. This implies a certain degree of correlation between previous stock returns and current relative bid volume as well as between previous stock returns and current relative ask volume. Notably that fewer coefficients of the previous TAIEX returns in Table 11 reach statistical significance. Therefore, we still are not able to conclude that the stock price performance for the previous minute has an important influence on investors' trading behavior for the current minute.

In regards to the influence of great events on the herding behavior of relative bid volume and relative ask volume, Table 11 presents the significant positive coefficient of the dummy of Event 1 in Model 2 with dependent variable of the current relative bid volume. It indicates that after the Financial Supervisory Commission took over the Chinese Bank, the conditional volatility of relative bid volume increased significantly. Among these three great events, however, only the takeover of the Chinese Bank by the Financial Supervisory Commission significantly influenced conditional volatility of the relative bid volume. Hence, when the relative bid volume and the relative ask volume are used as proxies for the investors' trading behavior, great events have limited influence on the conditional volatility of trading behavior of investors in the Taiwanese stock market. In general, the results of Table 3-5 are similar to those of Table 11, so the use of "absolute" or "relative" bid volume ("absolute" or "relative" ask volume) as the proxies of investors' behavior will acquire a similar conclusion.

From Table 12, because the sum of the relative bid volume and relative ask volume at the same period is 1, the same absolute value of the lead-lag coefficients of "BSI and the relative bid volume" and "BSI and the relative ask volume" (the difference is the positive and negative symbols) is the inevitable results arising from research design. In conclusion, the findings in Table 12 are shown as below: First, coefficients $D1_0$ and $D2_0$ are, respectively, significant positive and negative values. The above result indicates the high positive and negative concurrent correlation between "BSI and relative bid volume" and "BSI and relative ask volume." In addition, Table 12 indicates a significant positive value for coefficients $D1_1$, $D1_2$, and $D1_3$ but coefficients $D1_{-1}$, $D1_{-2}$, and $D1_{-3}$ are insignificantly different from zero. This means that investors' sentiments significantly lead stock-buying behavior of investors by three minutes but the stock-buying behavior of investors do not significantly lead investors' sentiments. In the end, Table 12 shows that coefficients $D2_1$, $D2_2$, and $D2_3$ are significantly smaller than zero but there are statistically insignificant values for coefficients $D2_{-1}$, $D2_{-2}$, and $D2_{-3}$. This implies that BSI leads the relative ask volume by three minutes but the relative ask volume does not significantly lead BSI. The comparison of Tables 6 and 12 draws the same conclusion that investors' sentiments lead their trading behavior.

6. Conclusions

Although the majority of the previous literature used daily or monthly data to examine the investors' herding behavior, they rarely conducted empirical studies on the herding inclination of investors' trading behavior with intraday data. Additionally, a further look at the herding tendency of investors' sentiments, the psychological status of investors before their behavioral decision-making, is also useful for the explanation of the irrational herds. The aim of this study is to explore the intraday herding inclination of stock-buying behavior, stock-selling behavior, and investors' sentiments, as well as the intraday interdependence among trading behavior, investors' sentiments, and share price performance. In detail, with the intraday data of bid volume, ask volume, BSI, and the TAIEX returns at three different lengths of frequency (1, 5, and 10 minutes), this study examines the intraday herding inclination of investors' behavior and sentiments. Furthermore, in order to expand the research scope of herding behavior, we investigate the influence of great events on investors' sentiments and trading behavior as well as inspect the lead-lag relationship among investors' sentiments, trading behavior, and stock returns. Finally, the absolute and relative bid/ask volumes are used as the proxies of investors' trading behavior to improve the robustness of empirical findings.

The empirical results first find that when the GARCH(1,1) model does not include a dummy variable for great events, significant herding inclination of trading behavior of investors in the Taiwanese stock market is observed but there has been a lack of herding tendency of investors' sentiments. Secondly, if the dummy variable of great events is included in the GARCH(1,1) model, our results indicate that besides the significant herding inclination of stock-buying behavior and stock-selling behavior, investors' sentiments are also prone to herding. Thirdly, regardless of the inclusion of a dummy variable for the great events in the GARCH(1, 1) model, both results conclude that share price performance for the previous minute is an insignificant predictor of current investors' behavior and sentiments. Fourthly, after the great events, the conditional volatility of investors' sentiments is reported with significant change. Fifthly, the results of the lead-lag relationship among investors' sentiments, investors' behavior, and stock price performance present that although investors' sentiments lead their trading behavior, due to the influence of data frequencies, initial underreaction to information shocks as well as the unwillingness to buy at high prices and to sell at low prices, investors' sentiments do not lead stock price performance. Finally, the empirical results are robust to alternative proxies of investors' behavior and alternative frequency intraday data.

We derive three implications from the above empirical results: First, because investors' sentiments lead their trading behavior, good use of the changes in investors' sentiments will help to understand the trading decisions of investors as well as to predict the herding tendency of investor behavior. Moreover, due to the investors' underreaction to information in a short period of time and the unwillingness to buy stocks at high prices (sell at low prices), slower responses of stock prices toward information are found. In the end, because the great events have a big impact on investors' sentiments, the priority task of an authority is to launch incentive measures that are able to effectively calm the panic sentiment in the market.

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