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Herding and China's market-wide circuit breaker☆

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China stock market regulators implemented market-wide circuit breakers when the market crash was imminent on the 4th of January 2016. This paper examines whether traders' herding behaviour led to the circuit breaker trigger and limited success in moderating market reaction. Using intraday data, we show extensive herding in the pre-halt and post-halt periods on the event day. We find herding and excessive market volatility are mutually causative. Importantly, we identify herding stems from both market sentiments and fundamentals around the circuit breaker trigger. In a market dominated by individual investors, non-fundamental herding primarily characterises the Chinese stock market. Nonetheless, the uncertain and disruptive impact of the circuit breaker led to massive and rapid stocks sale underlying the fundamental herding. Investors trade in the direction of the crowd giving rise to self-enforced herding and greater market volatility, and culminating in the circuit breaker trigger.

1. Introduction

Following a series of major international financial crises, researchers are concerned about the causes of financial system fragility and the mechanics by which financial markets unravel.[1] A key empirical finding on financial crises (see Kaminsky, 1999) is that the economy's fundamentals help predict the occurrence of a crisis. However, crises may (may not) occur despite sound (weak) fundamentals. Earlier studies show that imitative or herd-like behaviour can impede the flow of information in an economy when agents act sequentially rather than concurrently (Banerjee, 1992; Bikhchandani et al., 1992; Chamley and Gale, 1992; Caplin and Leahy, 1993, 1994; Bulow and Klemperer, 1994). The disconnect between sound fundamentals and asset prices results from investors who receive information about these fundamentals may not act according to their private information; instead, they herd. Herding behaviour causes financial markets to fail to aggregate private information efficiently, leading to misalignment of asset prices from their true value (Cipriani and Guarino, 2008).

This paper studies whether herding arose in the Chinese stock market crash on January 4, 2016. And if so, what is the role of herding in triggering the market-wide circuit breakers surrounding this event? This event is unique because the Chinese government intervened by implementing the market-wide circuit breaker to moderate stock returns volatility when stock prices fell sharply. It is well established that the circuit breaker did not provide a "time-out" cushion and instead induced the rapid occurrence of the magnet effect (i.e., increased probability of the stock price hitting the limits) in the stock market crash (Wang et al., 2019; Wong et al., 2020; Li et al., 2020). Examining the role of herding in this event is paramount because the most common causes of herding are information asymmetry and uncertainty, which tend to peak as the stock market volatility escalates. Avery and Zemsky (1998) show that when the market is uncertain, the asset's value changes from its initial expected value due to the shock's existence and effect, and herding can occur. However, the impact of herding on pricing may be small in this instance. When there is uncertainty about the average accuracy of trader's information and, therefore, more significant information asymmetry, herd behaviour can dominate, leading to substantial mispricing.

Given the benefits of hindsight about the failed market-wide circuit breaker in the Chinese stock market crash, this paper uses intraday trade and quote data from January 2015 to January 2017

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[1] These crises originated in Mexico in 1995, Southeast Asia in 1997-8, Russia in 1998, Brazil in 1998-9, and U.S. for the Dotcom bubble in 2000-2002 and the global financial crisis in 2007-2008.

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0378-4266/

to examine the herding behaviour of investors. Firstly, given the prediction of Park and Sabourian (2011), who attribute herding to a situation when investors receive information or a signal that has an uncertain impact on the stock market like the circuit breaker intervention, we test whether herding behaviour became more pronounced around the time when the market-wide circuit breaker was triggered.

Secondly, we study the relationship between investors' herding behaviour and market volatility during the stock market crash. Empirically, it is shown that herding is more likely to take place during periods of extreme market swings (Tan et al., 2008; Arjoon and Bhatnagar, 2017; Fang et al., 2017). Venezia et al. (2011) show that during herding, investors continue to trade in the direction of the crowd so that this self-enforced herding can give rise to more significant price movements. If this prediction holds, we conjecture that investors' herding behaviour and market volatility can be mutually reinforcing, triggering the market-wide circuit breaker.

Thirdly, we investigate what type of herding triggers the market-wide circuit breaker. Bikhchandani and Sharma (2000) distinguish between investors who face a similar information set driven by fundamentals ("spurious" herding) and who intentionally copy the behaviour of others ("intentional" herding). Bikhchandani and Sharma (2000) argue that intentional (or non-fundamental) herding can intensify the impact of the crisis and lead to fragile markets, excess volatility and systemic risk. Therefore, it is essential to identify the type of herding that perpetuates the downward movement in the stock market crash leading to the trigger of the market-wide circuit breaker.

Using Chang et al.'s (2000) herding measure, we test for the presence of intraday herding when there are no market-wide circuit breakers, which forms the benchmark for comparison. Our results show evidence of herding on days without circuit breakers; however, herding behaviour becomes more pronounced on the day when the circuit breaker was triggered. Our results support Park and Sabourian (2011); the market-wide circuit breakers could send a U-shaped signal to investors, leading them to discount the intermediate values and update the extreme values faster than on days when there were no such interventions.

We find large stock returns volatility on the day when the market-wide circuit breaker was triggered, which coincides with investors' herding behaviour. Since the two may be mutually causative, we treat them as endogenous and employ the Vector Autoregression model (VAR) to characterise the dynamic relationship between herding and market volatility. While the results support bi-directional causality between herding and high market volatility, the forecast error variance decomposition shows that herding dominantly explains the forecast error variance of market volatility. Thus, the driver behind the increased market volatility is the pronounced herding behaviour of investors on the event day. This interplay of increased volatility and herding could have led to the trigger of the market-wide circuit breaker.

Our results show that moderate non-fundamental herding is prevalent in the Chinese stock market on days without circuit breakers. However, when the circuit breaker was triggered, we find that non-fundamental herding continued to prevail in the stock market. This result is perhaps unsurprising since individual investors dominate the Chinese stock market, and they are shown to be more sensitive to market return shocks, emotions and sentiments (Hsieh, 2013; Li et al., 2017). In addition, we find extreme fundamentals-driven herding around the circuit breaker trigger, which stems from the common response of traders to reduce their portfolio by selling stocks when faced with the disruptive and uncertain impact of the circuit breaker. The combination of fundamental and non-fundamental herding behaviour around the circuit breaker trigger could have accelerated the fall in stock prices leading to excessive volatility.

This paper contributes to the literature on herding and market-wide circuit breakers. These two issues have never been examined concurrently. To our knowledge, this is the first study that shows how investors' herd-like trading behaviour can blunt the effectiveness of the market-wide circuit breakers in a stock market crisis. Our paper also contributes to the growing literature on the Chinese stock market crash that examines the market microstructure evidence associated with the failed market-wide circuit breakers (Wang et al., 2019; Wong et al., 2020; Li et al., 2020; Jian et al., 2020). Complementing these studies, we show herding as another channel that explains the inability of the circuit breaker to provide a cushion to improve the informativeness of stock prices and to moderate the extreme reaction, and stock returns volatility. The use of intraday data also uniquely shows the herding behaviour on continuous trading periods. This study contrasts extensive empirical studies on herding, which rely on a lower frequency (i.e., daily, weekly or even monthly) data (see Tan et al. 2008, for example). Finally, we show the pervasiveness of non-fundamental herding in the Chinese stock market dominated by individual investors is a cause for concern. In a stock market like China steep in poor information transparency, individual investors are prone to trade on sentiments that move the market, potentially destabilising stock prices. Thus, policymakers need to formulate policies that minimise the influence of non-fundamental herding and mitigate the risk of future stock market crises.

The rest of the paper is structured as follows. Section 2 provides a brief narrative of the institutional features of the Chinese stock market and the circuit breaker. This section also reviews the related literature and provides the hypotheses development. Section 3 describes the data and the construction of control samples. Section 4 outlines the empirical research models. Section 5 presents the empirical results, and Section 6 summarises the findings and concludes.

2. Literature review and hypotheses development

2.1. Institutional features of the Chinese stock market

The Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) were established on November 26, 1990, and December 1, 1990, respectively. The SSE and SZSE market capitalizations are around RMB30,448 billion and RMB23,511 billion, respectively, as of April 2017. Of the 3185 listed companies, 1247 firms were listed on the SSE and the remaining 1938 firms on the SZSE.

The Chinese stock market has a distinctive composition in that domestic individual investors, who are susceptible to make intentional herd-like trading, are major market players, whereas institutional investors mainly drive other developed stock markets including U.S and U.K. As of 2016 on the SSE, while institutional investors make up 75.5% of the total market capitalisation, individual investors hold 99.9% of the total number of active accounts and 85.6% of the turnover of stocks (Shanghai Stock Exchange, 2017). This predominance of individual investors in the Chinese stock market provides an ideal setting to detect the type of herding triggering the market-wide circuit breakers.

2.2. China's circuit breakers

Following the market plunge on August 24, 2015, the SSE, the SZSE and the China Financial Futures Exchange (CFFEX) introduced an index circuit breaker mechanism to curb extreme volatility of stock returns on September 7, 2015. The circuit breaker takes CSI 300 Index as a benchmark and triggers a 15-minute trading halt when the index goes up or down with a price movement of 5% from the previous close. After the halt, the continuous trading on that day will resume. Nevertheless, should the CSI 300 Index rise

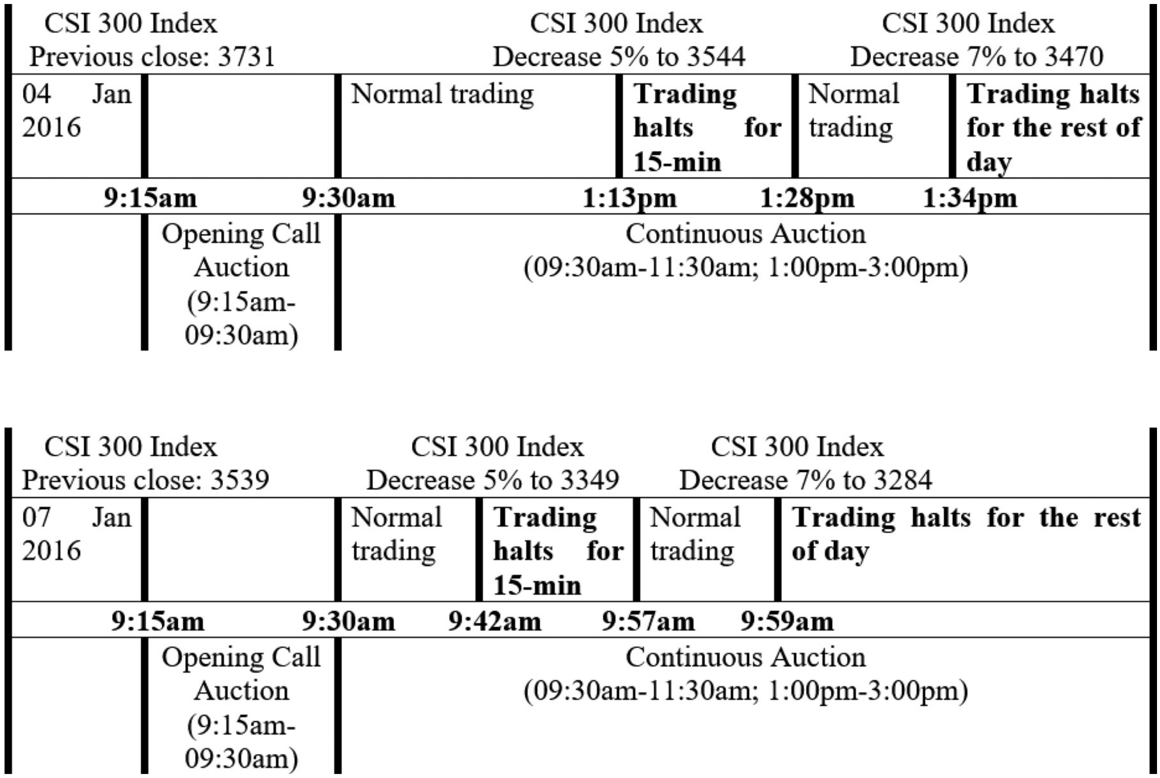


Fig. 1. Timelines on Event Days
This figure shows the timelines on the actual event days.

(or fall) by 5% at or after 2:30 pm local time or by 7% at any time, trading will be closed for the day (market closure).

The market-wide circuit breaker in this study took place on January 4, 2016. The CSI 300 Index plunged by 5% during the afternoon trading session, triggering a 15-minute trading halt at 1:13 pm. After trading resumed at 1:28 pm, the index tumbled again, hit the 7% threshold at 1:34 pm and caused a trading suspension for the rest of the day. After three trading days on January 7, 2016, another sharp fall on the index triggered the 15-minute trading halt at 9:42 am. When trading resumed at 9:57 am, it took just two minutes for CSI 300 Index to initiate the second trading halt, ending the trading session for the day. Fig. 1 shows the timeline of the events on January 4 and 7, 2016.

It is evident based on these events that the circuit breakers succumb to the downward pressure amidst volatility. Consequently, the SSE abolished the circuit breakers on January 8, 2016, "maintaining market stability" (Shenzhen Stock Exchange, 2016).

2.3. Theoretical framework of herding

There are two classes of theoretical models that explain herding. The first class of models is developed based on rational cognition, which focuses on reputational concerns (Scharfstein and Stein, 1990; Zwiebel, 1995; Graham, 1999) and informational cascade (Bikhchandani et al., 1992; Banerjee, 1992; Welch, 1992). Scharfstein and Stein (1990) claim that managers can learn from observing the decisions made by other managers and, therefore, mimic the investment strategies of their better-performing peers to maintain their reputational ability. Zwiebel (1995) asserts that reputational herding is rational and provides insurance against underperformance. Graham (1999) finds analysts tend to publish investment newsletters converged to the recommendation of best-known analysts to protect their reputation or hide their weak ability. The rational herd behaviour can also arise from informational cascades when individuals discard their private information and follow observable actions of better-informed individuals (Bikhchandani et al., 1992). Banerjee (1992) argues that agents make decisions using the information contained in others' decisions based on the belief that the knowledge possessed by others is superior. Similarly, Froot et al. (1992) find that speculators with short horizons may herd on common information, even unrelated to fundamentals, to decipher what other informed investors know.

The second class of models attributes herding to irrational behaviour. Herding results from psychological stimuli or investor sentiment, which drives asset prices away from fundamental values (Shleifer and Summers 1990; DeLong et al., 1991; Barberis et al., 1998; Daniel et al., 1998). Shleifer and Summers (1990) assume that market participants are irrational noise traders subject to systematic biases and find that irrational pseudo-signals (i.e. advice of brokers or financial gurus) rather than fundamentals can change investors' demand for securities. Similarly, DeLong et al. (1991) argue that irrational noise traders with erroneous stochastic beliefs create misperceptions about asset prices. Developing an investor sentiment model, Barberis et al. (1998) explain how conservatism (representativeness heuristic) can impact investors' beliefs, which makes investors underreact (overreact) to information. Similarly, Daniel et al. (1998) show that investors' overconfidence stems from biased self-attribution of investment outcomes. This type of herd behaviour is regarded as irrational because investors weigh their sentiments against the fundamental information about securities, destabilising prices and giving rise to bubble-like phenomena.

2.4. Empirical findings of herding

Among the two streams of empirical studies on herding detection in financial markets; i.e. (1) herding amongst institutional investors (Lakonishok et al., 1992; Wermers, 1999; Sias, 2004; Hsieh, 2013; Deng et al., 2018) with the use of micro-level data (e.g. accounts/transactions) and (2) market-wide herding (Christie and Huang, 1995; Chang et al., 2000) with the use of aggregate market data (i.e. securities' price), this paper focuses on the latter approach. Christie and Huang (1995) introduce the cross-sectional standard deviation of returns (CSSD) as a measure of return dispersion to detect herd behaviour in rational asset pricing models and find no evidence of herding in the US during periods of market stress. Chang et al. (2000) extend Christie and Huang's (1995) model by using the cross-sectional absolute deviation of returns (CSAD) and find significant herding in South Korean and Taiwanese markets. On balance, their results indicate that, due to incomplete information disclosure in emerging markets, macroeconomic information tends to play a crucial role in influencing the decision-making process of market participants. The methodologies of Christie and Huang (1995) and Chang et al. (2000) have been widely applied in several studies across markets, including Gleason et al. (2004) on Exchange Traded Funds, Goodfellow et al. (2009) in Poland, Chiang and Zheng (2010) for 18 countries, Demirer et al. (2010) in Taiwan, Yao et al. (2014) in China, Lam and Qiao (2015) in Hong Kong, Andrikopoulos et al. (2017) in Euronext's four constituent markets, and Vo and Phan (2019) in Vietnam.

Hwang and Salmon (2004) develop an alternative approach using deviations from the equilibrium prices derived from the Capital Asset Pricing Models (CAPM). While they observe the presence of herding in market portfolios in both bullish and bearish markets in the US and South Korea, they find no evidence of an increased level of herding during the Asian financial crisis of 1997–98 and the Russian Crisis of 1998. They argue that markets behave efficiently in these crises, consistent with Christie and Huang (1995) that market participants tend to make decisions based on fundamentals rather than overall market movements.

With empirical evidence on the Chinese stock market, conflicting and inconclusive results have been reported. The pioneering research conducted by Demirer and Kutan (2006) examines the daily CSSD during the periods of substantial upward and downward movements in the market index at both individual firms and sector levels. Although they find that stock returns behave similarly during the large downward movements of the market, there is no evidence of herding in both the SSE and SZSE, suggesting that investors in the Chinese stock market make their choices rationally (see Fu and Lin 2010). On the other hand, Tan et al. (2008) examine the CSAD of dual-listed A- and B-shares traded on both the SSE and SZSE, using daily, weekly and monthly data, and find herding in both rising and falling market conditions. Similarly, some empirical studies[2] report evidence of herding in both A- and B-shares markets. Other studies,[3] however, show that herd behaviour only exists in the A-shares market, and Yao et al. (2014) find significant evidence of herding only in the B-shares market. In terms of the market movement, Tan et al. (2008), Chiang and Zheng (2010), and Sharma et al. (2015) find that herd behaviour tends to be greater during the rising market, while Lao and Singh (2011), Yao et al. (2014) and Li et al. (2019) discover that herd behaviour is more pronounced during periods of market decline.

2.5. Hypotheses development

2.5.1. Herding and the circuit breaker

There is a dearth of empirical studies examining the relationship between herd behaviour and circuit breakers' (in)effectiveness. Previous studies on herding focus on daily price limits in which herding is found to persist despite the daily price limits in the South Korean and Taiwanese stock markets (Chang et al., 2000) and in the Vietnamese stock market (Dang and Lin, 2016). This paper focuses on the market-wide circuit breakers in China, a different type of market intervention. It examines whether herding increases the likelihood of market-wide circuit breakers being triggered. Wang et al. (2019) find that market-wide circuit breakers in the Chinese stock market, intended to moderate abnormal volatility, had an opposite effect on the market. The uncertainty associated with market-wide trading halt and market closure that disrupt the continuous trading market is larger than the uncertainty related to significant price movements during continuous trading. Market participants do not know how to respond to this extreme uncertainty. Park and Sabourian (2011) attribute herding to a situation when an investor who receives a U-shaped signal 'believes that extreme states are more likely to have generated the information than more moderate ones' (p. 974). Furthermore, this information (or U-shaped signal) is 'associated with an upcoming event that has an uncertain impact' (p. 976). In the context of the market-wide circuit breaker during the Chinese stock market turbulence, this intervention potentially has an uncertain effect on the stock market. Upon receiving this information, investors adjust their posterior belief by shifting their weight from the centre of the posterior distribution to the extremes or tail ends of the distribution, giving rise to a fat-tailed distribution. Thus, it is highly likely that investors trade on the decisions and beliefs of other investors instead of their own. For this reason, we hypothesise that:

Hypothesis 1. *Herding prevails around the time when the market-wide circuit breaker was triggered.*

2.5.2. Herding and market volatility

Extensive studies document that herding is associated with extreme market volatility. For example, Tan et al. (2008) find that herd behaviour by the A-shares investors in the SSE is more pronounced when trading volume and market volatility are high compared to other markets. This is because the A-shares market is predominated by domestic individual investors, who typically lack knowledge and experience in investments. Arjoon and Bhatnagar (2017) find that herding tendency increases in the frontier market (i.e., the Trinidad and Tobago Stock Exchange) when volatility increases because investors, especially of small firms, discard their information and follow others during periods of a high level of uncertainty. Similarly, Fang et al. (2017) find herding is more prevalent amongst smaller fund managers with resource and liquidity constraints since they fear performing worse during recessions and high market volatility. However, Holmes et al. (2013) and Guney et al. (2017) argue that low volatility tends to encourage investors to herd as it is easier for investors, especially fund managers, to observe and follow their peers during periods of low volatility (see Economou et al., 2011). Yet, Guney et al. (2017) find that this pattern is less apparent during the Global Financial Crisis (GFC) in 2007–2008. Given the contention that herding may be positively related to high market volatility, we conjecture:

Hypothesis 2a. *Herding is positively associated with stock return volatility around the trigger of the market-wide circuit breaker.*

While the evidence suggests that herding is closely associated with periods of excessive market volatility, there is a scarcity of empirical evidence examining whether herding is an attribute of extreme volatility. For instance, Venezia et al. (2011) find that herding causes market volatility in the Granger Causality sense, which is consistent with the notion that by mimicking the behaviour of other market participants as a method of free-riding on the information of others, this could partially increase excess mar-

[2] These studies are Chiang and Zheng (2010), Chiang et al. (2012), Sharma et al. (2015) and Alhaj-Yaseen and Yau (2018).

[3] The studies are Chiang et al. (2010), Lao and Singh (2011), Xie et al. (2015), Li et al. (2017) and Li et al. (2019).

ket volatility (Scharfstein and Stein, 1990; Banerjee, 1992). However, Litimi et al. (2016) argue herd behaviour has an inhibiting effect on overall and in-sector market volatility in large markets such as the US market due to the high amount of informed trading. Furthermore, they find that herd behaviour affects a relatively small number of specific stocks' volatilities; hence the overall market volatility falls as the remaining stocks' volatilities are not affected by herding decline. On balance, the extant literature points to plausibility that the interplay of herd behaviour and excess market volatility could be mutually causative, particularly given the presence of abnormal volatility when market-wide circuit breakers were triggered (Wang et al., 2019). Therefore, we conjecture that:

Hypothesis 2b. *Herding and stock return volatility mutually reinforce each other leading up to the trigger of the market-wide circuit breaker.*

2.5.3. Fundamental versus non-fundamental herding

While there is vast empirical literature examining herd behaviour in the stock markets, the question of what brings about herd behaviour has been relatively less researched. Bikhchandani and Sharma (2000) document it is crucial to differentiate fundamental-driven "spurious herding" from non-fundamental-driven "intentional herding". The former refers to investors who make similar decisions based on a similar problem and information sets, characterised as rational behaviour; whereas, the latter refers to investors who ignore their private information and chase trade trends regardless of the fundamentals regarded as irrational behaviour. For this reason, non-fundamental herding is inefficient and could lead to excess volatility and systematic risk.

To empirically examine what causes herd behaviour, Galariotis et al. (2015) propose an approach to separate deviations arising from the fundamental information and those caused by other reasons. They find that investors in the US market exhibit both fundamental-driven spurious herding and non-fundamental-driven intentional herding during various crises. In contrast, one can only observe fundamental herding in the UK market during the Dotcom bubble burst in 2000. Clearly, the drivers of herding are period- and country-specific. Following this approach, Dang and Lin (2016) find evidence of stronger fundamental and non-fundamental herding in the upward movement than the downward in the Vietnamese stock market. They attribute this asymmetric herding to stocks with small market capitalisation. Humayun Kabir (2018) examines the herd behaviour of investors in the US finance industry during the 2008 GFC and finds its impact on fundamental herding increases with conditional volatility of market return. Additionally, he only finds evidence of non-fundamental herding when market volatility is low; when market volatility is high, non-fundamental herding occurs less frequently relative to fundamental herding.

Since the Chinese stock market has unique features like unsophisticated individual investors, heavy regulations, and a lack of transparency, it is important to understand why and how investors herd. Alhaj-Yaseen and Yau (2018) find that the market liberalisation in 2001-02 in China improves the information environment with evidence of increased fundamental herding and decreased non-fundamental herding in the A-shares market following the market reforms. They also find that investors in the B-shares market only exhibit fundamental herding since they are primarily rational foreign institutional investors. They react to market fundamentals rather than intentionally imitating other investors. Venezia et al. (2011) find that the herd behaviour of amateurs (individual investors) poses a more significant threat to market stability compared to professionals (institutional investors), suggesting the need to improve transparency and reduce information asymmetry about firms to mitigate market instability. Hsieh (2013) shows that institutional investors earn more profits during volatile periods in the Taiwanese stock market because they rely on correlated new information or similar stock characteristics. On the other hand, individual investors tend to herd under intense market pressure; they experience more considerable losses because they are influenced by emotions, such as overconfidence, enjoyment of trading, and regret aversion. According to Li et al. (2017), less-informed individual investors in the Chinese stock market are more sensitive to market return shocks and sentiment. They argue that individual investors are prone to discard their information and follow others during periods of unusual market movements.

Based on the literature, we conjecture that the non-fundamental-based reason characterises abnormal herding when market-wide circuit breakers were triggered in the Chinese stock market. When the circuit breakers are activated, the price discovery process is disrupted, inhibiting capitalising of information into stock prices.

Hypothesis 3. *The non-fundamental herding is associated with the trigger of the market-wide circuit breaker.*

3. Data and control samples

3.1. Data

We use intraday trade and quote data for the CSI 300 Index and its 300 constituents from January 5, 2015, to January 6, 2017. The data are sourced from the Refinitiv Tick History, including bids, asks and depths (for quotes), execution price, and volumes (for trades). Stocks with missing data are excluded from the analysis, yielding a final sample of one index and 287 stocks. We use 1-minute intervals to examine intraday herding dynamics of the constituent stocks of the CSI 300 Index. We also rule out the first five minutes of the day[4] and two minutes before and after the lunch break closure to circumvent the overnight and lunch break closure effects. Although there are two event days when the market-wide circuit breakers were triggered, on January 4 and 7, 2016, we focus on the intraday herding dynamics only on January 4, due to insufficient data intervals[5] on January 7 to constitute a representative sample.

We divide the event day (January 4, 2016) into three periods: pre-halt period, halt period, and post-halt period. A pre-halt period covers the trading session before the 15-min trading (pseudo) halt is activated; the halt period refers to when the 15-min trading (pseudo) halt is in operation, and the post-halt indicates when the market resumes trading.

3.2. Constructing the control samples

To examine abnormal herd behaviour on the event day, we construct two non-event samples as controls for herd behaviour on trading days when market-wide circuit breakers-induced trading halts are absent. The control samples cover one year before and after the event day using the pseudo-halt[6] and pseudo-closure. The pseudo-halt starts simultaneously like the actual halt on the event day and lasts for the same duration (15 min). The pseudo-closure

[4] We do not exclude the last five minutes of the day because all observations in the post-halt period are critical for examining the relationship between herd behaviours and market-wide circuit breakers.

[5] On January 7, 2016, a sharp fall on the SSE and SZSE triggered the 15-minute trading halt at 9:42 am. When trading resumed at 9:57 am, it took just another 2 minutes for CSI 300 Index to initiate the second trading halt, ending the day's trading session. Consequently, there are only fourteen 1-minute intervals on that day.

[6] This strategy has been widely used in previous studies, for instance Lee et al. (1994) and Abad and Pascual (2007).

triggers at the same time as the actual closure. The data observations in the event sample are time-matched with those in the control sample. The first control sample, which we refer to as the full sample, includes all trading days between January 5, 2015, and January 6, 2017. The second control sample, referred to as the down sample, considers the days when the market experiences downward price movements or negative returns. Our empirical analysis distinguishes the event sample from the non-event control samples using a circuit breaker dummy.

4. Empirical models

4.1. Test of hypothesis 1: herding and the circuit breaker

Chang et al. (2000) (hereafter referred to as CCK) use the cross-sectional absolute deviation of returns (CSAD) to measure the dispersion associated with herding and incorporate a non-linear regression specification to examine the relationship between the dispersion and the overall market return. The CSAD is calculated as:

$$CSAD_i = \frac{1}{N}\sum_{j=1}^{N}\left|R_{j,i} - R_{m,i}\right| \quad (1)$$

where $R_{j,i}$ is the return of a stock j for interval i, $R_{m,i}$ is the equally-weighted average of stock returns (essentially, the average market return) during interval i, which is calculated as $R_{m,i} = \frac{1}{N}\sum_{j=1}^{N} R_{j,i}$. The non-linear regression is estimated as:

$$CSAD_i = \beta_0 + \beta_1|R_{m,i}| + \beta_2 {R_{m,i}}^2 + \varepsilon_i \quad (2)$$

CCK propose that under a rational asset pricing model, the dispersion is a linear and increasing function of the market return (reflected through $|R_{m,i}|$), captured by a positive and statistically significant β_1 coefficient. However, if herding exists, the relationship between $CSAD_i$ and $R_{m,i}$ can become non-linear. For *extreme* herding, the coefficient β_1 is negative and statistically significant, signifying a decrease in dispersion among returns. For *moderate* herding, the coefficient β_1 is positive and statistically significant, but the coefficient β_2 is significantly negative, implying that returns' dispersion increases at a less-than-proportional rate with the market return. One concern with estimating Eq. (2) is the potential multicollinearity problem arising from the explanatory variables $|R_{m,i}|$ and ${R_{m,i}}^2$. To circumvent this concern, Yao et al. (2014) modify the CCK's regression as follows:

$$CSAD_i = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i \quad (3)$$

where $\bar{R}_m$ is the arithmetic mean of $R_{m,i}$. Eq. (3) is our baseline model to test herding as it ameliorates multicollinearity and produces more reliable standard errors. We calculate intraday returns as $R_{j,i} = 100 * (\log(P_{j,i}) - \log(P_{j,i-1}))$ and the equally-weighted average of stock returns as $R_{m,i} = \frac{1}{N}\sum_{j=1}^{N} R_{j,i}$. Using an equally-weighted average of stock returns may yield biased results as it ignores the impact of firm size on stock returns. Hence, for robustness, we also use returns of the capitalisation-weighted index, CSI 300 Index, as a proxy for the average market return in all regressions.

A pivotal issue is whether herding limits the effectiveness of market-wide circuit breakers in the Chinese stock market. We examine whether herding dynamics varies before and after the circuit breaker is triggered and compare the result of event samples to that of non-event control samples. By categorising the sample into pre- and post-halt periods, we estimate the following regression:

$$\begin{aligned} CSAD_i = {} & \beta_0 + \beta_1|R_{m,i}| + \beta_2\left(R_{m,i} - \bar{R}_m\right)^2 + \beta_3 PRE_i CB_i|R_{m,i}| \\ & + \beta_4(1 - PRE_i)CB_i|R_{m,i}| + \beta_5 PRE_i CB_i\left(R_{m,i} - \bar{R}_m\right)^2 \\ & + \beta_6(1 - PRE_i)CB_i\left(R_{m,i} - \bar{R}_m\right)^2 + \varepsilon_i \end{aligned} \quad (4)$$

where *CB* denotes a dummy variable taking the value of one for the event day and zero for non-event days, and *PRE* indicates a dummy variable taking the value of one for pre-halt periods and zero for post-halt periods. In this model, if herding exists surrounding the trigger of the circuit breaker, we expect the coefficients β_5 (for pre-halt) and β_6 (for post-halt) to be negative and statistically significant to capture a stronger non-linear relationship between the dispersion and the average market return, supporting Hypothesis 1. We use the Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors since high-frequency time-series market data tend to exhibit a high level of serial correlation.

4.2. Test of hypothesis 2: herding and market volatility

To investigate whether herding is associated with significant market return volatility, we construct a high volatility sample following Tan et al. (2008), Economou et al. (2011) and Guney et al. (2017). The market volatility is high (low) when the observed daily volatility is above (below) the 30-day moving average. Consistent with Diebold and Yilmaz (2012), we calculate the market volatility using Parkinson's (1980) daily range-based volatility, which is the difference between the highest and lowest log price within each day, defined as:

$$\sigma^2_{t,j} = \frac{\left[\ln\left(H_{t,j}\right) - \ln\left(L_{t,j}\right)\right]^2}{4ln2} \quad (5)$$

$$VOLA^2_{t,m} = \frac{1}{N}\sum_{j=1}^{N}\sigma^2_{t,j} \quad (6)$$

where $\sigma^2_{t,j}$ is the variance of stock j on day t; $H_{t,j}$ ($L_{t,j}$) is the highest (lowest) trade price of stock j on day t; $VOLA^2_{t,m}$ is the equally-weighted average of the N stocks volatilities (essentially, the average market volatility) on day t. We also employ the volatility of the CSI 300 Index[7] in all regressions to test robustness. Having partitioned the sample into high volatility and low volatility samples, we perform the following regressions:

$$CSAD_i^{HIGH} = \beta_0 + \beta_1^{HIGH}\left|R_{m,i}^{HIGH}\right| + \beta_2^{HIGH}(R_{m,i}^{HIGH} - \bar{R}_m)^2 + \varepsilon_i \quad (7)$$

$$CSAD_i^{LOW} = \beta_0 + \beta_1^{LOW}\left|R_{m,i}^{LOW}\right| + \beta_2^{LOW}(R_{m,i}^{LOW} - \bar{R}_m)^2 + \varepsilon_i \quad (8)$$

where the superscript *HIGH* (*LOW*) refers to high (low) market volatility.

To examine whether abnormal herd behaviour occurs on the event day with high market volatility around the trigger of the market-wide circuit breakers, we perform the following regression using the high volatility sample:

$$\begin{aligned} CSAD_i^{HIGH} = {} & \beta_0 + \beta_1\left|R_{m,i}^{HIGH}\right| + \beta_2(R_{m,i}^{HIGH} - \bar{R}_m)^2 \\ & + \beta_3 PRE_i CB_i\left|R_{m,i}^{HIGH}\right| + \beta_4(1 - PRE_i)CB_i\left|R_{m,i}^{HIGH}\right| \\ & + \beta_5 PRE_i CB_i(R_{m,i}^{HIGH} - \bar{R}_m)^2 + \beta_6(1 - PRE_i)CB_i(R_{m,i}^{HIGH} - \bar{R}_m)^2 + \varepsilon_i \end{aligned} \quad (9)$$

where a superscript *HIGH* refers to a high market volatility sample; *CB* denotes a dummy variable taking the value of one for the

[7] Since the tick size of the Chinese stocks is RMB0.01 and the base point of the CSI 300 Index is 1000, we scale and calculate the market index volatility by dividing the index price by 100 base points.

event and zero for the non-event days; *PRE* denotes a dummy variable taking the value of one for pre-halt periods and zero otherwise. We expect the coefficients of interest β_5 (for pre-halt) and β_6 (for post-halt) to be negative and statistically significant to capture the presence of herding during high market volatility around the trigger of the circuit breaker, supporting Hypothesis 2a.

To test whether herding and market volatility mutually reinforce each other, and inducing the trigger of the circuit breaker (Hypothesis 2b), we estimate a bivariate vector autoregressive (VAR) model involving the 1-minute interval range-based volatility and the cross-sectional deviation of returns for the event sample and high volatility sample.[8] The range-based volatility for the one-minute interval is constructed using stock prices reflected in that one-minute interval. The subscript "t" in Eqs. (5) and (6) is replaced with the subscript "i" to signify the 1-minute interval. As such, in Eq. (5), the $H_{i,j}$ ($L_{i,j}$) is the highest (lowest) trade price of stock j obtained in that one-minute interval. We estimate the VAR model using the 1-minute interval data on a single day. We do this repeatedly for 176 days (i.e., the sample size of equally-weighted average stock return volatility) and 171 days (i.e., the sample size of return volatility of the CSI 300 Index). This modified VAR estimation circumvent the problem of non-existent data when estimating the model using a cross-day sample.

The VAR model is:

$$CSAD_i = \beta_{10} + \beta_{11}CSAD_{i-1} + \ldots + \beta_{1p}CSAD_{i-p} + \alpha_{11}VOLA_{m,i-1} + \ldots + \alpha_{1p}VOLA_{m,i-p} + \varepsilon_{10,i} \tag{10}$$

$$VOLA_{m,i} = \beta_{20} + \beta_{21}VOLA_{m,i-1} + \ldots + \beta_{2p}VOLA_{m,i-p} + \alpha_{21}CSAD_{i-1} + \ldots + \alpha_{2p}CSAD_{i-p} + \varepsilon_{20,i} \tag{11}$$

where $CSAD_i$ is the cross-sectional absolute deviation of returns during interval i; $VOLA_{m,i}$ is the market volatility during interval i, while p is the number of lags determined by the lowest Akaike Information Criterion (AIC). If extreme market volatility drives herding, then lags of market volatility should be significant in Eq. (10). Similarly, if herding causes excessive market volatility, lags of herding should be significant in Eq. (11). We perform the Granger (1969) causality test on the event day and for each day of the high volatility samples under the null hypothesis of $VOLA_{m,i}$ does not Granger cause $CSAD_i$ (i.e., $H_0: \ \alpha_{11} = \ldots = \alpha_{1p} = 0$) and the null hypothesis of $CSAD_i$ does not Granger cause $VOLA_{m,i}$ (i.e., $H_0: \ \alpha_{21} = \ldots = \alpha_{2p} = 0$). If the test rejects both null hypotheses on the event day, it implies that herding and high market volatility are mutually causative, leading to the circuit breaker's trigger. The Granger causality test result is interpreted differently for the high volatility sample. For the VAR model estimates on each day, we undertake the Granger causality test and report the proportion of the high volatility sample (in percentage, out of the 170 plus days sample) that rejects the null hypothesis at the 5% significance level. We employ the Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors in all regressions.

We also generate the impulse response function to provide the time profile of the short-term dynamic response of herding (market volatility) to its shock and the shock of market volatility (herding). Additionally, we decompose the forecast error variance to show the importance of these shocks explaining the variation of herding and market volatility. The impulse response function and the forecast error variance decomposition are obtained by averaging the VAR estimates on each day for the total numbers of days in the high volatility sample.

[8] Akay et al. (2010) show that Parkinson's range-based volatility with higher sampling frequencies reduces microstructure noise and takes into consideration the liquidity pressure from regular trading.

4.3. Test of hypothesis 3: fundamental and non-fundamental herding

We follow Xie et al. (2015) to construct the risk factors using the constituents from the CSI 300 Index. The CSI 300 Index measures the overall performance of the A-shares traded on the SSE and SZSE and accounts for over 60% of total market capitalisation on the SSE and SZSE. The constituents of the CSI 300 Index are selected with strict criteria with high-quality information disclosure and high-level corporate governance. In addition, unlike the asset pricing literature that relies on the entire market, we use the common risk factors to capture fundamental information that affects investors' decisions on the day when the market-wide circuit breaker was triggered. Consistent with the scope of our study using the CSI 300 Index as the benchmark for the event, we, therefore, use the constituents to develop the factors.

Following Galariotis et al. (2015), we decompose herding (i.e., the total CSAD measure) into fundamental and non-fundamental factors. Fundamental information that affects investors' decisions at the market level constitutes common risk factors, namely, High Minus Low return (HML_i), Small Minus Big return (SMB_i) (see Fama and French, 1995, 1996) and Momentum return (MOM_i) (see Carhart, 1997) are computed from the 1-minute data.[9] Similar to Lam and Tam (2011) and Lam and Qiao (2015), we construct the Fama-French factors by forming six value-weighted portfolios based on the intersection of firms' market equity (ME) and the book-to-market equity ratio (BE/ME) at the end of each quarter.[10] For each quarter, we divide our sample stocks into (i) two portfolio sizes (Small (S): 50% and Big (B): 50%) based on their ME values at the end of the previous quarter; and (ii) three portfolios (Low (L) for the bottom 30%; Medium (M) for the middle 40%; High (H) for the top 30%) based on their BE/ME, yielding six different value-weighted portfolios (SL, SM, SH, BL, BM, BH). For example, the SH portfolio contains small-size stocks with high BE/ME, and the BL portfolio contains big-size stocks with low BE/ME.

The SMB_i factor (i.e., the size-related portfolio return spreads) is the simple average of the three portfolio return differences: $(SL_i - BL_i)$, $(SM_i - BM_i)$, and $(SH_i - BH_i)$, each of which is the 1-minute quarterly difference between the small-size and big-size portfolios with the same BE/ME level:

$$SMB_i = \frac{(SL_i - BL_i) + (SM_i - BM_i) + (SH_i - BH_i)}{3} \tag{12}$$

The HML_i factor (i.e., the book-to-market ratio-related portfolio return spreads) is the simple average of the two portfolio return differences: $(SH_i - SL_i)$ and $(BH_i - BL_i)$, each of which is the 1-min quarterly difference between the high BE/ME and low BE/ME portfolios with the same size:

$$HML_i = \frac{(SH_i - SL_i) + (BH_i - BL_i)}{2} \tag{13}$$

The Carhart's Momentum return factor is constructed using six value-weighted portfolios based on the intersection of firms' ME and their prior performance using the previous 2–12 months' returns.[11] We then divide the same sample stocks into three portfolios comprising Losers (Los) for the bottom 30%, Neutrals (Neu) for the middle 40% and Winners (Win) for the top 30% based on their last performance before the end of the previous quarter. Accordingly, we have six different value-weighted portfolios (i.e.,

[9] Khandani & Lo (2011) and Hu et al.(2020) also use transaction data to construct the Fama-French factors and the momentum return factor.

[10] Conventional asset pricing studies use sorting mechanism based on yearly variables with daily data. For the purpose of this study involving intra-day data, our sorting mechanism is based on quarterly variable given that the portfolio is rebalanced more frequently in a market turmoil.

[11] Following Lam and Tam (2011), we exclude the most recent month to avoid the continuation effect caused by the bid-ask spread.

SLos, SNeu, SWin, BLos, BNeu, BWin). For example, the SLos portfolio contains small-size stocks with low prior returns, and the BWin portfolio contains big-size stocks with high prior returns. The MOM_i factor (i.e., the prior-performance-related portfolio return spreads) is the simple average of the two portfolio return differences: $(SWin_i - SLos_i)$ and $(BWin_i - BLos_i)$, each of which is the 1-minute quarterly difference between the high prior return and low prior return portfolios with the same size:

$$MOM_i = \frac{(SWin_i - SLos_i) + (BWin_i - BLos_i)}{2} \tag{14}$$

This is followed by estimating the regression:

$$CSAD_i = \beta_0 + \beta_1\left(R_{m,i} - R_f\right) + \beta_2 HML_i + \beta_3 SMB_i + \beta_4 MOM_i + \varepsilon_i \tag{15}$$

where $(R_{m,i} - R_f)$ is the excess return on the market portfolio; R_f is the risk-free return for the daily compounded value of 1-year government bond yield; HML_i, SMB_i and MOM_i are the High Minus Low, Small Minus Big and the Momentum return factor. After controlling the fundamental factors, the resulting residuals from Eq. (15) can be considered as the cross-sectional deviation ($\widehat{CSAD}_{nonfund,i}$) attributed to non-fundamental factors. Meanwhile, the cross-sectional deviation due to the fundamental factors can be defined as $CSAD_{fund,i} = CSAD_i - \widehat{CSAD}_{nonfund,i}$. Next, we use $CSAD_{fund,i}$ ($CSAD_{nonfund,i}$) as a proxy for fundamental (non-fundamental) herding and estimate the following two regressions:

$$CSAD_{fund,i} = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i \tag{16}$$

$$CSAD_{nonfund,i} = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i \tag{17}$$

Similar to Eq. (4), we estimate Eqs. (18) and (19) for the fundamental and non-fundamental CSAD measures as dependent variables to determine the type of herding that occurs around the circuit breaker on the event day. The regressions are as follows:

$$\begin{aligned} CSAD_{fund,i} = {} & \beta_0 + \beta_1|R_{m,i}| + \beta_2\left(R_{m,i} - \overline{R}_m\right)^2 + \beta_3 PRE_i CB_i|R_{m,i}| \\ & + \beta_4(1 - PRE_i)CB_i|R_{m,i}| + \beta_5 PRE_i CB_i\left(R_{m,i} - \overline{R}_m\right)^2 \\ & + \beta_6(1 - PRE_i)CB_i\left(R_{m,i} - \overline{R}_m\right)^2 + \varepsilon_i \end{aligned} \tag{18}$$

$$\begin{aligned} CSAD_{nonfund,i} = {} & \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \beta_3 PRE_i CB_i|R_{m,i}| \\ & + \beta_4(1 - PRE_i)CB_i|R_{m,i}| + \beta_5 PRE_i CB_i(R_{m,i} - \bar{R}_m)^2 \\ & + \beta_6(1 - PRE_i)CB_i(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i \end{aligned} \tag{19}$$

In this model, if *moderate* herding prevails on the event day, we expect the coefficients β_5 and β_6 to be negative and statistically significant, capturing a stronger non-linear relationship between the dispersion and average market return. On the other hand, if *extreme* herding occurs, we expect the coefficients β_3 and β_4 to be negative and statistically significant. We employ Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors.

5. Empirical results

5.1. Results for hypothesis 1: herding and the circuit breaker

Table 1 provides the descriptive statistics for the $CSAD_i$ and $|R_{m,i}|$ using the equally-weighted average of stock returns (Panel A) and returns of the CSI 300 Index (Panel B) for three study samples, including the event sample and each of the control samples (full and down samples) at a 1-minute frequency. In both panels, they show that the means and standard deviations of $CSAD_i$ and $|R_{m,i}|$ for the event sample (i.e., on 4th January) are relatively

Table 1

Descriptive Statistics for $CSAD_i$ and $|R_{m,i}|$

This table presents the intraday mean, standard deviation, median, skewness, kurtosis and Augmented Dickey-Fuller test statistic of the cross-sectional absolute deviation of returns ($\boldsymbol{CSAD_i}$) and absolute value of average market return ($|\boldsymbol{R_{m,i}}|$) at 1-min frequency. The cross-sectional absolute deviation of returns ($\boldsymbol{CSAD_i}$) is calculated as:$\boldsymbol{CSAD_i} = \frac{1}{N}\sum_{j=1}^{N}|\boldsymbol{R_{j,i}} - \boldsymbol{R_{m,i}}|$, where $\boldsymbol{R_{j,i}}$ is the return of stock $\boldsymbol{j}$ for interval $\boldsymbol{i}$, $\boldsymbol{R_{m,i}}$ is the average market return during interval $\boldsymbol{i}$. The "Full sample" consists of all days from January 5, 2015, to January 6, 2017. The "Down sample" refers to the days when the market has downward movements ($\boldsymbol{R_{m,i}}<0$). Panel A presents the statistics using equally-weighted average of stock returns, where $\boldsymbol{R_{m,i}} = \frac{1}{N}\sum_{j=1}^{N}\boldsymbol{R_{j,i}}$. Panel B presents the statistics using returns of the market index (CSI 300 Index). The full and down samples reported here include the number of observations in the event sample on January 4, 2016 (i.e., 133 observations).[a]

Panel A: Equally-Weighted Average Stock Returns

	Mean		Standard Deviation		Median		Skewness		Kurtosis		ADF test (p-value)		Number of Observations
	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	
Event sample	0.1794	0.1111	0.0704	0.1122	0.1584	0.0760	2.1554	1.9025	5.3549	4.4101	0.0240	0.0011	133
Full sample	0.1322	0.0578	0.0628	0.0803	0.1166	0.0326	3.3558	4.8869	20.5415	46.1024	0.0001	0.0001	65170
Down sample	0.1311	0.0582	0.0636	0.0817	0.1140	0.0319	3.2451	4.8349	20.0096	45.4334	0.0001	0.0001	31654

Panel B: CSI 300 Index Returns

	Mean		Standard Deviation		Median		Skewness		Kurtosis		ADF test (p-value)		Number of Observations
	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	$CSAD_i$	$\|R_{m,i}\|$	
Event Sample (4^{th} Jan)	0.1795	0.0923	0.0706	0.0936	0.1579	0.0650	2.1530	1.9236	5.2924	4.3520	0.0233	0.0011	133
Full sample	0.1332	0.0507	0.0642	0.0673	0.1171	0.0298	3.4364	4.6331	21.6303	41.4088	0.0001	0.0001	65170
Down sample	0.1349	0.0527	0.0656	0.0702	0.1180	0.0308	3.2784	4.4812	20.0222	37.1389	0.0001	0.0001	31122[b]

[a] For the morning trading session, trading occurred from 9:30 am to 11:30 am (i.e., 120 minutes), comprising 113 observations after excluding the first 5 minutes of the day and the 2 minutes before the lunch break. For the afternoon session, pre-halt trading occurred from 1:00 pm to 1:13:13 pm, comprising 12 observations excluding the 2 minutes after the lunch break. Post-halt trading occurred from 1:27:50 pm to 1:34:24 pm, comprising 8 observations. Hence, there are 113+12+8=133 observations for morning and afternoon trading sessions.

[b] Since the "Down sample" refers to days when the market experiences downward movements ($R_{m,i}<0$), the number of observations differs for the CSI 300 Index returns compared to the average market returns.

Table 2
Estimation of Herd Behaviour

This table reports the results of the regression:
$CSAD_i = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i$ (3)
where $CSAD_i$ is the cross-sectional absolute deviation of returns during interval i; $R_{m,i}$ is the average market return during interval i; $\bar{R}_m$ is the arithmetic mean of $R_{m,i}$. The "Full sample" consists of all days from January 5, 2015, to January 6, 2017. The "Down sample" refers to the days when the market has downward movements ($R_{m,i}$<0). Panel A (Panel B) presents the estimation results using equally-weighted average stock returns (CSI 300 Index returns) as market return. Numbers in parentheses are p-values. The full and down samples for the equally-weighted average stock returns (CSI 300 Index returns) comprise 65,170 and 31,654 (65,170 and 31,122) observations, respectively.

Panel A: Equally-Weighted Average Stock Returns			
	β_0	β_1	β_2
Full sample	0.0955	0.6611	-0.1541
	(<.0001)	(<.0001)	(<.0001)
Down sample	0.0939	0.6653	-0.1513
	(<.0001)	(<.0001)	(<.0001)
Panel B: CSI 300 Index Returns			
	β_0	β_1	β_2
Full sample	0.0947	0.7888	-0.2205
	(<.0001)	(<.0001)	(<.0001)
Down sample	0.0957	0.7733	-0.2045
	(<.0001)	(<.0001)	(<.0001)

higher than the full and down samples. Both $CSAD_i$ and $|R_{m,i}|$ are stationary since the ADF test statistics rejects the null hypothesis of non-stationarity across all samples.

Table 2 reports the results of estimating the herding regression in Eq. (3) for the full and down samples. Panel A presents the regression results using the equally-weighted average stock returns as a proxy for the market returns, while Panel B uses the CSI 300 Index returns. We find a consistently positive and statistically significant coefficient of β_1. For both samples and the different measures of market returns, the β_2 coefficient is negative and statistically significant. These results indicate an increase in the return dispersion at a decreasing rate as market return increases for the full sample and the sample when the market has downward movements. Together, they imply the presence of herd behaviour.

Results in Table 3 provide evidence on whether investors exhibit herding on the day when the market-wide circuit breaker was triggered. Using either equally-weighted average stock returns or returns of the CSI 300 Index as market return, the estimates of the full sample and down sample show a positive sign for the coefficients $\beta_3$and $\beta_4$of $PRE_iCB_i|R_{m,i}|$and $(1 - PRE_i)CB_i|R_{m,i}|$, respectively, and a negative sign for the coefficients β_5 and β_6 of $PRE_iCB_i(R_{m,i} - \bar{R}_m)^2$ and $(1 - PRE_i)CB_i(R_{m,i} - \bar{R}_m)^2$, respectively. Since the coefficients are statistically significant and reflect the expected signs, the market observes abnormal herd behaviour before and after the 15-minute trading halt on the event day. In addition, it is interesting to note that the magnitude of the coefficients using the equally-weighted average stock returns (Panel A) is smaller than that using returns of the CSI 300 Index (Panel B). This is because the CSI 300 Index returns give greater weights to large capitalisation stocks, while an equally-weighted average of stock returns gives equal weight to each stock. For example, the coefficient β_6 for the full sample is -1.4269 in Panel A and -1.9212 in Panel B. This finding provides support for Hypothesis 1. In the presence of extreme uncertainty associated with the market-wide circuit breaker, investors abandon their beliefs and herd on the event day. Our findings are also consistent with the notion of a U-shaped signal by Park and Sabourian (2011); the information associated with an upcoming event (i.e. the trigger of the circuit breaker) that has an uncertain impact on the market do give rise to significant herding in the pre-halt period.

5.2. Results for hypothesis 2: herding and market volatility

To investigate whether herding is associated with higher market return volatility, we estimate Eqs. (7) and (8) and report the results in Table 4 Panels A and B, respectively. The results in Panel A and Panel B show that the coefficients of $|R_{m,i}^{HIGH}|$ (β_1^{HIGH}) and $|R_{m,i}^{LOW}|$ (β_1^{LOW}) are statistically significant and positive, while the coefficients of $(R_{m,i}^{HIGH} - \bar{R}_m)^2$ (β_2^{HIGH}) and $(R_{m,i}^{LOW} - \bar{R}_m)^2$ (β_2^{LOW}) are statistically significant and negative. Together, these results imply the presence of herding on days with both high and low market volatility. Our results contrast those of Tan et al. (2008), who find no evidence of herding during periods of low volatility. Differences in results could be attributed to the different frequency of data, sample period, and data types.[12] Panel C provides evidence on whether investors exhibit herding on the day when the market-wide circuit breaker was triggered. For the equally-weighted average stock returns, we find that the coefficients β_5 and β_6 (-0.5961 and -1.3437) for the pre- and post-halt periods on the event day are significant and negative, implying herding is prevalent with the higher volatility observed around the circuit breaker trigger. The $|\hat{\beta}_6| > |\hat{\beta}_5|$ suggests that herding intensified in the period after the 15-minute trading halt imposed by the circuit breaker. For the return volatility of the CSI 300 Index, we find that the magnitude of β_5 and β_6 coefficients are greater (-1.0983 and -1.7812) than those for the equally-weighted average stock returns, indicating that herding is more pronounced in large capitalisation stocks. Overall, these results support Hypothesis 2a.

We turn to the causality effects between the cross-sectional absolute deviation of returns ($CSAD_i$) and average market volatility ($VOLA_{m,i}$). Table 5 provides the descriptive statistics for the cross-sectional absolute deviation of returns ($CSAD_i$) and market volatility for the equally-weighted average stock returns (Panel A) and the CSI 300 Index returns (Panel B) at the 1-min frequency for the event sample and the high volatility sample. The mean values of $CSAD_i$ *and* $VOLA_{m,i}$ for the event sample are higher than those of the high volatility sample, highlighting the greater volatility in the market on the event day. In addition, the null hypothesis of non-stationarity is rejected by the Augmented Dickey-Fuller test at the 1% level of significance for both $CSAD_i$ and $VOLA_{m,i}$ across the four samples.

For the event sample, the lag lengths of 1 and 2 have been chosen based on the lowest AIC for the samples using the equally-weighted average stock return volatility and the return volatility of the CSI 300 Index, respectively. For the high volatility sample, 63.07% (32.95%) of sample days select a VAR model with 1 (2) lag associated with the lowest AIC for the equally-weighted average stock return volatility. For the return volatility of the CSI 300 index, 47.37% (45.03%) of sample days select a VAR model with 1 (2) lag associated with the lowest AIC. For the reported results, we use the same lag length of the VAR model for the high volatility sample and the event sample[13].

Table 6 reports the Granger Causality test results to identify the direction of causality between $CSAD_i$ and $VOLA_{m,i}$. For the event sample with the return volatility of the CSI 300 Index, we reject the null hypothesis of $CSAD_i$ does not Granger cause $VOLA_{m,i}$and the null hypothesis of $VOLA_{m,i}$ does not Granger cause $CSAD_i$, implying bidirectional causality. For the high volatility sample with the CSI 300 Index return volatility, less than 50% of the sample rejects both null hypotheses at the 5% significance level, implying

[12] Tan et al. (2008) use daily, weekly and monthly data from 1994 to 2003 for 87 dual-listed shares.

[13] For the high volatility sample of the return volatility of the CSI 300 Index, we also use the VAR(1) model to test the robustness of our results. The results remain qualitatively unchanged. We do not report the results for brevity, but they are available from the authors upon request.

Table 3

Estimation of Herd Behaviour around the Trigger of the Circuit Breaker

This table reports the results of the regression:

$$CSAD_i = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \beta_3 PRE_i CB_i|R_{m,i}| + \beta_4(1 - PRE_i)CB_i|R_{m,i}| + \beta_5 PRE_i CB_i(R_{m,i} - \bar{R}_m)^2 + \beta_6(1 - PRE_i)CB_i(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i \quad (4)$$

where $CSAD_i$ is the cross-sectional absolute deviation of returns during interval i; $R_{m,i}$ is the average market return during interval i; $\bar{R}_m$ is the arithmetic mean of $R_{m,i}$; CB denotes a dummy variable taking the value 1 for event days and 0 for non-event days, while PRE denotes a dummy variable taking the value 1 for pre-halt periods and 0 for post-halt periods. The "Full sample" consists of all days from January 5, 2015, to January 6, 2017. The "Down sample" refers to the days when the market has downward movements ($R_{m,i}$<0). Panel A (Panel B) presents the estimation results using equally-weighted average stock returns (CSI 300 Index returns) as market return. Numbers in parentheses are p-values. The full and down samples for the equally-weighted average stock returns (CSI 300 Index returns) comprise 65,170 and 31,654 (65,170 and 31,122) observations, respectively.

Panel A: Equally-Weighted Average of Stock Returns

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Full sample	0.0955	0.6611	-0.1540	0.1575	0.7807	-0.8234	-1.4269
	(<.0001)	(<.0001)	(<.0001)	(0.0511)	(0.0443)	(<.0001)	(0.0437)
Down sample	0.0938	0.6653	-0.1510	0.1732	0.7880	-0.8715	-1.4461
	(<.0001)	(<.0001)	(<.0001)	(0.0310)	(0.0423)	(<.0001)	(0.0410)

Panel B: CSI 300 Index Returns

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Full sample	0.0947	0.7887	-0.2202	0.2538	0.8800	-1.4318	-1.9212
	(<.0001)	(<.0001)	(<.0001)	(0.0084)	(0.0067)	(<.0001)	(0.0060)
Down sample	0.0957	0.7731	-0.2039	0.2552	0.8881	-1.4093	-1.9250
	(<.0001)	(<.0001)	(<.0001)	(0.0084)	(0.0063)	(<.0001)	(0.0059)

Table 4

Estimation of Herd Behaviour for the High and Low Volatility Samples

This table reports the results of the regression:

$$CSAD_i^{HIGH} = \beta_0 + \beta_1^{HIGH}|R_{m,i}^{HIGH}| + \beta_2^{HIGH}(R_{m,i}^{HIGH} - \bar{R}_m)^2 + \varepsilon_i \quad (7)$$

$$CSAD_i^{LOW} = \beta_0 + \beta_1^{LOW}|R_{m,i}^{LOW}| + \beta_2^{LOW}(R_{m,i}^{LOW} - \bar{R}_m)^2 + \varepsilon_i \quad (8)$$

$$CSAD_i^{HIGH} = \beta_0 + \beta_1|R_{m,i}^{HIGH}| + \beta_2(R_{m,i}^{HIGH} - \bar{R}_m)^2 + \beta_3 PRE_i CB_i|R_{m,i}^{HIGH}| + \beta_4(1 - PRE_i) CB_i|R_{m,i}^{HIGH}| + \beta_5 PRE_i CB_i(R_{m,i}^{HIGH} - \bar{R}_m)^2 + \beta_6(1 - PRE_i)CB_i(R_{m,i}^{HIGH} - \bar{R}_m)^2 + \varepsilon_i \quad (9)$$

where $CSAD_i^{HIGH}$ ($CSAD_i^{LOW}$) is the cross-sectional absolute deviation of returns during interval i on the days when market volatility is high (low); $R_{m,i}^{HIGH}$ ($R_{m,i}^{LOW}$) is the average market return during interval i on the days when market volatility is high (low); $\bar{R}_m$ is the arithmetic mean of $R_{m,i}$; CB denotes a dummy variable taking the value 1 for event days and 0 for non-event days, while PRE denotes a dummy variable taking the value 1 for pre-halt periods and 0 for post-halt periods. Panel A presents the estimation results of Eq. (7) using either the equally-weighted average stock returns or the CSI 300 Index returns as market returns, while Panel B presents the estimation results of Eq. (8). Panel C reports the estimation results of Eq. (9). Numbers in parentheses are p-values. The high volatility samples for the equally-weighted average stock returns and the CSI 300 Index returns comprise 23,541 and 22,876 observations, respectively. The low volatility samples for the equally-weighted average stock returns and the CSI 300 Index returns comprise 37,772 and 38,437 observations, respectively.

Panel A: Regression Results of Eq. (7)

	β_0	β_1	β_2
Equally-weighted average stock returns	0.1035	0.6725	-0.1556
	(<.0001)	(<.0001)	(<.0001)
CSI 300 Index	0.1016	0.8250	-0.2686
	(<.0001)	(<.0001)	(<.0001)

Panel B: Regression Results of Eq. (8)

	β_0	β_1	β_2
Equally-weighted average stock returns	0.0902	0.6410	-0.1791
	(<.0001)	(<.0001)	(<.0001)
CSI 300 Index	0.0911	0.7550	-0.1840
	(<.0001)	(<.0001)	(0.0009)

Panel C: Regression Results of Eq. (9)

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Equally-weighted average stock returns	0.1035	0.6735	-0.1562	0.0455	0.7107	-0.5961	-1.3437
	(<.0001)	(<.0001)	(<.0001)	(0.5926)	(0.0670)	(0.0108)	(0.0572)
CSI 300 Index	0.1016	0.8258	-0.2693	0.1125	0.7879	-1.0983	-1.7812
	(<.0001)	(<.0001)	(<.0001)	(0.2585)	(0.0156)	(0.0002)	(0.0111)

the lack of evidence for bidirectional causality in the high volatility sample. These results show bi-directional causality between herd behaviour and market volatility on the event day, thus supporting Hypothesis 2B.

Fig. 2 displays the orthogonalized impulse response functions for the event sample (Panel A) and high volatility sample (Panel B) using the equally-weighted average stock return volatility and the return volatility of the CSI 300 Index. The orthogonalized impulse response function depicts the intraday dynamic responses of herding ($CSAD_i$) and market volatility ($VOLA_{m,i}$) to a one standard deviation shock of herding ($CSAD_i$) in quadrant (a) and to a one standard deviation shock of market volatility ($VOLA_{m,i}$) in quadrant (b) for the equally-weighted average market return volatility. For the CSI 300 return volatility, quadrant (c) (quadrant (d)) depicts the impulse responses of herding ($CSAD_i$) and market volatility ($VOLA_{m,i}$) to a one standard deviation shock of herding ($CSAD_i$) (market volatility ($VOLA_{m,i}$)). The thick middle line represents the impulse response estimates sandwiched by the two standard devi-

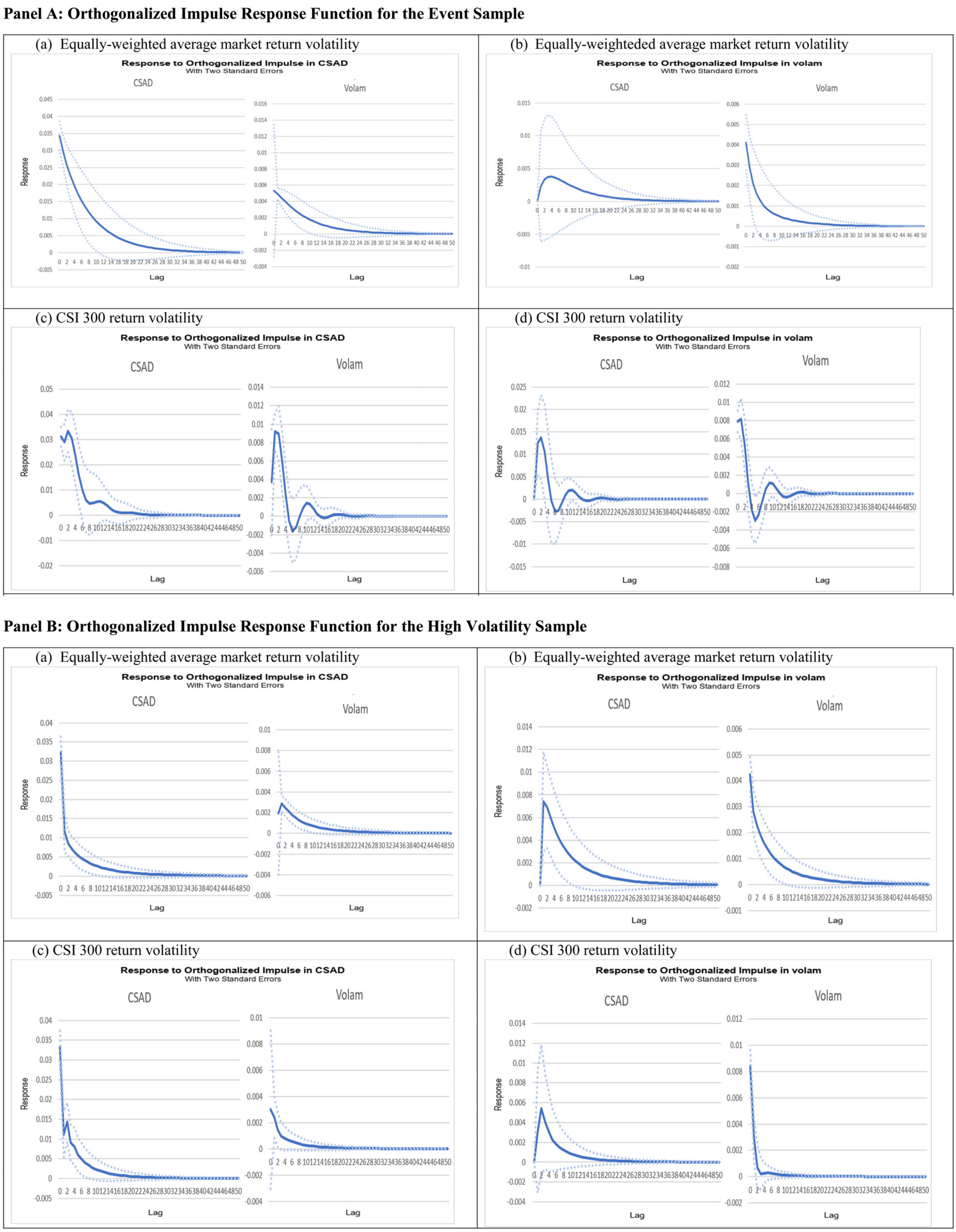


Fig. 2. Orthogonalized Impulse Response Function
This figure presents the orthogonalized impulse response function for the event sample (Panel A) and the high volatility sample (Panel B) using the equally-weighted average stock return volatility and return volatility of the market index (CSI 300 Index). The orthogonalized impulse response function depicts the intraday dynamic responses of herding ($\boldsymbol{CSAD_i}$) and market volatility ($\boldsymbol{VOLA_{m,i}}$) to a standard deviation shocks of herding ($\boldsymbol{CSAD_i}$) in (a) and to a standard deviation shocks of market volatility ($\boldsymbol{VOLA_{m,i}}$) in (b) for the equally-weighted average stock return volatility. Similarly, the impulse responses depicted for (c) and (d) are for the return volatility of the CSI 300 Index. The impulse response estimates are represented by the middle thick line sandwiched by the two standard deviation bands.

Table 5
Descriptive Statistics for $CSAD_i$ and $VOLA_{m,i}$
This table presents the intraday mean, standard deviation, median, skewness and kurtosis and Augmented Dickey-Fuller test statistic of the cross-sectional absolute deviation of returns ($CSAD_i$) and market volatility ($VOLA_{m,i}$) at 1-min frequency. The cross-sectional absolute deviation of returns ($CSAD_i$) is calculated as: $CSAD_i = \frac{1}{N}\sum_{j=1}^{N}|R_{j,i} - R_{m,i}|$, where $R_{j,i}$ is the return of stock j for interval i, $VOLA_{m,i}$ is the average market volatility during interval i. The "High volatility sample" refers to the days when the daily market volatility is higher than the moving average of volatility over the previous 30 days. The equally-weighted average stock returns is computed as $R_{m,i} = \frac{1}{N}\sum_{j=1}^{N} R_{j,i}$. The high volatility sample reported here includes the number of observations in the event sample on January 4, 2016 (i.e., 133 observations).

	Mean		Standard Deviation		Median		Skewness		Kurtosis		ADF test (p-value)		Number of Observations
	$CSAD_i$	$VOLA_{m,i}$	$CSAD_i$	$VOLA_{m,i}$	$CSAD_i$	$VOLA_{m,i}$	$CSAD_i$	$VOLA_{m,i}$	$CSAD_i$	$VOLA_{m,i}$	$CSAD_i$	$VOLA_{m,i}$	
Equally-Weighted Average Stock Returns													
Event Sample	0.1794	0.0384	0.0704	0.0136	0.1584	0.0362	2.1554	1.1379	5.3549	1.2019	0.0240	0.0196	133
High volatility sample	0.1493	0.0343	0.0781	0.0217	0.1284	0.0287	3.1404	2.1061	15.9540	7.5769	0.0001	0.0001	23541
CSI300 Index Returns													
Event Sample	0.1795	0.0199	0.0706	0.0177	0.1579	0.0155	2.1530	2.0992	5.2924	5.1644	0.0233	0.0011	133
High volatility sample	0.1530	0.0158	0.0830	0.0181	0.1300	0.0096	3.0168	3.8917	15.1938	24.7912	0.0001	0.0001	22876

Table 6
Granger Causality Tests Between $CSAD_i$ and $VOLA_{m,i}$
This table reports the Granger Causality tests between herding ($\boldsymbol{CSAD_i}$) and market volatility ($\boldsymbol{VOLA_{m,i}}$):
$\boldsymbol{CSAD_i = \beta_{10} + \beta_{11}CSAD_{i-1} + \ldots + \beta_{1p}CSAD_{i-p} + \alpha_{11}VOLA_{m,i-1} + \ldots + \alpha_{1p}VOLA_{m,i-p} + \varepsilon_{10,i}}$ (10)
$\boldsymbol{VOLA_{m,i} = \beta_{20} + \beta_{21}VOLA_{m,i-1} + \ldots + \beta_{2p}VOLA_{m,i-p} + \alpha_{21}CSAD_{i-1} + \ldots + \alpha_{2p}CSAD_{i-p} + \varepsilon_{20,i}}$ (11)
where $\boldsymbol{CSAD_i}$ is the cross-sectional absolute deviation of returns during interval $\boldsymbol{i}$; $\boldsymbol{VOLA_{m,i}}$ is the market volatility during interval $\boldsymbol{i}$, while $\boldsymbol{p}$ is the number of lags determined by the lowest Akaike Information Criterion (AIC). The market volatility is calculated using the equally-weighted average of stock return volatility and return volatility of the market index (CSI 300 Index). The "High volatility sample" refers to the days when the daily market volatility is higher than the moving average of volatility over the previous 30 days. Panel A presents the results in p-value for the event sample on January 4, 2016. Panel B presents the results for the high volatility sample in terms of the proportion of days that rejects the null hypothesis at the 5% significance level. The event sample on January 4, 2016 comprises 133 observations. The high volatility samples for the equally-weighted average stock returns and the CSI 300 Index returns comprise 23,541 observations (176 days) and 22,876 observations (171 days), respectively.

Panel A: Event Sample			
		Equally-weighted average stock return volatility	Return volatility of the CSI 300 Index
$CSAD_i$ does not cause $VOLA_{m,i}$	p-value	0.1015	<.0001
$VOLA_{m,i}$ does not cause $CSAD_i$	p-value	0.3379	<.0001
Panel B: High Volatility Sample			
		Equally-weighted average stock return volatility	Return volatility of the CSI 300 Index
$CSAD_i$ does not cause $VOLA_{m,i}$	p-value<0.05	93.75%	47.36%
$VOLA_{m,i}$ does not cause $CSAD_i$	p-value<0.05	94.65%	36.67%

ation bands. On the event day, herding ($CSAD_i$) responds more to its shock than to market return volatility shock regardless of the return volatility proxies. Further, herding ($CSAD_i$) responds more to CSI 300 return volatility shock than the CSI 300 return volatility responds to its shock. This result supports our finding for the bidirectional causality between herding and market volatility as presented by the Granger causality test. For the high volatility sample with CSI 300 market return volatility, the responses of herding ($CSAD_i$) to CSI 300 market volatility shock are not statistically significant. Similarly, the responses of CSI 300 market volatility to herding ($CSAD_i$) shock are statistically insignificant, thus supporting the Granger causality results of no bidirectional causality between market return volatility and herding in the high volatility sample with CSI 300.

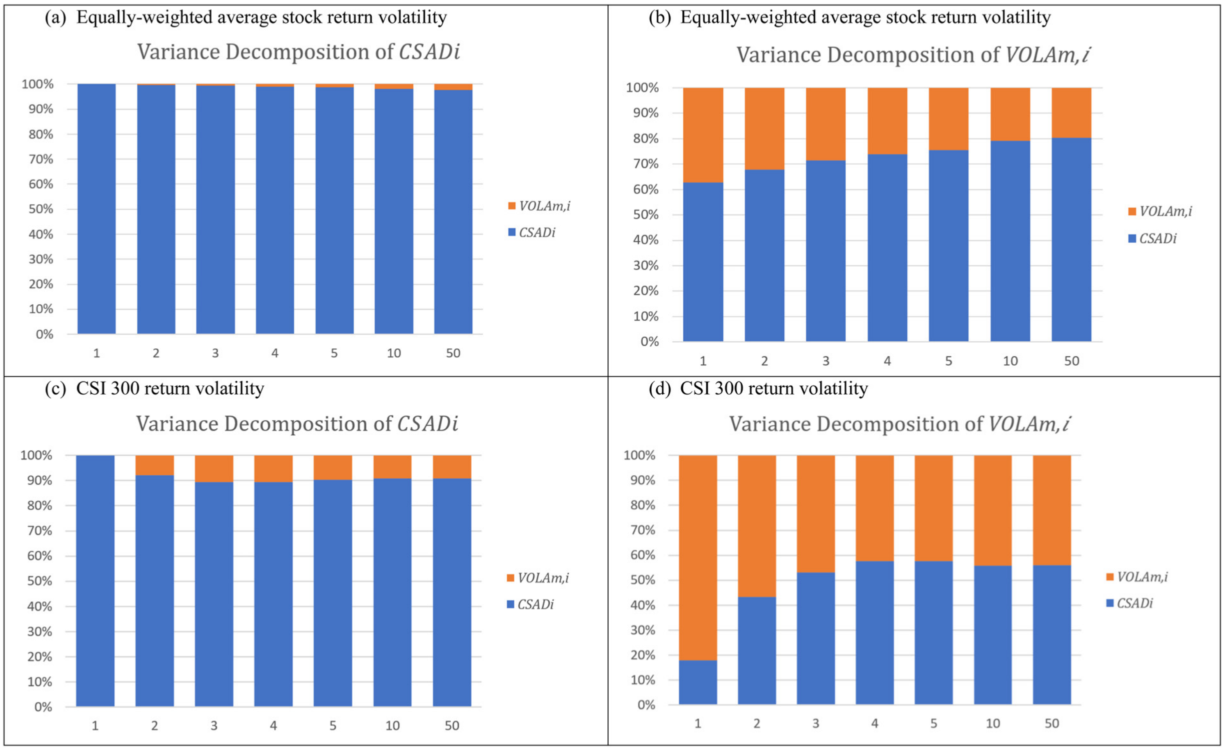
Fig. 3 presents the forecast error variance decomposition of both $CSAD_i$ and $VOLA_{m,i}$ for the event sample (Panel A) and the high volatility sample (Panel B). For the equally-weighted average stock return volatility, market volatility shocks minimally explain herding forecast error variance on the event day (i.e., nearly 2%). In contrast, herding shocks on event day explain about 60% of market volatility forecast error variance initially, and it grows in relative importance (i.e., up to 80%) at longer horizons. These results suggest that while herding and market volatility mutually causes each other, herding dominantly explains a large part of the forecast error variance of market volatility on the event day. In addition, when market-wide circuit breakers were triggered, herding shocks had a more substantial explanatory power over itself and market volatility forecast error variance compared to the high volatility sample. This is indicative that while herding and heightened market volatility are mutually reinforcing, herding primarily drives high market volatility on the event day, which could have led to the trigger of the market-wide circuit breaker. This result, again, supports Hypothesis 2B.

5.3. Results for hypothesis 3: fundamental and non-fundamental herding

We decompose the total $CSAD_i$ into fundamental factors ($CSAD_{fund,i}$) and non-fundamental factors ($CSAD_{nonfund,i}$) using Eq. (15) and present the estimated results of Eqs. (16) and (17) in Table 7. Table 8 reports the regression results, focusing on the type of herding that prevails on the event day based on Eqs. (18) and (19). In Tables 7 and 8, Panel A (B) reports the results of the equally-weighted average stock returns (the CSI 300 Index returns).

We have previously identified the presence of herding in the full sample, the down sample and the high volatility sample for the equally-weighted average stock returns as well as the CSI 300 Index returns (see Tables 2–4). In Table 7 Panel A for the equally-weighted average stock returns, the coefficients β_1 and β_2 in the fundamental herding regression results are not statistically significant for the three different samples; however, for the non-fundamental herding regression, these coefficients have the ex-

Panel A: Forecast Error Variance Decomposition for the Event Sample



Panel B: Forecast Error Variance Decomposition for the High Volatility Sample

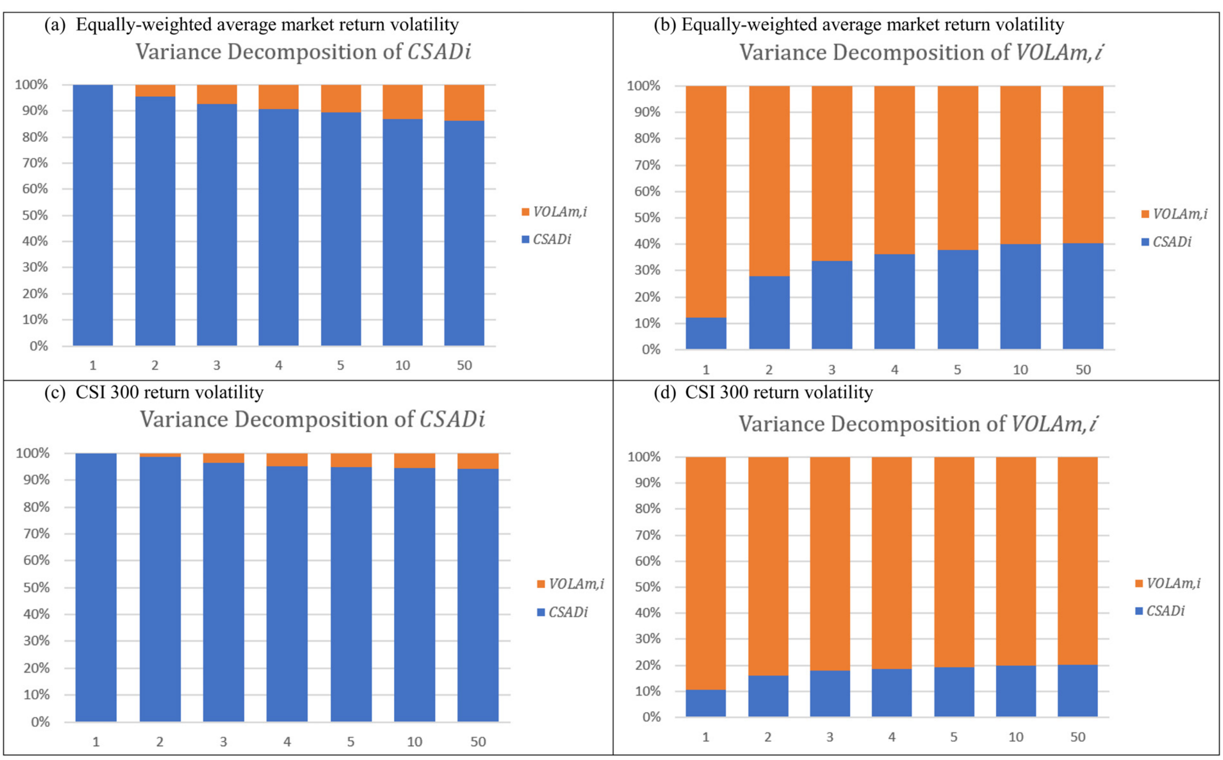


Fig. 3. Forecast Error Variance Decomposition of $CSAD_i$ and $VOLA_{m,i}$
This figure presents the decomposition of forecast error variance in $\boldsymbol{CSAD_i}$ and $\boldsymbol{VOLA_{m,i}}$, respectively, for the event sample (Panel A) and the high volatility sample (Panel B) using the equally-weighted average stock return volatility and return volatility of the market index (CSI 300 Index). The decomposition of forecast error variance in $\boldsymbol{CSAD_i}$ and $\boldsymbol{VOLA_{m,i}}$ is presented in (a) and (b), respectively, for the equally-weighted average stock return volatility. Similarly, the decomposition of forecast error variance for (c) and (d) are for the return volatility of the CSI 300 Index.

Table 7
Estimation of $CSAD_{fund,i}$ and $CSAD_{nonfund,i}$
This table reports the results from the regressions:
$CSAD_{fund,i} = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i$ (16)
$CSAD_{nonfund,i} = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i$ (17)
$CSAD_{nonfund,i}$, a proxy for non-fundamental herding, is the residuals from regression $CSAD_i = \beta_0 + \beta_1(R_{m,i} - R_f) + \beta_2 HML_i + \beta_3 SMB_i + \beta_4 MOM_i + \varepsilon_i$, while $CSAD_{fund,i}$, a proxy for fundamental herding, is computed as $CSAD_{fund,i} = CSAD_i - CSAD_{nonfund,i}$; $R_{m,i}$ is the average market return during interval i; $\bar{R}_m$ is the arithmetic mean of $R_{m,i}$. Panel A presents the estimation results of fundamental-driven deviation using equally-weighted average stock returns; Panel B presents the estimation results of non-fundamental-driven deviation using equally-weighted average stock returns; Panel C presents the estimation results of fundamental-driven deviation using returns of the market index (CSI 300 Index), while Panel D presents the estimation results of non-fundamental-driven deviation using returns of the market index (CSI 300 Index). Numbers in parentheses are p-values. The full and down samples for the equally-weighted average stock returns (CSI 300 Index returns) comprise 65,170 and 31,654 (65,170 and 31,122) observations, respectively. The high volatility samples for the equally-weighted average stock returns and the CSI 300 Index returns comprise 23,541 and 22,876 observations, respectively.

Panel A: Equally-Weighted Average Stock Returns			
Fundamental-Driven Deviation ($CSAD_{fund,i}$)	β_0	β_1	β_2
Full sample	0.1277	0.0002	0.0040
	(<.0001)	(0.9427)	(0.4920)
Down sample	0.1277	-0.0020	-0.0043
	(<.0001)	(0.4892)	(0.5711)
High volatility sample	0.1278	-0.0018	0.0039
	(<.0001)	(0.5700)	(0.5847)
Non-Fundamental-Driven Deviation ($CSAD_{nonfund,i}$)			
Full sample	-0.0322	0.6610	-0.1581
	(<.0001)	(<.0001)	(<.0001)
Down sample	-0.0338	0.6673	-0.1469
	(<.0001)	(<.0001)	(<.0001)
High volatility sample	-0.0243	0.6744	-0.1595
	(<.0001)	(<.0001)	(<.0001)
Panel B: CSI 300 Index Returns			
Fundamental-Driven Deviation ($CSAD_{fund,i}$)	β_0	β_1	β_2
Full sample	0.1294	-0.0047	0.0274
	(<.0001)	(0.0218)	(0.0009)
Down sample	0.1295	-0.0116	0.0367
	(<.0001)	(<.0001)	(0.0002)
High volatility sample	0.1295	-0.0079	0.0317
	(<.0001)	(0.0064)	(0.0008)
Non-Fundamental-Driven Deviation ($CSAD_{nonfund,i}$)			
Full sample	-0.0326	0.7756	-0.1892
	(<.0001)	(<.0001)	(0.0003)
Down sample	-0.0341	0.8017	-0.2398
	(<.0001)	(<.0001)	(0.0002)
High volatility sample	-0.0256	0.8220	-0.2652
	(<.0001)	(<.0001)	(<.0001)

pected sign and are statistically significant in all three samples. The results imply that non-fundamental herding prevails in the Chinese stock market from Jan 2015 to Jan 2017, during market downturns and when the market experiences high volatility. Using the CSI 300 Index returns reported in Panel B, we find similar results for the non-fundamental herding; however, the fundamental herding regression result shows a negative and significant β_1 estimates indicating extreme herding. The different outcomes between Panel A and B suggest investors of small capitalisation stocks tend to exhibit non-fundamental herding. Since there is less information on small capitalisation stocks, investors are more likely to mimic the trading strategies of others and to respond to market sentiments. Our findings are consistent with that of Lakonishok et al. (1992) and Venezia et al. (2011).

Table 8 reports the driving forces of herding for the pre- and post-halt periods on the event day across three samples. In line with the results of total $CSAD_i$ in Tables 3 and 4, herding behaviour in both pre- and post-halt periods on the event day is observed in the full sample, down, and high volatility samples. Moderate non-fundamental factors characterise the herding behaviour in the Chinese stock market for all three samples using two types of market returns (see Panels A and B of Table 8). In the non-fundamental herding regression for both market returns, the coefficients β_3 (for pre-halt) and β_4 (for post-halt) are positive and statistically significant, while the coefficients β_5 (for pre-halt) and β_6 (for post-halt) are negative and statistically significant. Further, the coefficient estimates $|\hat{\beta}_6| > |\hat{\beta}_5|$ suggest that herding intensified in the period after the 15-minute trading halt imposed by the circuit breaker. Consistent with the model's prediction, these results indicate that *moderate* non-fundamental herding prevails around the circuit breaker trigger, supporting Hypothesis 3.

At the same time, in addition to the presence of non-fundamental herding, we find *extreme* fundamental herding around the trigger of the circuit breaker, as evidenced in both the coefficients of β_3 (for pre-halt) and β_4 (for post-halt) being negative and statistically significant, reported in Panel A of Table 8. Extreme fundamental herding also intensifies in the post-halt period since the coefficient estimates $|\hat{\beta}_4| > |\hat{\beta}_3|$. In addition, the coefficients of β_1 and β_2 in the fundamental herding regression are not statistically significant, suggesting that fundamental herding does not prevail outside of the period around the circuit breaker trigger. According to Bikhchandani and Sharma (2000), fundamental herding can occur when groups make identical decisions when facing similar problems and information sets, leading to an optimal outcome. Traders show a common reaction to the potential trigger of the circuit breaker by selling off stocks to minimize their losses. Their decision to reduce their shares of stocks in the portfolio before the circuit breaker's trigger must be considered an optimal outcome.

The results remain qualitatively the same for the CSI 300 Index returns, except that fundamental herding is prevalent outside the circuit breaker trigger (see Panel B for fundamentals driven regression results). However, this result is consistent with that reported in Table 7. Since the CSI 300 index is never traded and investors trade on individual stocks, we conclude that extreme fundamen-

Table 8
Estimation of $CSAD_{fund,i}$ and $CSAD_{nonfund,i}$ around the Trigger of the Circuit Breaker
This table reports the results of the regressions:

$$CSAD_{fund,i} = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \beta_3 PRE_i CB_i|R_{m,i}| + \beta_4(1 - PRE_i)CB_i|R_{m,i}| + \beta_5 PRE_i CB_i(R_{m,i} - \bar{R}_m)^2 + \beta_6(1 - PRE_i)CB_i(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i \quad (18)$$

$$CSAD_{nonfund,i} = \beta_0 + \beta_1|R_{m,i}| + \beta_2(R_{m,i} - \bar{R}_m)^2 + \beta_3 PRE_i CB_i|R_{m,i}| + \beta_4(1 - PRE_i)CB_i|R_{m,i}| + \beta_5 PRE_i CB_i(R_{m,i} - \bar{R}_m)^2 + \beta_6(1 - PRE_i)CB_i(R_{m,i} - \bar{R}_m)^2 + \varepsilon_i \quad (19)$$

$CSAD_{nonfund,i}$, a proxy for non-fundamental herding, is the residuals from the regression $CSAD_i = \beta_0 + \beta_1(R_{m,i} - R_f) + \beta_2 HML_i + \beta_3 SMB_i + \beta_4 MOM_i + \varepsilon_i$, while $CSAD_{fund,i}$, a proxy for fundamental herding, is computed as $CSAD_{fund,i} = CSAD_i - CSAD_{nonfund,i}$; $R_{m,i}$ is the average market return during interval i; $\bar{R}_m$ is the arithmetic mean of $R_{m,i}$; CB denotes a dummy variable taking the value 1 for event days and 0 for non-event days, while PRE denotes a dummy variable taking the value 1 for pre-halt periods and 0 for post-halt periods. Panel A (Panel B) presents the results of the equally-weighted average stock returns (CSI 300 Index returns). Numbers in parentheses are p-values. The full and down samples for the equally-weighted average stock returns (CSI 300 Index returns) comprise 65,170 and 31,654 (65,170 and 31,122) observations, respectively. The high volatility samples for the equally-weighted average stock returns and the CSI 300 Index returns comprise 23,541 and 22,876 observations, respectively.

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Panel A: Equally-Weighted Average Stock Returns							
Fundamental-Driven Deviation ($CSAD_{fund,i}$)							
Full sample	0.1277	0.0003	0.0039	-0.0371	-0.0688	0.0889	0.0420
	(<.0001)	(0.8702)	(0.5009)	(0.0062)	(<.0001)	(0.2268)	(0.0037)
Down sample	0.1277	-0.0017	-0.0045	-0.0350	-0.0668	0.0971	0.0503
	(<.0001)	(0.5621)	(0.5595)	(0.0101)	(<.0001)	(0.1876)	(0.0009)
High volatility sample	0.1278	-0.0015	0.0037	-0.0368	-0.0679	0.0926	0.0434
	(<.0001)	(0.6515)	(0.6076)	(0.0063)	(<.0001)	(0.2042)	(0.0034)
Non-Fundamental-Driven Deviation ($CSAD_{nonfund,i}$)							
Full sample	-0.0322	0.6608	-0.1579	0.1945	0.8495	-0.9123	-1.4689
	(<.0001)	(<.0001)	(<.0001)	(0.0231)	(0.0305)	(0.0003)	(0.0406)
Down sample	-0.0338	0.6670	-0.1465	0.2082	0.8548	-0.9686	-1.4964
	(<.0001)	(<.0001)	(<.0001)	(0.0143)	(0.0295)	(<.0001)	(0.0371)
High volatility sample	-0.0243	0.6749	-0.1599	0.0823	0.7787	-0.6887	-1.3871
	(<.0001)	(<.0001)	(<.0001)	(0.3643)	(0.0473)	(0.0149)	(0.0529)
Panel B: CSI 300 Index Returns							
Fundamental-Driven Deviation ($CSAD_{fund,i}$)	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Full sample	0.1294	-0.0045	0.0276	-0.0349	-0.0570	0.0879	0.0001
	(<.0001)	(0.0265)	(0.0009)	(0.0158)	(<.0001)	(0.3652)	(0.9974)
Down sample	0.1294	-0.0113	0.0367	-0.0295	-0.0510	0.0827	-0.0078
	(<.0001)	(<.0001)	(0.0002)	(0.0399)	(<.0001)	(0.3909)	(0.7817)
High volatility sample	0.1295	-0.0075	0.0316	-0.0344	-0.0554	0.0909	-0.0016
	(<.0001)	(0.0092)	(0.0009)	(0.0161)	(<.0001)	(0.3428)	(0.9533)
Non-Fundamental-Driven Deviation ($CSAD_{nonfund,i}$)							
Full sample	-0.0326	0.7753	-0.1888	0.2740	0.9477	-1.4877	-1.9744
	(<.0001)	(<.0001)	(0.0003)	(0.0071)	(0.0038)	(<.0001)	(0.0051)
Down sample	-0.0341	0.8012	-0.2390	0.2704	0.9336	-1.4981	-1.9437
	(<.0001)	(<.0001)	(0.0002)	(0.0077)	(0.0044)	(<.0001)	(0.0059)
High volatility sample	-0.0257	0.8226	-0.2658	0.1205	0.8441	-1.1205	-1.8037
	(<.0001)	(<.0001)	(<.0001)	(0.2577)	(0.0100)	(0.0016)	(0.0105)

tal herding and moderate non-fundamental herding prevail around the circuit breaker trigger.

5.4. Robustness test results

The empirical results presented thus far are based on the full sample, the down sample and the high volatility sample. To corroborate our findings, we constructed two additional control samples based on return-matched benchmarks to control any significant price movement on non-event days. A 5% sample is produced by matching the event day with trading days when the CSI 300 Index falls by 5% and applying a 15-minute pseudo-halt, which starts when the index drops by 5% and ends before the actual market closure on the event day. After screening, the non-event days of the 5% sample include observations on June 4, 2015, July 7, 2015, July 28, 2015, and September 1, 2015.[14] We also construct a 7% sample by matching the event day with trading days when the CSI 300 Index falls by 7% and applying a 15-minute pseudo-halt when the index drops by 5% and a pseudo-closure when the index falls by 7%. The non-event days of the 7% sample include observations on June 26, 2015, and July 3, 2015. The 5% and 7% samples are chosen because when the CSI 300 Index falls by 5%, there are instances when the index continues to fall, and at other times the index reverses and goes up. Therefore, it is essential to distinguish between days when the index falls by 5% and days by 7%. Doing so will mitigate concerns about the randomness of the stock market performance during market turmoil and can measure two different levels of market distress. We find that, by and large, the results using the 5% and 7% samples remain qualitatively unchanged from the main results.[15]

6. Conclusion

This study investigates a market-wide circuit breaker's failed intervention for the Chinese stock market crash on January 4, 2016. Specifically, we examine whether herding serves as a possible cause of the circuit breaker trigger and impedes the effectiveness of the circuit breaker in moderating market volatility. Using intraday data at a 1-minute frequency, we discover the herding dynamic of investors associated with the circuit breaker on the event day. This novel study contributes to the literature on both herding and circuit breakers, which have never been studied concurrently before.

[14] See details in Appendix A.

[15] For brevity, we do not report the results of our robustness tests, but they are available from the authors upon request.

We find that the Chinese stock market exhibit presence of herding even when there is no market-wide circuit breaker. Moreover, overwhelming evidence suggests that herding continues to prevail before and after the trigger of the market-wide circuit breaker. We rationalise that this observation is consistent with the prediction of Park and Sabourian (2011). They attribute herding to investors receiving a U-shaped signal about extreme states and the uncertainty of the impact of the circuit breaker on the stock market. Under this circumstance, investors imitate the decisions of other traders, leading to more intense herding. We also find that herding is associated with high market volatility, particularly around the trigger of the circuit breaker. By treating herding and high market volatility as endogenously determined, we find evidence suggesting the two mutually influence each other. However, herding plays a dominant role on the event day and induces higher volatility that triggers the circuit breaker. Finally, we identify two types of herding that occur around the circuit breaker trigger. First, there is extreme fundamental herding stemming from traders' common reaction of selling stocks in the face of the uncertain impact of the circuit breaker. At the same time, moderate non-fundamental herding also characterises the behaviour of traders on the event day. The latter is pertinent for the Chinese stock market, which is steep in poor information transparency and where individual investors are prone to trade on sentiments that move the market. Non-fundamental herding primarily prevails in the Chinese stock market even in the absence of the circuit breaker. As such, non-fundamental herding can potentially destabilise the stock market and limit the effectiveness of the circuit breaker.

A key lesson from our findings is that regulators should not underestimate the power of market participants' reaction to the uncertainty associated with the newly implemented intervention – the circuit breaker. As indicated in our results, this extreme uncertainty related to the market-wide circuit breaker that disrupts the continuous trading market induces herding, be it fundamental or non-fundamental, amongst market participants. Such a level of uncertainty is not comparable to the uncertainty associated with the large price movements during continuous trading. As such, our results have substantial regulatory policy implications. The extant literature on the effectiveness of circuit breakers, including price limits, single-stock discretionary trading halts and market-wide circuit breakers, only focus on their impacts on stock performance. Our study provides valuable insights into why China's recent market-wide circuit breaker fails to stabilise the stock market and how traders' behaviour, particularly herding, can impede the circuit breaker's effectiveness.

In conclusion, our results empirically contribute to the scarce literature on the relationship between circuit breakers and herd behaviour amongst market participants in stock markets. Moreover, by focusing on the intraday herd behaviour in emerging stock markets like China, where individual investors dominate the stock market compared to institutional investors, we enrich the literature on herding, which centres mainly on developed economies.

CRediT authorship contribution statement

Xinru Wang: Conceptualization, Methodology, Software, Validation, Resources, Data curation, Writing – original draft, Visualization. **Maria H. Kim:** Conceptualization, Validation, Formal analysis, Writing – review & editing, Supervision, Project administration. **Sandy Suardi:** Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing, Supervision, Project administration.

Appendix A. Details of non-event days in 5% and 7% down samples.

Date	5% triggered	Market resumes	7% triggered	Price change at market closure (%)	5% down sample	7% down sample
04 Jun 2015	13:05:29	Yes	No	+0.75%	Yes	
26 Jun 2015	11:24:24	Yes	14:05:51	-7.88%		Yes
03 Jul 2015	10:05:04	Yes	10:24:56	-5.47%		Yes
07 Jul 2015	10:54:42	Yes	No	-1.81%	Yes	
28 Jul 2015	10:00:15	Yes	No	-0.21%	Yes	
01 Sep 2015	10:09:20	Yes	No	-0.13%	Yes	

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