Market Microstructure Evidence of China's Market-Wide Circuit Breakers

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Abstract

This paper provides market microstructure evidence, including price discovery, magnet effect and volatility spillover effect, on the failed market-wide circuit breakers in China's stock exchanges on January 4 and 7, 2016. The results for event samples are compared with non-event samples which control for normal trading behaviour around information release but absent regarding trading halts. We find trading halts provide no "time-out" cushion given that strong positive return autocorrelation on the days circuit breakers were triggered, and no improvement in the informativeness of stock prices given the smaller price contribution during halt relative to non-halt periods. Traders face time constraints from impending trading halts which force them to quickly close their positions as information asymmetry peaked, thus causing price to accelerate towards its limit (a magnet effect) and triggering a subsequent halt. Volatility of within-stock spills over into post-halt and overnight non-trading periods while cross-sectional volatility spillover between A- and B-shares increases in post-halt periods. Collectively the empirical evidence justifies the abolition of market-wide circuit breakers by government policy-makers and/or regulators.

Keywords: Market microstructure; Circuit breaker; Price discovery; Magnet effect; Volatility spillover; China

JEL Classification: G10; G14; G18

1. Introduction

Regulators are concerned with massive market movements during financial crises which generate seriously damaging outcomes for market participants and the economy. Since the stock market crash of October 1987, the United States Presidential Task Force on Market Mechanisms (1988; hereafter referred to as the Brady Commission report) recommended implementing circuit breakers in the form of price limits and coordinated trading halts. This regulatory instrument which is triggered by large swings in a security or a market index serves to prevent excessive speculative gains or losses on a security or massive losses in the finance markets. They are also designed to protect the market system and monitor activities by providing a "time-out" cushion so that market participants can incorporate and analyse the latest events when making rational trading decisions.[1] Based on the World Federation of Exchanges (WFE) 2016 survey concerning the use of circuit breakers, 86% of WFE members' exchanges implement circuit breakers including price limits and trading halts.[2] This number marks a significant increase compared to the 60% in 2008 (Gomber et al. 2016). Despite the prevalence of circuit breakers in many trading venues, the effectiveness of these mechanisms remains controversial.

This paper investigates the effectiveness of Chinese stock exchanges' *market-wide* circuit breakers which were first triggered on January 4, 2016. These circuit breakers, however, exacerbated and accelerated the market crash to the extent that the mechanisms were abolished four days after they were introduced. According to the Brady Commission report (1988), market-wide circuit breakers are designed to: (1) reduce credit risks and control the loss of financial confidence, (2) promote the price discovery process, and (3) respond to the illusion of liquidity[3]. Based on these criteria we provide market microstructure evidence on the ineffectiveness of China's market-wide circuit breakers. Firstly, do market-wide circuit breakers facilitate or impede the price discovery process in the stock markets during a financial turmoil? In other words, are there price continuations post-trading halts? Does the price change during the trading halts significantly contribute to the price discovery process? Secondly, is there a magnet effect with respect to the benchmark index (i.e. the CSI 300 index) as it approaches the trigger levels? Thirdly, do market-wide circuit breakers influence the within-stock and/or cross-sectional volatility spillover effects? Specifically, is there a spillover effect in the post-halt period? Does the volatility of the constituent stocks, A-shares, spill over to their corresponding B-shares after the trading halts?

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[1] The Brady Commission report (1988) also recognises that circuit breaker mechanisms may hinder investors' strategies to trade and hedge, and restrict from exiting the stock markets during the "time-out" cushion.

[2] The survey covers 63 member trading venues and 9 additional non-members of the WFE, of which 44 trading venues responded to the survey (Gomber et al. 2016).

[3] The illusion of liquidity refers to a false sense of optimism a financial actor (be that a company, fund manager or a government) has about the safety and resilience of a portfolio and/or market as a whole.

Theories on circuit breakers provide a number of testable predictions which lead to the above research questions. Proponents of circuit breakers argue they help restore the informativeness of market prices through price discovery, and thereby alleviate uncertainty and moderating information asymmetries (Greenwald and Stein 1991). When the market is not in distress, value buyers who look for attractive opportunities will trade and prevent prices from falling too far. However, in times of market distress they may be less likely to place orders due to the uncertainty of execution price (i.e. high transactional risk). The use of circuit breakers in such a circumstance is to reduce that transactional risk and encourage value buyers to trade in the market so that the fundamental price is facilitated to adjust accordingly. The information imperfection in a market crash that gives rise to a volume shock amongst potential risk bearers in the market can hopefully be alleviated through a circuit breaker mechanism, which is because improved information is made available to traders when they submit their orders.

On the other hand, opponents of circuit breakers argue that circuit breakers distort optimal trading decisions of large institutions, according to Subrahmanyam (1994). He finds that discretionary traders trade in a concentrated order rather than splitting their trades into small orders when the price is close to the circuit breakers limits. Consequently, circuit breakers increase *ex ante* price variability and the probability of the price hitting the limits (i.e. the magnet effect). Further, in a two-market situation, price variability and market liquidity may transfer from a dominant market to a satellite market since discretionary traders switch to the satellite market to reduce the likelihood of share prices moving toward new equilibrium levels when new information arrives in the market, to the extent that price limits serve no purpose other than to delay price discovery. Lehmann (1989) also opines that supply and demand imbalances in trading induce prices to reach price limits, which suggests that transactions are transferred to subsequent days. Accordingly, price limits may cause volatility to spread out over a longer period of time, including subsequent days.

In summary, proponents of circuit breakers argue that the mechanism is able to calm the market, reduce information asymmetry and its volatility, whereas its critics claim that it accelerates price movements (magnet effect), postpones price discovery (delayed price discovery effect), and even transmits price changes to other satellite markets (volatility spillover effect). It is interesting to note that the theory developed by Greenwald and Stein (1991) is based on markets in which market makers compete. However, the Chinese stock markets do not have market makers to supply liquidity; it is an order-driven market to the extent that this special market structure - also be found in other economies - provides another motivation to examine the behaviours of investors when there is high uncertainty of execution price in times of market distress. Subrahmanyam (1994) focuses on analysing how circuit breakers alter trading decisions of large institutions. Although there are institutional investors in the Chinese stock markets, individual investors play an equally important role in influencing the market performance in China (e.g. Ng and Wu 2007). As such, this paper sheds insight into testing whether the predictions implied from the model of Subrahmanyam (1994) can be observed in emerging markets like China. Finally, the cross-listing of A- and B-shares in the Chinese stock exchanges provides a unique opportunity for testing the transmission of price variability and market liquidity between dominant markets (A-share markets) and satellite markets (B-share markets).

We document negative return autocorrelation on non-event days which signifies return reversals. In contrast, the strong positive return autocorrelation on the days that the circuit breakers were triggered suggests that the trading halt mechanism did not provide a “time-out” cushion. In addition, on event days the price contribution during the halt period is significantly smaller than that during the pre-halt and post-halt periods, which suggests that market-wide circuit breakers slowed down price contribution during trading halts; thus, failing to restore the informativeness of stock prices. When viewed together, the results fail to support the price discovery hypothesis that price changes during the halt period provide a significant contribution to the daily price discovery process. Instead, there is evidence to suggest that market-wide circuit breakers in the Chinese stock market delayed the price discovery process. Further, we find that market participants are reluctant to enter the market due to uncertainty surrounding the impact of market-wide circuit breakers on market performance. More importantly, trading halts, rather than preventing stock markets’ overreaction, cause traders who are already in the markets to encounter time constraints and these force them to quickly close their positions.

These results are consistent with the magnet effect as proposed by Subrahmanyam (1994). Finally, we also discover that volatility not only continues to increase during the post-halt period on event days but also spreads out to the overnight non-trading period and remains abnormally high on the next trading day, suggesting that price movements become pent-up on event days, giving rise to volatility spillovers in the following day. Moreover, the spillover effect from A-shares to B-shares is statistically and significantly higher during the post-halt period on the event days as arbitrageurs increase their speculative activities and view the post-halt period, particularly in B-share markets, as an opportunity to profit from the market. Collectively, our findings are consistent with our hypotheses that market-wide circuit breakers fail to moderate the volatility during the event days and fail to impede any volatility spillover between A- and B-shares.

This paper makes three important contributions to the literature. First, based entirely on the real event of the market-wide circuit breakers in China, this paper enriches the scant literature[4] on the consequences and implications of stock market regulation through stock prices and traders' behaviour, which enables the effectiveness of trading halts to be evaluated. Past studies have examined the implications of price limits and trading halts for the price discovery process (Kim and Rhee 1997; Kim and Sweeney 2000); however, this mechanism is commonly applied to individual stocks in stock exchanges and operates differently from a market-wide circuit breaker. The former mechanism permits trading only at prices within a pre-specified range. Trading resumes as long as traders are willing to trade within the range. However, for the market-wide circuit breakers trading halt occurs for the entire market for a pre-specified duration when the designated index hits a pre-specified level. Nonetheless, the market-wide circuit breakers possess features of the regulatory mechanism which resemble that of price limits and trading halts, and as such we are able to draw upon the vast literature on price limits and trading halts to analyse the impact of market-wide circuit breakers on the price discovery process, magnet effect and volatility spillover in Chinese stock exchanges.

Secondly, given that circuit breakers are triggered infrequently, only a few studies have documented their effectiveness. Kuhn et al. (1991) analyse the cash and stock index futures markets on October 13 and 16, 1989, but fail to find evidence that circuit breakers moderated volatility in these index futures markets. Gerety and Mulherin (1992) investigate how the volatility affects daily opening and closing trading volume using NYSE data from 1933–1988. They find that closing volume is positively related to expected overnight volatility, whereas opening volume is positively related to expected and unexpected volatility from the previous night. As such the desire of investors to trade prior to market closings indicates the cost of mandating market-wide circuit breakers. Due to data paucity stemming from infrequent triggers of circuit breakers, Ackert et al. (2001) rely on an experimental study to examine the effects of mandated market-wide closures and temporary halts triggered by extreme market movements on market behaviour. They find that the main driver of price deviations from the fundamental value is information in the market and that circuit breakers accelerate trading activity (i.e. trading volume) in the presence of an imminent interruption. We complement earlier studies by undertaking a rigorous market microstructure analysis through the use of a control sample to provide comparative assessment on the effectiveness of the market-wide circuit breakers. Our finding of a magnet effect mirrors the experimental results of Ackert et al. (2001). More importantly, given the predominance of individual investors and the extremely volatile market conditions in the Chinese markets, this paper provides a comparative

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[4] Only a few studies have examined the market-wide circuit breakers due to the nature of this event's infrequent occurrence.

analysis of the empirical evidence with those of developed stock markets. It also critically explains why the market-wide circuit breakers in the Chinese stock markets fail to deliver the intended outcomes when prices fell sharply.

Finally, our findings complement a number of papers and contribute to the themes of magnet effects and contagion related to the recently triggered market-wide circuit breakers in China. Jian et al. (2018) show the conditional probability of observing a price jump with imminent market-wide trading halt increases significantly, and thereby increasing the chances of triggering market-wide circuit breakers. This is compounded by the deterioration of market liquidity which together gives rise to the magnet effect. Lera et al. (2018) mathematically formalise investors' continuous anticipations when developing their tactical position in the presence of circuit breakers. In effect this creates a conduit for circuit breakers to feedback on the price. They develop a theory that demonstrates the counteracting effect of a repelling "momentum" as investors anchor on trends and an attractive "rational drift" as investors anticipate the impact of the halt period. They show that the magnet effect transpires due to the larger negative drifts of the fundamental price when it is close to the circuit breaker level (or price limits). Wang et al. (2019) show the lack of evidence for the market-wide circuit breakers to decelerate falling prices, to decrease market volatility and order imbalance, but they trigger significant magnet effects.

This paper shows that information asymmetry amongst market participants is prevalent as reflected by a steep one-sided market on event days. There is also evidence to suggest that market participants altered their trading strategies in order to maximise their trading flexibility during extreme market movements. They did this by increasing their trading activities significantly prior to triggers of the circuit breaker compared with non-event days to the extent that this leads to the realisation of trading halts. Our findings of extended period of abnormal volatility post-halt and cross-stock volatility spillover are consistent with the findings of Liu and Zeng (2018) who demonstrate that the circuit breakers result in crash and volatility contagion. The rest of the paper is structured as follows. Section 2 provides a brief narrative on the institutional features of the Chinese stock markets, China's circuit breaker mechanisms, and the hypotheses development. Section 3 describes the sample data and research design. Section 4 presents the results and robustness test results, while Section 5 concludes with policy implications.

2. China Stock Markets and Circuit Breakers

2.1 Institutional Features of Chinese Stock Markets

The Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) were founded on November 26th, 1990 and December 1st, 1990, respectively. The market capitalisations of the SSE and the SZSE are around RMB30,448 billion and RMB23,511 billion, respectively, as of April 2017. There are 3185 listed companies, of which 1247 firms were listed on the SSE and the remaining 1938 firms on the SZSE. Of the 1226 listed shares on the SSE, 1175 were A-shares and 51 were B-shares excluding other funds and bonds[1]; of the 515 listed shares on the SZSE, 466 were A-shares and 49 were B-shares excluding other funds and bonds[5].

Both the A-shares and B-shares are the main tradable securities in the Chinese markets. However, prior to changes in the regulation in 2001 and 2002, the A-shares were traded only by domestic investors in Renminbi (RMB) while the B-shares were traded by foreign investors in U.S. dollar (USD) on the SSE and in Hong Kong dollar (HKD) on the SZSE. The possibility of trading A-shares has been extended to Qualified Foreign Institutional Investors (QFII) and RMB Qualified Foreign Institutional Investors (RQFII); B-shares are available for domestic investors who have foreign exchange reserves in their bank accounts. By the end of 2012, individual trading accounts comprised 83.60% of total trades, whereas trading by professional institutional investors made up the rest, i.e. 17.40% (Shanghai Stock Exchange 2016). In November 2014, the Shanghai-Hong Kong Connect (SHHKConnect) was launched and this resulted in both institutional and retail investors being able to invest in A-shares listed in the 'Northbound trading'[6] via Hong Kong brokers.

Both the SSE and SZSE are pure order-driven markets, with no market makers or specialists, and they operate in an automated trading system, known as electronic Consolidated Open Limit Order Book (COLOB). The trading system accepts both limit and market orders and displays all bid and ask sizes and prices in the markets. Securities trades in the markets are settled on T+1 for A-shares and T+3 for B-shares according to the China Securities Depository and Clearing Corporation Limited (CSDCC). Securities purchased by investors cannot be resold before settlement.

The Chinese markets are unique in that they have both morning and afternoon sessions. The morning session consists of an opening call auction period from 9:15am to 9:25am and a continuous auction period from 9:30 am to 11:30 am, and they trade continuously from 1:00 pm to 3:00 pm in the afternoon session. During the auction trading session, buyers and sellers compete for the best price based on the principle of price priority and time priority. The exchanges in China impose the daily price up/down limits of 10% on trading of stocks and mutual funds. For those stocks or

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[5] The total number of listed shares includes A-shares, B-shares, funds and bonds. These figures were sourced from the respective SSE and SZSE websites: http://english.sse.com.cn/ and http://www.szse.cn/main/en/.

[6] Investors via Hong Kong brokers could invest in the shares listed in the 'Northbound trading' and investors in mainland China could invest in the shares listed in the 'Southbound trading'.

mutual funds that reach their daily price limit, traders are still able to trade only when their quotation price is within the price limits.

There are several indices that measure the Chinese stock exchanges’ performance. One of the most commonly used market indices, the CSI300, is a category-weighted index, which is the first equity index launched by the SSE and SZSE. With the aim of reflecting the overall market performance of A-shares, it consists of the 300 largest and most liquid A-shares listed in the SSE and the SZSE, of which 30.4% are listed in the latter and 69.7% in the former. The base date of the CSI300 is December 31, 2004 with a base point of 1000.

2.2 China’s Circuit Breakers

In response to the market plunge on August 24, 2015, the SSE, upon approval by the China Securities Regulatory Commission (CSRC), announced that the SSE, the SZSE and the China Financial Futures Exchange (CFFEX) planned to introduce an index circuit breaker mechanism to control the risk of dramatic fluctuations in the market on September 7, 2015. The circuit breakers mechanism takes CSI300 as the benchmark index where a movement of 5% in either upward or downward direction from the index’s previous close will trigger a 15-minute trading halt across SSE, SZSE and CFFEX. After that, a call auction is held and the continuous trading on that day will resume. Nevertheless, if the CSI300 index rises or falls 5% at or after 2:30 pm local time or 7% at any time, trading will stop until 3:00 pm and will not resume on the current trading day. Both circuit breaker thresholds will only be activated once a day.

On January 4, 2016 (hereafter called the first event), the market-wide circuit breakers mechanism in Chinese stock exchanges was triggered. The CSI300 index plunged 5% in the afternoon trading session, triggering a 15-minute trading halt at 1:13 pm. After trading resumed at 1:28 pm, the index tumbled further, hitting a 7% threshold at 1:34 pm and bringing a trading halt for the rest of the day. On January 7, 2016 (hereafter called the second event), 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 CSI300 to initiate the second trading halt, ending the day’s session. Figure 1 shows the timeline for each event on January 4 and 7, 2016.

[Figure 1]

It is evident based on these events that the circuit breakers did not control the downward pressure amidst volatility, and consequently the SSE suspended the circuit breakers on January 8, 2016 to “maintain market stability” (Shenzhen Stock Exchange 2016).

2.3 Empirical Literature and Hypotheses Development

2.3.1 Price Discovery Process

Equity market literature documents that price limits disrupt the process of incorporating information into stock prices and delaying the price discovery process (Kim and Rhee 1997; Kim and Limpaphayom 2000; Henke and Voronkova 2005; Bildik and Gülay 2006; Deb et al. 2013). Kim and Rhee (1997) find stocks reaching the price limits display price continuation more frequently than stocks that do not reach limits, which suggests that limits prevent stocks from reaching their equilibrium prices. In contrast, the empirical evidence on the effect of price limits in China shows that they facilitate the downward price movements (Chen et al. 2005; Wong et al. 2009; Kim et al. 2013; Li et al. 2014; Adcock et al. 2019), and this finding is consistent with most studies on single-stock discretionary trading halts in other countries (Chen et al. 2003; Hauser et al. 2006; Madura et al. 2006; Chakrabarty et al. 2011; Hautsch and Horvath 2016). Kim et al. (2013) argue that price limits accelerate the equilibrium price discovery process and facilitate overall market recovery as they mitigate the size of the overreaction-induced large price change in the Chinese stock exchanges, thus rejecting the delayed price discovery nature of price limits. These conflicting arguments raise concerns about the impact of market-wide circuit breakers on price discovery process.

Unlike price limits in which trading is permissible within the limit range, market-wide circuit breakers disrupt continuous trading markets and substantially increase the uncertainty of execution in times of market distress. Furthermore, unlike other stock markets with single-stock discretionary trading halts, China’s stock markets are extremely volatile and individual investors are prone to trade on sentiment that moves markets and possibly misinformation (Ackert et al. 2015). As such, it remains an empirical question as to whether there is price continuation, price reversal or no change after the market-wide circuit breakers kick in, and whether price contribution during the trading halt is significant in the Chinese stock markets. In line with the theoretical study by Fama (1988), who proposes that price limits serve no purpose other than to delay price discovery, we hypothesise that:

Hypothesis 1(a): After controlling for the volume effect, there are abnormal price continuations after the stock markets resume trading following a circuit breaker-induced trading halt[7].

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[7] Our hypothesis is in line with the Efficient Market Hypothesis, which asserts that price changes must be unforecastable in an informationally efficient market. Further, Lo (2004) finds that prices are reflected by the combination of environmental conditions and the nature of market participants in the economy, which is known as the Adaptive Market Efficiency. Thus, since market efficiency is able to adapt to an ever-changing environment, it is possible there are price continuations following a circuit breaker-induced trading halt.

Hypothesis 1(b): The price changes during the halt period provide an insignificant contribution to the daily price discovery process.

2.3.2 Magnet Effect

We hypothesise that by putting constraints on price movements, market-wide circuit breakers may cause prices to accelerate towards the limits, leading to the eventual realisation of circuit breakers since traders are concerned with the likely impediments to execute their orders in a timely fashion (Abad and Pascual 2013). This phenomenon is well substantiated in the literature on circuit breakers, including price limits, single-stock discretionary trading halts and market-wide circuit breakers. Cho et al. (2003), who undertook the first empirical verification of the magnet effect, find that daily price limits in the Taiwan Stock Exchange may cause stock price to approach the limit quickly rather than prevent the overreaction in stock markets. Other studies on price limits also support the presence of magnet effects in a number of markets: the Kuala Lumpur Stock Exchange (Chan et al. 2005), Istanbul Stock Exchange (Bildik and Gülay 2006), Korea Stock Exchange (Du et al. 2006), Shanghai Stock Exchange (Wong et al. 2009), and the Egyptian Stock Exchange (Tooma 2011). Referring to discretionary trading halts, Hautsch and Horvath (2016) find that spot volatility begins to gradually increase before the trading halts, which provides evidence for the magnet effect. On market-wide circuit breakers, Goldstein and Kavajecz (2004) find that as the probability of a market-wide circuit breaker being triggered increases, traders, fearing the inability to trade when the market is halted, tend to avoid being constrained not to trade and close their positions quickly. In line with the theme of magnet effects related to the recently triggered market-wide circuit breakers in China (Wong et al. 2016; Hao 2016; Jian et al. 2018; Lera et al. 2018; Wang et al. 2019), we hypothesise that due to the unique market-wide circuit breakers and market microstructure in the Chinese stock exchanges, magnet effects will prevail in equity markets.

Hypothesis 2(a): As the probability of a market-wide circuit breaker being triggered increases, market participants accelerate their trading activities, especially volume and volatility, towards the trigger levels and accelerate the realisation of trading halts.

The market microstructure models of Kyle (1985) suggest that trades are motivated by information asymmetry or by liquidity need. Consistent with Kyle (1985), Madura et al. (2006) claim that trading halts tend to occur when there is high information asymmetry amongst market participants. Since market-wide circuit breakers are designed to provide time for information to be disseminated to all traders, a test of magnet effects associated with asymmetric information will offer insights into the effectiveness of this market mechanism. This leads to a related magnet effect hypothesis:

Hypothesis 2(b): The trading halt triggered by market-wide circuit breakers is driven by the high information asymmetry among market participants.

2.3.3 Volatility Spillover Effect

The literature offers two perspectives when examining the impact of circuit breakers on stock's volatility in the equity market. First, the within-stock spillover effects suggest that when price limits halt stocks with high volatility, the volatility of a halted stock spreads out over a longer period (e.g., Kim and Rhee 1997; Berkman and Lee 2002; Cho et al. 2003; Chen et al. 2005; Henke and Voronkova 2005; Bildik and Gülay 2006; Deb et al. 2013; Adcock et al. 2019). Kim and Rhee (1997) use a 21-day event window around limit-hit day to test the volatility spillover hypothesis and find that the volatility of halted stocks does not return to normal levels as quickly as the stocks that did not reach price limits, thus supporting the hypothesis. Second, the cross-sectional spillover effects propose that trading halts influence the volatility of not only the halted stocks but also other related stocks due to the speculative activities of arbitrageurs. (e.g., Jiang et al. 2009; Brugler and Linton 2016; Cui and Gozluklu 2016; Guo et al. 2017). Jiang et al. (2009) examine the stocks that are informationally related to the halted stocks during trading halts and find that those information-related stocks have increased transaction costs and higher price impacts during the halts. This indicates a large liquidity impact, suggesting that single-stock circuit breakers influence non-halted stocks through the speculative trading strategies of arbitrageurs. Accordingly, we hypothesise that market-wide circuit breakers in China not only cause the volatility of a single stock to spread out over a longer period, they also cause the volatility of A-shares to be transmitted to the volatility of corresponding B-shares[8]:

Hypothesis 3(a): The volatility of the constituent stocks of the CSI300 index is abnormally high after the trading halt triggered by market-wide circuit breakers.

Hypothesis 3(b): The volatility spillover effect between A-shares and their corresponding B-shares is abnormally high after the trading halt triggered by market-wide circuit breakers.

3. Research Design

3.1 Data and the Construction of Non-Event Control Sample

The intraday data employed in this paper are sourced from the Securities Industry Research Centre of Asia-Pacific (SIRCA). The sample includes trade and quote data from the CSI300 index, along with its 300 constituents. Stocks with missing data are excluded from the analysis, yielding a

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[8] The benchmark CSI300 index for the market-wide circuit breakers only includes A-shares. Consequently, although all A-shares, B-shares and futures markets are halted when circuit breakers are triggered by the 300 A-shares, it is worth evaluating whether the volatility of A-shares transmits into corresponding B-shares.

final sample of 1 index and 288 stocks. These data contain bids, asks and depths (for quotes) and execution price and volumes (for trades).

During the implementation of market-wide circuit breakers from January 4, 2016 to January 7, 2016 in China, there are two event days when the market-wide circuit breakers are triggered, namely the 4th and 7th of January. However, an analysis of these two events will be conducted separately. Despite the fact that both events triggered the market-wide circuit breakers, they have different characteristics, with the second event lasting for a much shorter time before the 7% threshold is reached. With the experience gained from the first event, investors, especially individual investors, might learn and consequently adjust their behaviours or strategies to improve their investment performance (Seru et al. 2009). As such, we cannot ignore how quickly investors in the Chinese stock markets learn from trading and from their experience based on the first market-wide circuit breakers on January 4, 2016.

To examine abnormal trading behaviours around halts, we construct a non-event sample as a control for normal behaviour around an information release, but in the absence of a market-wide circuit breaker induced trading halt. Lee et al. (1994) develop a reference sample for the same firm matched by time-of-day and stock price return to control for firm-specific, time-of-day effects and the amount of information released. Our paper adopts a similar procedure to Lee et al. (1994), in order to construct the non-event sample. Due to the characteristics of the market-wide circuit breakers in China, this procedure controls for firm-specific, time-of-day effects, day-of-the-week effects and the amount of information released by identifying the observation for the same firms matched on time-of-day, day-of-the-week and net-of-market return. It is important to note that we do consider constructing a control sample that contains the dates matched with a 5% downward movement in the CSI300 index. However, a comparison between the event and this control sample is not feasible since the actual and pseudo halts are triggered at different times and on different dates for the 5% downward movement in the CSI300 index.

We first compute stock returns over the halt using the closing price of the trade or midpoint price of the last quote before the trading halt and the reopening price of the batch trade or the midpoint price of a quote if trading resumed with a quote. This procedure mitigates bid-ask biases in the intraday returns. To obtain net-of-market or excess returns, the market returns on the CSI300 index are subtracted from individual stock returns. Then we look at 1 year before and 1 year after the event days, which is from January 2015 to January 2017. To control for firm-specific and day-of-the-week effects, we compare each event day to data from the same firm's non-event trading days, matched on the day of week. We control for the amount of information released by finding the non-event days with a similar magnitude in net-of-market returns. In particular, we require the difference between the absolute net-of-market return for actual halt and the absolute net-of-market return for pseudo halt to be at most 0.5% to ensure a close match. Compared to the 1% restriction used by Lee et al. (1994), we tighten the restriction to construct a better control sample and obtain more precise results[9]. For each day in the non-event sample, we control for time-of-day effect by applying the pseudo halt[10], which begins at the same time of day and lasts for the same duration (15 minutes) as the actual halt when the circuit breakers kicked in.

To investigate the influence of market-wide circuit breakers on price discovery process and magnet effect, we categorise each event (non-event) day into four periods. The first period is before the 15-minute trading (pseudo) halt is triggered (hereafter called pre-halt period), the second period is when the 15-minute trading (pseudo) halt is in operation (hereafter called halt period), the third period is when the market resumes trading (hereafter called post-halt period)[11].

3.2 Empirical Models

3.2.1 Test of Hypothesis 1(a): Price Continuation

Our Hypothesis 1(a) posits that stocks experience abnormal price continuations in the periods following the halts, which is consistent with the delayed price discovery hypothesis. As stocks experience price continuations, reversals or no change, the price continuation on the event day should be abnormally larger than non-event days, which leads to the conclusion that market-wide circuit breakers delay the price discovery process. Accordingly, we examine price continuation behaviours of the stocks around the actual halt on event day and stocks around pseudo halts on non-event days.

Our measures of price continuation follow the analyses by Shen and Wang (1998) and Henke and Voronkova (2005). We estimate return autocorrelation for each constituent stock on the periods before and after the halt using the following regression:

$$R_{j,t} = \beta_0 + (\beta_1 + \beta_2 CB)R_{j,t-1} + \varepsilon_{j,t} \qquad (1)$$

where $R_{j,t}$ is the average logarithmic trade-to-trade return for the stock j at time t (post-halt period); $R_{j,t-1}$ is the average logarithmic trade-to-trade return for the stock j at time $t-1$ (pre-halt period); CB is a dummy variable taking the value 1 for event days and 0 for non-event days; and $\varepsilon_{j,t}$ is the error term of the regression. It is also important to note that the post-halt period is much

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[9] We also allow the difference to be at most 1% as an alternative in the robustness test to further validate our findings.

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

[11] Although daily 10% price limits for individual stocks restrict their price movement, they would not halt trading or force the market to close; therefore, it would not be an issue in here.

shorter than the pre-halt period on both event days[12]. To take this duration issue into account, we consider the same time length before and after the halt, which means the time length for the pre-halt period is determined by the time length for the post-halt period (6.5 minutes for the first event and 2 minutes for the second event). The estimated coefficient β_1 captures first-order autocorrelation on the non-event days. In the case of trading halts on event days, the impact of circuit breakers on autocorrelation is captured by the estimated coefficient β_2.

As suggested by Boudoukh et al. (1994) and Henke and Voronkova (2005), trading volume may decrease the extent of autocorrelation, especially after the periods of high trading activity. For this reason, we estimate another regression by including turnover ($TO_{j,t-1}$) as a proxy for trading volume to control for this volume effect:

$$R_{j,t} = \beta_0 + \left(\beta_3 + \beta_4 CB + \beta_5 TO_{j,t-1}\right) R_{j,t-1} + \varepsilon_{j,t} \tag{2}$$

where $TO_{j,t-1}$ is the trading volume at time $t-1$ (the pre-halt period) divided by the number of shares outstanding on the same day. The estimated coefficient β_5 gauges the volume effect on autocorrelation in the stock return series. To avoid spurious regression, we perform the Augmented Dickey-Fuller (ADF) test for unit root in the time-series sample to ensure that the series are all I(0).

3.2.2 Test of Hypothesis 1(b): Price Contribution

To test whether the price changes during the halt period provide an insignificant or significant contribution to the daily price discovery process (Hypothesis 1(b)), we study how pre-halt, halt and post-halt periods contribute to the price discovery process throughout the continuous trading period. We follow Cao et al. (2000) in calculating the relative time-weighted price contribution (RTWPC), which includes the time length of each period in the weight. Using the time-weighted price contribution during the pre-halt period as a benchmark, the RTWPC for each period is measured as follows:

$$RTWPC_{p,j} = \frac{WPC_{p,j} / \sum_{t=1}^{T} Time_{p,j}}{WPC_{pre,j} / \sum_{t=1}^{T} Time_{pre,j}} \tag{3}$$

where $WPC_{p,j}$ is the weighted price contribution of period p to its daily price change; $Time_{p,j}$ is the number of minutes for each stock j during period p.

WPC is widely used in many studies, such as Barclay and Hendershott (2003), Madura et al. (2006), Moshirian et al. (2012) and Wang and Yang (2015). The $WPC_{p,j}$ for each stock j during period p is calculated as follows:

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[12] For the first event, the time lengths of the pre- and post-halt periods are 133 and 6.5 minutes, respectively. For the second event, the time lengths of the pre- and post-halt periods are 12 and 2 minutes, respectively.

$$WPC_{p,j} = \sum_{t=1}^{T} \left[\left(\frac{|\Delta P_{t,j}|}{\sum_{t=1}^{T} |\Delta P_{t,j}|} \right) * \left(\frac{\Delta P_{p,t,j}}{\Delta P_{t,j}} \right) \right] \quad (4)$$

where $\Delta P_{p,t,j}$ is the price change for the stock j during period p on day t and $\Delta P_{t,j}$ is the daily price change for stock j on day t. Since our paper focuses on evaluating the stock price contribution during the continuous trading period, we calculate the fraction of the price change over period p relative to the open-to-close or close-to-open price change on each event and non-event day[13]. The contribution of each stock for each period is measured by the weighting factor for each day (first term of WPC) with the relative contribution of the price change during period i on day t to its daily price change (second term of WPC). Given that we only have one event day for each event, the computation of the $WPC_{p,j}$ is simplified to:

$$WPC_{p,j} = \frac{\Delta P_{p,t,j}}{\Delta P_{t,j}} \quad (5)$$

Finally, we examine whether the RTWPC on the day that market-wide circuit breakers are triggered is different from that on non-event days to ascertain whether the circuit breakers affect the price discovery process. The null of equality in the two RTWPC is tested using the Kruskal-Wallis tests[14]. We also test whether the price changes during the halt period are the same as those during the post-halt period to determine whether the price changes during the halt period provide an insignificant contribution to the daily price discovery process.

3.2.3 Test of Hypothesis 2(a): Magnet Effect

Our Hypothesis 2(a) focuses on whether market participants accelerate their trading activities when the fall in stock index is approaching the market-wide circuit breakers trigger level. We follow the methodology employed by Goldstein and Kavajecz (2004) and analyse three 15-minute periods[15] for the first event and three 4-minute periods for the second event[16] before the first trading halt took place when triggered by a 5% drop in price. For example, for the first event, the first period is not close to the circuit breakers trigger (10:58 am-11:13 am) the second period is close to the trigger but does not trigger a halt (11:13 am-11:28 am), and the last period is the one that triggers the circuit breakers (11:28 am-13:13 pm[17]).

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[13] Since our paper focuses on the price contribution for the trading periods, we calculate the open-to-close price change for pre-halt period, close-to-open price change for halt period and open-to-close price change for post-halt period.

[14] The Kruskal-Wallis test is a rank-based nonparametric test that seeks to determine whether there are significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable.

[15] We select three 15-minute periods and this is consistent with the time length of trading halt, which is 15 minutes.

[16] Since the pre-halt period for the second event only lasts for 12 minutes, we evenly divide the pre-halt period into three 4-minute periods.

[17] Since the continuous auction periods in the Chinese stock exchanges are from 9:30 am to 11:30 am and 13:00 pm to 15:00 pm, we exclude the period from 11:30 am to 13:00 pm in our sample.

Analysing the three 15-minute (4-minute) periods is to control for the possibility that the magnet effects are caused by large price movement rather than the circuit breakers. The first period is used to control for the large price movement effect on the event day, the second period is used to control for the market being close to the trigger level, and the third period is used to examine how the circuit breaker is triggered. Following the magnet effect hypothesis, we expect to observe trading acceleration in the two periods that are close to triggering the circuit breaker, yet not in the first period when the fall in price is far from the trigger level.

We examine share volume, volatility, bid size and ask size, market depth, and effective bid-ask spread over fifteen (or four for the second event) 1-minute intervals for all three periods. Volatility is computed as the difference between the highest and lowest log price within each interval[18]; market depth is calculated as the sum of bid and ask sizes, and effective bid-ask spread is computed as twice the difference between actual execution price and the mid-point market quote at the time of order entry. Furthermore, we also study the reaction of market participants involving seven 1-minute intervals for the first event and two 1-minute intervals for the second event. However, we do not focus on the realisation of second trading halt, triggered by a 7% drop, because the second halt is conditional on the first halt being triggered and it causes a halt in trading for the remainder of the day rather than for only 15 minutes.

Another possible explanation for the abnormal trading activities on the event days is the intraday momentum effects (Cho et al. 2003; Du et al. 2006)[19]. To control the intraday momentum effect, we also compare trading activities on the event days to the same characteristics surrounding pseudo halts relative to the non-event sample. In the absence of market-wide circuit breakers, any trading activities on non-event days should be attributed to the intraday momentum effect. Therefore, the abnormal trading activities, indicating the magnet effects on the event day are led by market-wide circuit breakers per se. We follow Lee et al. (1994) and Corwin and Lipson (2000) in calculating abnormal measures on the event days relative to non-event days. For example, the abnormal volatility of stock j for interval i on the event day is computed as:

$$100 * \left[\frac{Volatility\ on\ the\ Event\ Day - Mean\ Volatility\ on\ the\ Non-event\ Day}{Mean\ Volatility\ on\ the\ Non-event\ Day}\right] \tag{6}$$

Due to the potential issues of heteroskedasticity and autocorrelation when examining the composite index and constituent stocks from different firm size, we use the heteroskedasticity and autocorrelation consistent (HAC) standard errors.

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[18] See details in the Within-Stock Volatility Spillover Effect section under Empirical Models.

[19] Momentum, first documented by Jegadeesh and Titman (1993), describes the stocks with unusually good performance in the past and which are more likely to perform better in the near future and vice versa.

3.2.4 Test of Hypothesis 2(b): Information Asymmetry

To test Hypothesis 2(b), we use the measure of market sidedness proposed by Sarkar and Schwartz (2009) to examine whether the increase in market participants' trading activities is motivated by the existence of more information asymmetry. Sarkar and Schwartz (2009) suggest that trading is driven by information asymmetry (differential information or beliefs) if the correlation between the number of buyer- and seller-initiated trades increases (decreases), implying a more one-side (two-side) market.

In line with Sarkar and Schwartz (2009), we use the Lee and Ready (1991) algorithm to identify a buyer- (seller-) initiated trade if the trade price is closer to the most recent ask (bid) price. For prices equal to quote midpoint, it is a buyer- (seller-) initiated trade if the price is higher (lower) than the price of previous trade. Consistent with the sample periods in the magnet effect tests, we calculate the number of buyer- (seller-) initiated trade for each 1-minute (30-second[20]) interval and examine the market sidedness for three 15-minute (4-minute) pre-halt periods and post-halt periods on event (non-event) days. Market sidedness is estimated by the correlation between ZBUY and ZSELL as follows:

$$ZBUY = \frac{BUY - Mean(BUY)}{SD(BUY)} \tag{7}$$

$$ZSELL = \frac{SELL - Mean(SELL)}{SD(SELL)} \tag{8}$$

where BUY ($SELL$) is the number of buyer- (seller-) initiated trades in an interval, and $Mean$ and SD are the sample mean and standard deviation. If the correlation between $ZBUY$ and $ZSELL$ is lower (higher) on event days compared to the non-event days, then the market is more one-sided (two-sided), suggesting that the market is motivated by information asymmetry (differential information or beliefs). We compare the median correlation using the Kruskal-Wallis test.

3.2.5 Test of Hypothesis 3(a): Within-stock Volatility Spillover Effect

To test the within-stock volatility spillover hypothesis (Hypothesis 3(a)), we examine the volatility pattern on the event day (D_0) and a day before and after the event day (D_{-1}, D_{+1})[21]. Our study is similar to that of Kim and Rhee (1997) and Bildik and Gülay (2006), but unlike them we focus on the intraday spillover effect. During the continuous trading period, we use 1-minute intervals for both events to examine the pattern of intraday volatility of the constituent stocks of the

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[20] Due to the insufficient number of observations on the second event, we use 30-second intervals to generate the correlation.

[21] Based on the findings of Chen et al. (2005) and Lu (2016) by analysing daily data, the 3-day event window for our intraday data analyses is sufficient to capture the within-stock volatility spillover effects. Chen et al. (2005) find that the within-stock volatility spillover persists for two days for large companies, while Lu (2016) finds that for stocks with high trading activity the spillover effects become statistically insignificant.

CSI300 index[22]. We follow Alizadeh et al. (2002), Harris et al. (2011) and Diebold and Yilmaz (2012) in calculating the intraday range-based volatility on a minute-by-minute basis, which is the difference between the highest and lowest log price within each interval. We have:

$$\sigma_{i,t,j}^2 = \frac{[\ln(H_{i,t,j}) - [\ln(L_{i,t,j})]^2}{4ln2} \tag{9}$$

where $\sigma_{i,t,j}^2$ is the variance of stock j for interval i on day t; $H_{i,t,j}$ is the highest trade price of stock j for interval i on day t; $L_{i,t,j}$ is the lowest trade price of stock j for interval i on day t. We also compute the level of volatility during the overnight period, lunch break and halt period, essentially to examine how volatility reacts during the non-trading period. As well, we calculate intraday volatility for all non-event days to examine the abnormal volatility on the event days relative to non-event days. If the stocks on the event day experiences significant abnormal volatility after the halt compared to those on the non-event days after the pseudo halt, then this finding supports the within-stock volatility spillover hypothesis.

3.2.6 Test of Hypothesis 3(b): Cross-sectional Volatility Spillover Effect

We explore the repercussions of market-wide circuit breakers on other related stocks, B-shares specifically, during the trading halts as the speculative activities of the arbitrageurs may cause cross-sectional volatility spillover during the trading halts. To test the cross-sectional volatility spillover effect (Hypothesis 3(b)), we examine the A- and B-shares issued by the same firm since they are the same in terms of fundamental factors, i.e. firm size and expected future cash flows. Thus, our sample contains 8 firms issuing both A- and B-shares, of which 5 firms are listed on the SSE and 3 firms on the SZSE (see Appendix A for details of these firms).

To examine the volatility spillover effects between A- and B-shares, we conduct our analysis for each market separately, by performing the Ordinary Least Squares (OLS) regressions as follows.

$$VB_{f,t} = \beta_0 + \beta_1 VA_{f,t} + \beta_2 CB + \beta_3 POST_t + \beta_4 VA_{f,t} * POST_t + \beta_5 VA_{f,t} * CB * POST_t + \varepsilon_{f,t} \tag{10}$$

$$VA_{f,t} = \beta_0 + \beta_1 VB_{f,t} + \beta_2 CB + \beta_3 POST_t + \beta_4 VB_{f,t} * POST_t + \beta_5 VB_{f,t} * CB * POST_t + \varepsilon_{f,t} \tag{11}$$

where $VA_{f,t}$ is the range-base volatility of A-shares on minute-by-minute basis for firm f on day t; $VB_{f,t}$ is the range-base volatility of B-shares on minute-by-minute basis for firm f on day t; CB is

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[22] Although some stocks have reached their own price limit (10%) before the market closed or even before the 15-minute halt, it would not be an issue when we examine the pattern of intraday volatility. This is because any orders whose quotation prices are within the price limit are still valid, which means that traders are still able to purchase or sell stocks within the price limit. We will consider the price limit effects when we interpret our results.

a dummy variable taking the value 1 for event day and 0 for non-event days; $POST_t$ is a dummy variable taking the value 1 for post-halt periods (actual and pseudo halts) and 0 for pre-halt periods on day t; and $\varepsilon_{f,t}$ is the error term of the regression. We do not include the variable $CB * POST_t$ and $VB_{f,t} * CB$ $(VA_{f,t} * CB)$ as they are highly correlated;$Corr(CB * POST_t, VA_{f,t} * CB * POST_t)$ =0.94043, $Corr(VB_{f,t} * CB, VB_{f,t} * CB * POST_t)$ =0.93013, and $Corr(VA_{f,t} * CB, VA_{f,t} * CB * POST_t) =$ 0.9071.

It is important to note that we only include volatility spillovers on day t (i.e. the event date and pseudo-event date) in the tests. In accordance with the features of our data that contain observations on selective Mondays for the first event (Thursdays for the second event), the rationale for examining cross-sectional volatility spillover on day t is to observe the effect of market-wide circuit breaker on market dynamics in times of market distress. As we compute the intraday range-based volatility on minute-by-minute frequency on the event and pseudo-event day t, we do not envisage that the lead-lag effect of cross-market volatility spillover across days is important, hence this is not factored in our regression. If at all, the cross-market volatility spillover is expected to take place rapidly and its effect will dissipate within the event day.

4. Results and Robustness Test

4.1 Empirical Results

4.1.1 Results for Hypothesis 1(a): Price Continuation

We observe strong positive return autocorrelation on the day that the circuit breakers were triggered, which supports our null Hypothesis 1(a) that there is abnormal price continuation after the stock markets resume trading following a circuit breaker-induced trading halt. Table 1 and Table 2 display the estimation results for stock returns autocorrelation for each constituent stock on the periods before and after the halt, and on the first event day (4th Jan 2016) and the second event day (7th Jan 2016), respectively.

Results in Panel A of Table 1 indicate that return autocorrelation on the event day is statistically significantly higher than that on non-event days, with a coefficient of 1.6367. Such a considerable extent of positive return autocorrelation is also found in Table 2 but with a smaller magnitude of 0.4878. We surmise that the small magnitude is caused by the stocks that reach their daily price down limit of 10% during the 2-minute post-halt period[23]. For those stocks that reach the 10% price down limit, they cannot be traded at the price which exceeds the limit; therefore, less price continuation is found in the second event. After controlling for the volume effect, the

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[23] On the second event day, there are 63 out of 288 stocks that reach the daily price down limit of 10% during the post-halt period.

magnitude of the dummy variable coefficient, reported in Panel B in Tables 1 and 2, is slightly reduced, providing the robustness of our results. However, the additional explanatory power of the volume effect is rather small because of the modest increase in the adjust R^2. This implies that the volume effect documented by Boudoukh et al. (1994) is absent in the Chinese stock markets.

It is also interesting to note that the coefficients for return autocorrelation on non-event days are negative (-0.0464 for the first event and -0.0437 for the second event), indicating price reversals on non-event days. The findings that there are different signs of the coefficients (positive or negative) for the impact of circuit breakers on return autocorrelation on event and non-event days indicates the market-wide circuit breakers do not provide a “time-out” cushion or help restore the informativeness of stock prices.

[Insert Table 1]

[Insert Table 2]

4.1.2 Results for Hypothesis 1(b): Price Contribution

Our findings are consistent with Hypothesis 1(b) that the price changes during the halt period do not provide a significant contribution to the daily price discovery process. Tables 3 and 4 present the relative time-weighted price contributions of each period to the daily cumulative price change, which are expressed relative to the stock price change during the pre-halt period. Table 3 displays the results for the first event, while Table 4 is for the second event. The results in Panel A of Table 3 show that on the day the market-wide circuit breakers were triggered, the price contribution per unit of time during the halt period is smaller than during the pre-halt period, with a ratio of 0.0694, and the contribution during the post-halt period is larger by a factor of 11.8601. It is interesting to note that the contributions during halt and post-halt periods on non-event days are negative, with a ratio of -0.1234 and -0.0249, respectively. A negative RTWPC indicates that the trades are pushing price against the daily cumulative price change, which implies there is a price contribution in reversing the stock price.

Our results in Panel B of Table 3 show that the RTWPC on event days is significantly higher than that on non-event days for both halt period (χ^2=26.72, P<0.0001) and post-halt period (χ^2=303.51, P<0.0001), suggesting that the impact of market-wide circuit breakers on the price discovery process is significant. Panel C reports that the price contribution of the post-halt is higher than that of the halt period on the event day (χ^2=371.17, P<0.0001). These results suggest that the market-wide circuit breakers impede price contributions during the actual trading halts, which ultimately lead to a massive price contribution during the post-halt period on event days.

[Insert Table 3]

As indicated in Panel A of Table 4, on the second event, the price contribution during the halt period on the event day (0.2402) is smaller than that during the post-halt period on the non-event days (0.8382), suggesting a delay in the price contribution during the actual halt. However, unlike the first event, the price contribution during the post-halt period on the non-event days (7.5066) is larger than that during the post-halt period on the event days (1.6687). This is as expected since a large number of stocks are reaching their daily price down limit during the 2-minute post-halt period, which results in a lower level of price contribution. The results in Panel B show strong evidence in support of the difference in the price contribution between event and non-event days during the halt (χ^2=11.0645, P=0.0009) and post-halt periods (χ^2=53.5663, P<0.0001). Additional evidence of a significant difference in the price contribution between halt and post-halt periods on the event day (χ^2=91.5569, P<0.0001) further corroborates that market-wide circuit breakers impede price contributions during the actual trading halts.

[Insert Table 4]

Overall, our findings are consistent with the delayed price discovery hypotheses (Hypotheses 1(a) & 1(b)) that the market-wide circuit breakers, rather than allowing markets time to restore the information of stock price, caused a delay in the price discovery process in the financial markets. Specifically, the 15-minute period when the market-wide circuit breaker halts trading impedes the price contribution, which gives rise to a massive price contribution after markets resume. In contrast to Kim et al. (2013) and Li et al. (2014) who state that circuit breakers facilitate the price discovery process, our results show that market-wide circuit breakers delay this process.

4.1.3 Results for Hypothesis 2(a): Magnet Effect

Figure 2 depicts the patterns of abnormal measures, including volatility, volume, bid and ask sizes, market depth and effective bid-ask spread[24]. The analyses present several interesting findings[25]. Consistent with Hypothesis 2(a), Panels A and B show that the positive abnormal volatility and abnormal volume start increasing in the third 15-minute period on the first event day and in the second and third 4-minute periods on the second event day[26]. This provides evidence of a magnet effect, that is the market is drawn towards its 5% trigger level, thus causing a market-wide trading halt. Additionally, the dramatic increase in abnormal volatility and abnormal volume during the post-halt periods on both the first and second event days suggest that the trading halt, rather than

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[24] The results of abnormal measures on the event days relative to non-event days are statistically significant. The results are presented in Appendix B.

[25] Since the last 1-mintue interval in the post-halt period on the first event (4th Jan 2016) includes 30-seconds only, it is reasonable to have decreases in market variables during that last interval.

[26] The increases in abnormal measures in the first 15-minute (4-minute) period are caused by the market's closure in the morning session.

preventing the overreaction in the stock markets, causes traders with time constraints to quickly close their positions after markets resume. In other words, traders who fear they will be unable to trade after a halt being triggered exacerbate the problem by pushing the price closer to the 7% trigger level, forcing the closure of the stock markets.

[Figure 2]

The negative abnormal bid and ask size and abnormal depth on the first event day, shown in Panels C, D and E, indicate that the levels of bid and ask sizes and market depths are significantly lower than those on non-event days. These significant reductions on the first event day suggest that market participants are reluctant to enter the market due to the uncertainty engendered by market-wide circuit breakers which impact on market performance. More importantly, the remarkable increase in abnormal bid and ask size and abnormal depth during the third 15-minute period on the first event day and the post-halt periods on both event days suggest that traders accelerate their trading activities towards the trigger levels, leading to the realisation of trading halt and market closure. Although the abnormal bid size and abnormal depth during the third 4-minute period on the second event day are insignificant, the positive abnormal ask size shows that the level of ask size on the second event day is significantly higher than that on the non-event days, which leads to the trading halt being realised.

Furthermore, the increasing abnormal effective bid-ask spread in Panel F shows that the effective bid-ask spread becomes wider when the probability of a 15-minute halt being triggered increases on the event days, suggesting a higher level of liquidity among market participants when the trading halt is about to be triggered. We also find a wider effective bid-ask spread during the post-halt period compared with the pre-halt period, comparing the abnormal effective bid-ask spread during the post-halt period with pre-halt period. This phenomenon suggests that trading halt does not serve as a “time-out” cushion for information to spread to all traders. It is interesting to note that the effective bid-ask spreads on the first event day are narrower compared with non-event days. One possible explanation is that in an environment of higher regulatory uncertainty, fierce competition between traders and aggressive execution translate into lower effective bid-ask spread.

4.1.4 Results for Hypothesis 2(b): Information Asymmetry

Hypothesis 2(b) predicts that the trading halt triggered by market-wide circuit breakers is driven by the high information asymmetry amongst market participants. Panels A and B of Table 5 report the median of the correlation between $ZBUY$ and $ZSELL$ on event and non-event days. We find that the median correlations are significantly lower on event days compared to non-event days. For example, the median correlation is 31% (0.15 vs 0.46) and 39% (0.12 vs 0.51) lower on the third pre-halt periods on the first and second event days, respectively, and these differences are statistically significant. These results imply that the market on the event day is more one-sided compared to that on non-event days, suggesting that the trades on event day are motivated by greater information asymmetry. These findings are consistent with Madura et al. (2006), who claim that trading halts tend to occur when there is high information asymmetry amongst market participants.

It is also interesting to note that the negative correlations on event days (i.e. a correlation of -0.12 during the post-halt period on the first event day) indicate that the number of buyer-initiated trades is moving against the number of seller-initiated trades. Consistent with our results of abnormal bid and ask sizes in Panels C and D in Figure 2, these findings show that the number of market participants who want to sell stocks is significantly higher than those who want to buy, suggesting that the sell-initiated traders accelerate their trading activities towards the trigger levels leading to the realisation of trading halt and market closure.

[Insert Table 5]

Overall, our results support the magnet effect hypotheses (Hypotheses 2(a) & 2(b)) which assert that during the last trading period which triggers the circuit breaker on event days, market participants, motivated by information asymmetry, increase their trading activities significantly compared with non-event days to the extent that this leads to the realisation of trading halts. In this way, along with recent studies (Lera et al. 2018; Wang et al. 2019), our results in the Chinese stock markets are consistent with those documented by Goldstein and Kavajecz (2004), who show for the market-wide circuit breakers in the NYSE that market participants altered their trading strategies. They did this to maximise their trading flexibility during extreme market movements.

4.1.5 Results for Hypothesis 3(a): Within-stock Volatility Spillover Effect

Figure 3 shows the volatility pattern on a 1-minute interval basis on the event day (D_0) and a day before and after the event day (D_{-1}, D_{+1}) for both event and non-event samples. On $D_{-1,}$ we observe that stocks in both first and second events display regular volatility compared with that in non-event sample, suggesting that volatility does not start to increase but fluctuate during the trading period prior to the event day (D_0). In addition, as shown in Table 6, it is interesting to note that the stocks in the second event experience greater overnight volatility on D_{-1} (abnormal volatility of 1.6435) and this effect is found to be statistically significant at the 5% level[27]. This outcome suggests that return volatility starts to increase during the overnight non-trading period for the second event, which to some extent signals the occurrence of market distress in the following day's morning session.

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[27] The results of abnormal volatility in full can be provided as requested.

[Insert Figure 3]

[Insert Table 6]

As per our Hypothesis 3(a), our focus is on the event day and the day after. On Day t, we observe that all stocks in both first and second events experience their highest level of return volatility and the volatility in the post-halt period is almost twice as large as the volatility in the pre-halt period. This implies that the 15-minute trading halt does not serve as a “time-out” cushion to decrease volatility; instead it leads to a persistently greater volatility after markets resume. When we examine the overnight volatility, we find that the overnight volatility for the event sample is statistically and significantly greater than that for non-event sample on D_0; the abnormal volatility of 1.4164 and 1.1502 in the first and second events, respectively. This result suggests that the market closure triggered by the market-wide circuit breaker (i.e. the 7% threshold) does not reduce return volatility but causes volatility to spill over into the overnight non-trading period.

Furthermore, consistent with Lehmann’s (1989) insight that circuit breakers may cause volatility to last for a longer period of time, we find that the higher volatility remains statistically significant for the whole day on D_{+1} and return to the regular level on the next day (see the volatility pattern on D_{-1} in Panel B of Figure 3) in the first event. For the second event, we find that higher volatility remains statistically significant for the morning session but it returns to the regular level in the afternoon session. It is of interest to note that the within-stock volatility spillover effect is weaker in the second event. One possible explanation is that the announcement made by regulators regarding the suspension of the market-wide circuit breaker, beginning on January 8th 2016, may help restore confidence among domestic investors and stabilise the markets on that day.

Unlike previous studies (Kim and Rhee 1997; Chen et al. 2005; Bildik and Gulay 2006) that have relied on daily data over a 21-day event window and demonstrated the volatility of a single stock tends to spread out to subsequent trading days, in this study we show through the intraday pattern of volatility on the 1-minute interval that return volatility not only continues to increase during the post-halt period on event days, it also spreads out to the overnight non-trading period and remains abnormally high for up to one day in the next trading day. We interpret our findings as evidence that stocks experiencing trading halts and market closure are prevented from experiencing price movement on D_0; hence, price movement becomes pent-up, giving rise to volatility spillovers on the following day.

4.1.6 Results for Hypothesis 3(b): Cross-sectional Volatility Spillover Effect

Tables 7 and 8 report the results for the test of Hypothesis 3(b) that the volatility spillover effect between A-shares and their corresponding B-shares is abnormally high after the trading halt triggered by market-wide circuit breakers. Table 7 shows the estimation results for the first event, while Table 8 summarises the results for the second event. The positive coefficients of $VB_{f,t}$ and $VA_{f,t}$show that the return volatility of A-shares (B-shares) has a significant positive impact on the corresponding B-shares (A-shares), which confirms the existence of a cross-sectional volatility spillover effect between A- and B-shares in both directions. However, the negative coefficient of $VB_{f,t} * POST_t$ and $VA_{f,t} * POST_t$ indicates that the volatility spillover effect between A- and B-shares decreases during the post-halt periods. This includes both actual and pseudo halts, suggesting that during the continuous trading session, there is a reduction in the information asymmetry between A- and B-share markets throughout the event and non-event days. Our results shed light on the intraday dynamic of cross-sectional volatility spillover effect between A- and B-shares.

It is of particular interest to note that while there is no evidence supporting an abnormal volatility spillover effect from B-shares to A-shares on the event days, the spillover effect from A-shares to B-shares, shown in Panel A of Tables 7 and 8, is statistically and significantly higher during the post-halt period on the event days, with a coefficient of 0.148661 for the first event and 0.470926 for the second event. We surmise that arbitrageurs may increase their speculative activities in trading B-shares to take advantage of the trading halt induced by the CSI300 index (300 A-shares), which implies that they treat the post-halt period, especially in B-share markets, as an opportunity to profit from the market. In particular, the magnitude of the coefficient is higher in the second event, suggesting that more speculative activities could take place because arbitrageurs have learnt from the first event.

Furthermore, we find that the impact of market-wide circuit breakers on the volatility of A-shares, shown in Panel B of Tables 7 and 8, is statistically significant and positive with a coefficient of 0.001172 for the first event and 0.00258 for the second event, which is consistent with our previous findings that market-wide circuit breakers cause investors with time constraints to quickly execute their trades, leading to an increase in the volatility of A-shares.

[Insert Table 7]

[Insert Table 8]

Overall, we provide evidence regarding the within-stock and cross-sectional volatility spillover effects which point to the market-wide circuit breakers playing a detrimental role during extreme downward price movement. This is consistent with our Hypotheses 3(a) & 3(b) that market-wide circuit breakers fail to moderate the volatility during the event days and to impede any volatility spillover between A- and B-shares. Our findings for an extended period of abnormal volatility post-halt and cross-stock volatility spillover are consistent with the findings of Liu and Zeng (2018) who demonstrate that the circuit breakers result in crash and volatility contagion.

4.2 Robustness Test

Recall that our non-event sample is based on the controls of firm-specific, time-of-day effects, day-of-the-week effects and the amount of information released. To ensure a close match with respect to the amount of information released, we require that there will be at most 0.5% difference between the absolute net-of-market return for actual halt and the absolute net-of-market return for pseudo halt. Following the 1% restriction used by Lee et al. (1994), we construct a new non-event sample using the difference between the absolute net-of-market return for actual halt and the absolute net-of-market return for pseudo halt to be at most 1%. We then determine whether our results are sensitive to the difference between the absolute net-of-market returns for event and non-event samples. The results remain qualitatively unchanged albeit in some cases we observe lower significant levels[28].

5. Conclusion

This paper examines the effectiveness of market-wide circuit breakers by empirically testing the price discovery hypothesis, magnet effect hypothesis and volatility spillover hypothesis. Our study which is based on the real event of the market-wide circuit breakers in China adds to the extremely scant literature on the consequences and implications of regulation on stock market behaviour, and evaluates the effectiveness of the trading halts.

We find that market-wide circuit breakers in the Chinese financial market turmoil do not help restore the informativeness of stock prices and they slow down price contribution during the actual trading halts. These results fail to support the Brady Commission report’s (1988) claim that circuit breakers promote the price discovery process by providing a “time-out” cushion. Additionally, we find that the trading halt, rather than preventing the overreaction in the stock markets, causes investors who were already trading in the financial markets to be time constrained and to quickly close their positions, thereby showcasing the magnet effect. Further, market-wide circuit breakers fail to moderate volatility during the event days and they fail to impede the volatility spillover effect between A- and B-shares. Taken together, our findings provide microstructure evidence for the failure of circuit breakers which support the view that they should be abolished by Chinese government regulators. The results also point to a consideration of other alternative regulatory mechanisms that will curtail market volatility within China’s complex trading environment.

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[28] The robustness test results can be furnished by the author upon request.

While extreme market movements play a role in our results, the impacts of market-wide circuit breakers on market performance are still significant. As such, our results have strong regulatory policy implications. The extant literature examining whether circuit breakers, including price limits and discretionary trading halts, could stabilise the market during financial turmoil has been a point of contention. Our findings suggest that the uncertainty associated with market-wide trading halts and market closures that disrupt continuous trading markets is larger than the uncertainty related to the large price movement during the continuous trading markets. Continuous trading markets confer benefits to market participants by facilitating the flow of information so that traders are willing to actively engage in financial markets. Our findings show that the implementation of market-wide circuit breakers, which was meant to stabilise the stock markets, in fact yielded the reverse outcome; they accelerate market participants' trading activities towards the trigger levels leading to the realisation of trading halts.

In conclusion, our results empirically contribute to the identified scarcity of literature on the impact of market-wide circuit breakers on price discovery process, magnet effect and volatility spillover effect. By focusing on the consequences and implications of market-wide circuit breaker in emerging markets, we enrich the literature which is predominantly on developed economies' markets.

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Table 1

Estimation Results for Stock Return Autocorrelation

This table reports the impact of market-wide circuit breakers on price continuation, estimating return autocorrelation for each constituent stock on the periods before and after the halt on the first event day (4th Jan 2016):

$$R_{j,t} = \beta_0 + (\beta_1 + \beta_2 CB)R_{j,t-1} + \varepsilon_{j,t} \quad (1)$$

$$R_{j,t} = \beta_0 + \left(\beta_3 + \beta_4 CB + \beta_5 TO_{j,t-1}\right)R_{j,t-1} + \varepsilon_{j,t} \quad (2)$$

where $R_{j,t}$ is the average logarithmic trade-to-trade return for the stock j at time t (post-halt period); $R_{j,t-1}$ is the average logarithmic trade-to-trade return for the stock j at time $t-1$ (pre-halt period); CB is a dummy variable taking the value 1 for event days and 0 for non-event days; $TO_{j,t-1}$ is a proxy for volume effect, computed as the trading volume at time $t-1$ (pre-halt period) divided by the number of shares outstanding on the same day; and $\varepsilon_{j,t}$ is the error term of the regression. Panel A presents the estimation results of equation (1), while Panel B reports the estimation results of equation (2).

Panel A: Stock Return Autocorrelation Without Controlling for Volume Effect

	β_0	β_1	β_2
Parameter	-0.0000022	-0.0251139	1.6367453
t-value	-10.03	-1.59	14.02
p-value	<.0001	0.1118	<.0001
Adj R^2	0.1210		

Panel B: Stock Return Autocorrelation With Controlling for Volume Effect

	β_0	β_3	β_4	β_5
Parameter	-0.0000022	-0.0463977	1.6206377	0.0591759
t-value	-10.04	-2.66	13.75	2.12
p-value	<.0001	0.0079	<.0001	0.0344
Adj R^2	0.1224			

Table 2
Estimation Results for Stock Return Autocorrelation

This table reports the impact of market-wide circuit breaker on price continuation, estimating return autocorrelation for each constituent stock on the periods before and after the halt on the second event day (7th Jan 2016):

$$R_{j,t} = \beta_0 + (\beta_1 + \beta_2 CB)R_{j,t-1} + \varepsilon_{j,t} \tag{1}$$

$$R_{j,t} = \beta_0 + \left(\beta_3 + \beta_4 CB + \beta_5 TO_{j,t-1}\right)R_{j,t-1} + \varepsilon_{j,t} \tag{2}$$

where $R_{j,t}$ is the average logarithmic trade-to-trade return for the stock j at time t (post-halt period); $R_{j,t-1}$ is the average logarithmic trade-to-trade return for the stock j at time $t-1$ (pre-halt period); CB is a dummy variable taking the value 1 for event days and 0 for non-event days; $TO_{j,t-1}$ is a proxy for volume effect, computed as the trading volume at time $t-1$ (pre-halt period) divided by the number of shares outstanding on the same day; and $\varepsilon_{j,t}$ is the error term of the regression. Panel A presents the estimation results of equation (1), while Panel B reports the estimation results of equation (2).

Panel A: Stock Return Autocorrelation Without Controlling for Volume Effect

	β_0	β_1	β_2
Parameter	-0.0000012	-0.0595225	0.4878490
t-value	-1.47	-1.15	5.52
p-value	0.1417	0.2518	<.0001
Adj R^2	0.0415		

Panel B: Stock Return Autocorrelation With Controlling for Volume Effect

	β_0	β_3	β_4	β_5
Parameter	-0.0000012	-0.0437492	0.5199178	-0.0756170
t-value	-1.45	-0.80	5.48	-1.28
p-value	0.1462	0.4262	<.0001	0.1992
Adj R^2	0.0427			

Table 3
Relative Time-Weighted Price Contributions to Daily Price Change

This table reports the relative time-weighted price contributions (RTWPC) of pre-halt period, halt period and post-halt period on the first event day (4th Jan 2016), which are expressed relative to the stock price change during the pre-halt period. Panel A provides the mean RTWPC and its corresponding standard deviation (shown in parentheses) of each period on both event and non-event days. Panel B reports the difference of RTWPC between event and non-event days with the use of the Kruskal-Wallis tests, while Panel C reports the difference of RTWPC between halt and post-halt periods.

Panel A: Relative Time-Weighted Price Contribution

Mean	Pre-halt	Halt	Post-halt
Event days	1	0.0694	11.8601
		(0.9553)	(14.8620)
Non-event days	1	-0.1235	-0.0249
		(1.2619)	(7.2789)

Panel B: Event Days Versus Non-event Days

	Pre-halt	Halt	Post-halt
Chi-Square	0	26.7150	303.5100
Pr>Chi-Square	1	<.0001	<.0001

Panel C: Halt Period Versus Post-halt Period

	Event day	Non-event days
Chi-Square	371.1703	31.2820
Pr>Chi-Square	<.0001	<.0001

Table 4

Relative Time-Weighted Price Contributions to Daily Price Change

This table reports the relative time-weighted price contributions (RTWPC) of pre-halt period, halt period and post-halt period on the second event day (7th Jan 2016), which are expressed relative to the stock price change during the pre-halt period. Panel A provides the mean RTWPC and its corresponding standard deviation (shown in parentheses) of each period on both event and non-event days. Panel B reports the difference of RTWPC between event and non-event days with the use of the Kruskal-Wallis tests, while Panel C reports the difference of RTWPC between halt and post-halt periods.

Panel A: Relative Time-Weighted Price Contribution

Mean	Pre-halt	Halt	Post-halt
Event days	1	0.2402	1.6687
		(0.5973)	(4.8769)
Non-event days	1	0.8382	7.5066
		(23.6473)	(108.6399)

Panel B: Event Days Versus Non-event Days

	Pre-halt	Halt	Post-halt
Chi-Square	0	11.0645	53.5663
Pr>Chi-Square	1	0.0009	<.0001

Panel C: Halt Period Versus Post-halt Period

	Event day	Non-event days
Chi-Square	91.5569	0.2458
Pr>Chi-Square	<.0001	0.62

Table 5
Correlation of Buyer- and Seller-Initiated Trades

This table reports the correlation between the number of buyer- and seller-initiated trades (ZBUY and ZSELL) on event days compared to the non-event days. We calculate the number of buyer- (seller-) initiated trade for each 1-minute (30-second) interval and examine the market sidedness for three 15-minute (4-minute) pre-halt periods and post-halt periods on event (non-event) days. ZBUY and ZSELL are calculated as follows:

$$ZBUY = \frac{BUY - Mean(BUY)}{SD(BUY)} \tag{7}$$

$$ZSELL = \frac{SELL - Mean(SELL)}{SD(SELL)} \tag{8}$$

where BUY ($SELL$) is the number of buyer- (seller-) initiated trades in an interval, and $Mean$ and SD are the sample mean and standard deviation, respectively. We compare the median correlation using the Kruskal-Wallis test. Panel A provides the median correlation on the first event. Panel B reports median correlation on the second event.

Panel A: Median Correlation for the First Event				
Mean	1st 15-minute	2nd 15-minute	3rd 15-minute	Post-halt
Event days	0.04	0.08	0.15	-0.12
Non-event days	0.41	0.37	0.46	0.34
Kruskal-Wallis (p-value)	<.0001	<.0001	<.0001	<.0001
Panel B: Median Correlation for the Second Event				
	1st 4-minute	2nd 4-minute	3rd 4-minute	Post-halt
Event days	0.02	-0.43	0.12	-0.62
Non-event days	0.61	0.54	0.51	0.38
Kruskal-Wallis (p-value)	<.0001	<.0001	<.0001	<.0001

Table 6

Abnormal Volatility During the Overnight Period, Lunch Break and Halt Period

This table reports the abnormal volatility during the overnight period, lunch break and halt period on the event day (D_0) and a day before and after the event day (D_{-1}, D_{+1}). The abnormal volatility of stock j for interval i on the event day is computed as:

$$100 * \left[\frac{Volatility\ on\ the\ Event\ Day - Mean\ Volatility\ on\ the\ Non-event\ Day}{Mean\ Volatility\ on\ the\ Non-event\ Day}\right] \quad (6)$$

The range-based volatility is calculated as follows:

$$\sigma^2_{i,t,j} = \frac{[\ln(H_{i,t,j}) - [\ln(L_{i,t,j})]^2}{4ln2} \quad (9)$$

where $\sigma^2_{i,t,j}$ is the variance of stock j for interval i on day t; $H_{i,t,j}$ is the highest trade price of stock j for interval i on day t; $L_{i,t,j}$ is the lowest trade price of stock j for interval i on day t. We also compute the volatility during the overnight period, lunch break and halt period to examine how volatility reacts during the non-trading period. Panel A reports the abnormal volatility and its corresponding p-value (shown in parentheses) for the first event (trading halt was triggered after the lunch break), while Panel B reports the abnormal volatility and its corresponding p-value (shown in parentheses) for the second event (trading halt was triggered before the lunch break).

Panel A: Abnormal Volatility for the First Event

	Overnight	Lunch break	Trading halt
D_{-1} (31st Dec 2015)		-0.0918	
		(<.0001)	
D_0 (4th Jan 2016)	-0.4318	0.4516	-0.6320
	(<.0001)	(0.0918)	(<.0001)
D_{+1} (5th Jan 2016)	1.4164	0.1333	
	(<.0001)	(0.0285)	

Panel B: Abnormal Volatility for the Second Event

	Overnight	Trading halt	Lunch break
D_{-1} (6th Jan 2016)			0.2542
			(0.0797)
D_0 (7th Jan 2016)	1.6435	0.3872	
	(<.0001)	(<.0001)	
D_{+1} (8th Jan 2016)	1.1502		0.6947
	(<.0001)		(0.014)

Table 7
Estimation Results for Cross-sectional Volatility Spillover Effect

This table reports the impact of market-wide circuit breakers on the cross-sectional volatility spillover effect between A- and B-shares on the first event (4th Jan 2016), by performing the Ordinary Least Squares (OLS) regressions as follows.

$$VB_{f,t} = \beta_0 + \beta_1 VA_{f,t} + \beta_2 CB + \beta_3 POST_t + \beta_4 VA_{f,t} * POST_t + \beta_5 VA_{f,t} * CB * POST_t + \varepsilon_{f,t} \quad (10)$$

$$VA_{f,t} = \beta_0 + \beta_1 VB_{f,t} + \beta_2 CB + \beta_3 POST_t + \beta_4 VB_{f,t} * POST_t + \beta_5 VB_{f,t} * CB * POST_t + \varepsilon_{f,t} \quad (11)$$

where $VA_{f,t}$ is the range-base volatility of A-shares on minute-by-minute basis for firm f on day t; $VB_{f,t}$ is the range-base volatility of B-shares on minute-by-minute basis for firm f on day t; CB is a dummy variable taking the value 1 for event day and 0 for non-event days; $POST_t$ is a dummy variable taking the value 1 for post-halt periods (actual and pseudo halts) and 0 for pre-halt periods on day t; and $\varepsilon_{f,t}$ is the error term of the regression. Panel A presents the estimation results of equation (10), while Panel B reports the estimation results of equation (11).

Panel A: Volatility Spillover Effect from A-shares to B-shares						
	β_0	β_1	β_2	β_3	β_4	β_5
Parameter	0.0003	0.2132	0.0008	-0.00003	-0.0923	0.1487
t-value	5.51	5.90	3.72	-0.42	-1.87	1.99
p-value	<.0001	<.0001	0.0002	0.6781	0.0619	0.0466
Adj R^2	0.1089					
Panel B: Volatility Spillover Effect from B-shares to A-shares						
	β_0	β_1	β_2	β_3	β_4	β_5
Parameter	0.0013	0.3523	0.0012	-0.00014	-0.2048	0.1006
t-value	27.93	6.44	5.85	-2.44	-2.94	1.13
p-value	<.0001	<.0001	<.0001	0.0149	0.0033	0.2597
Adj R^2	0.1311					

Table 8
Estimation Results for Cross-sectional Volatility Spillover Effect

This table reports the impact of market-wide circuit breakers on the cross-sectional volatility spillover effect between A- and B-shares on the second event (7th Jan 2016), by performing the Ordinary Least Squares (OLS) regressions as follows.

$$VB_{f,t} = \beta_0 + \beta_1 VA_{f,t} + \beta_2 CB + \beta_3 POST_t + \beta_4 VA_{f,t} * POST_t + \beta_5 VA_{f,t} * CB * POST_t + \varepsilon_{f,t} \quad (10)$$

$$VA_{f,t} = \beta_0 + \beta_1 VB_{f,t} + \beta_2 CB + \beta_3 POST_t + \beta_4 VB_{f,t} * POST_t + \beta_5 VB_{f,t} * CB * POST_t + \varepsilon_{f,t} \quad (11)$$

where $VA_{f,t}$ is the range-base volatility of A-shares on minute-by-minute basis for firm f on day t; $VB_{f,t}$ is the range-base volatility of B-shares on minute-by-minute basis for firm f on day t; CB is a dummy variable taking the value 1 for event day and 0 for non-event days; $POST_t$ is a dummy variable taking the value 1 for post-halt periods (actual and pseudo halts) and 0 for pre-halt periods on day t; and $\varepsilon_{f,t}$ is the error term of the regression. Panel A presents the estimation results of equation (10), while Panel B reports the estimation results of equation (11).

Panel A: Volatility Spillover Effect from A-shares to B-shares

	β_0	β_1	β_2	β_3	β_4	β_5
Parameter	0.0003	0.3433	0.0006	0.00018	-0.1952	0.4709
t-value	2.32	6.05	1.63	1.06	-2.37	4.55
p-value	0.0206	<.0001	0.1047	0.2900	0.0180	<.0001
Adj R^2	0.2294					

Panel B: Volatility Spillover Effect from B-shares to A-shares

	β_0	β_1	β_2	β_3	β_4	β_5
Parameter	0.0016	0.3606	0.0026	-0.00015	-0.1785	0.0064
t-value	19.55	6.10	8.76	-1.34	-1.98	0.07
p-value	<.0001	<.0001	<.0001	0.1813	0.0486	0.9456
Adj R^2	0.2858					

Figure 1
Timelines on Event Days

This figure shows the timelines on the actual event days.

CSI 300 Previous close: 3731			CSI300 decrease 5% to 3544		CSI300 decrease 7% to 3470
04 Jan 2016	No circuit breaker	Normal trading	**Trading halts for 15-min**	Normal trading	**Trading halts for the rest of the day**
	9:15am	**9:30am**	**1:13pm**	**1:28pm**	**1:34pm**
	Opening Call Auction (9:15am-09:30am)	Continuous Auction (09:30am-11:30am; 1:00pm-3:00pm)			

CSI 300 Previous close: 3539			CSI300 decrease 5% to 3349		CSI300 decrease 7% to 3284
07 Jan 2016	No circuit breaker	Normal trading	**Trading halts for 15-min**	Normal trading	**Trading halts for the rest of the day**
	9:15am	**9:30am**	**9:42am**	**9:57am**	**9:59am**
	Opening Call Auction (9:15am-09:30am)	Continuous Auction (09:30am-11:30am; 1:00pm-3:00pm)			

Figure 2

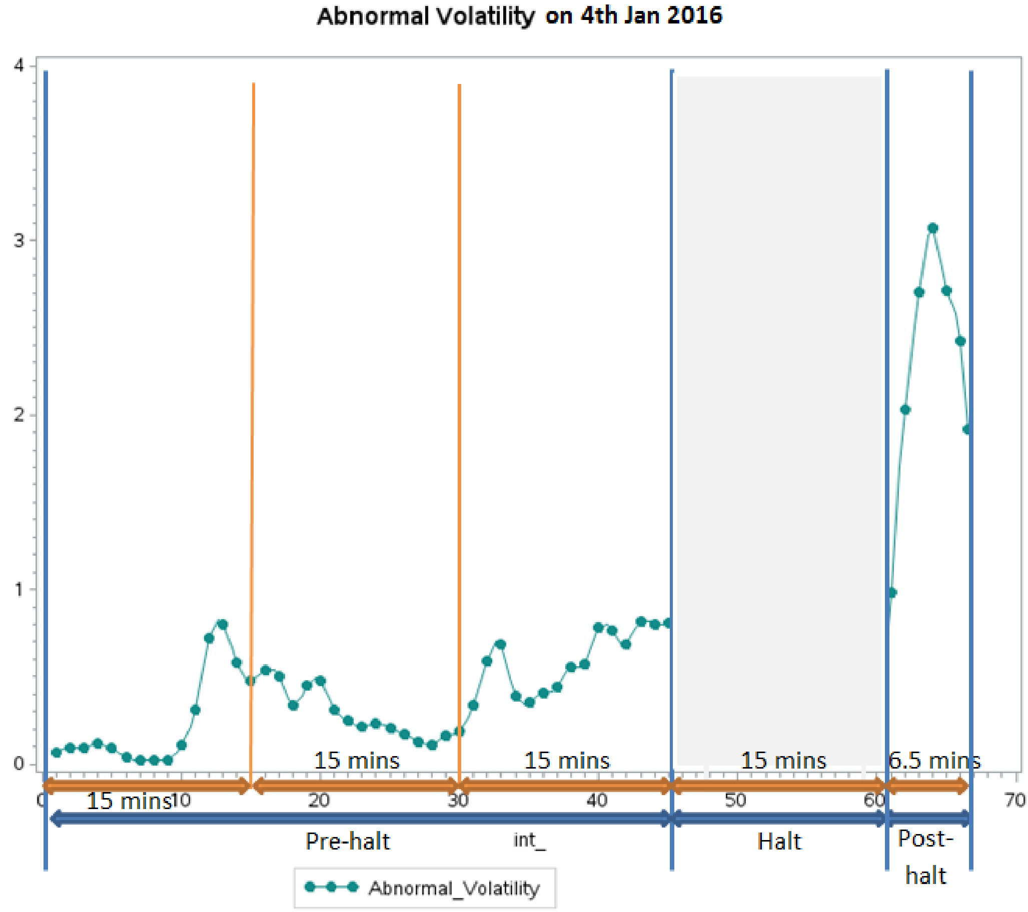
Patterns of Market Variables Using Abnormal Measures

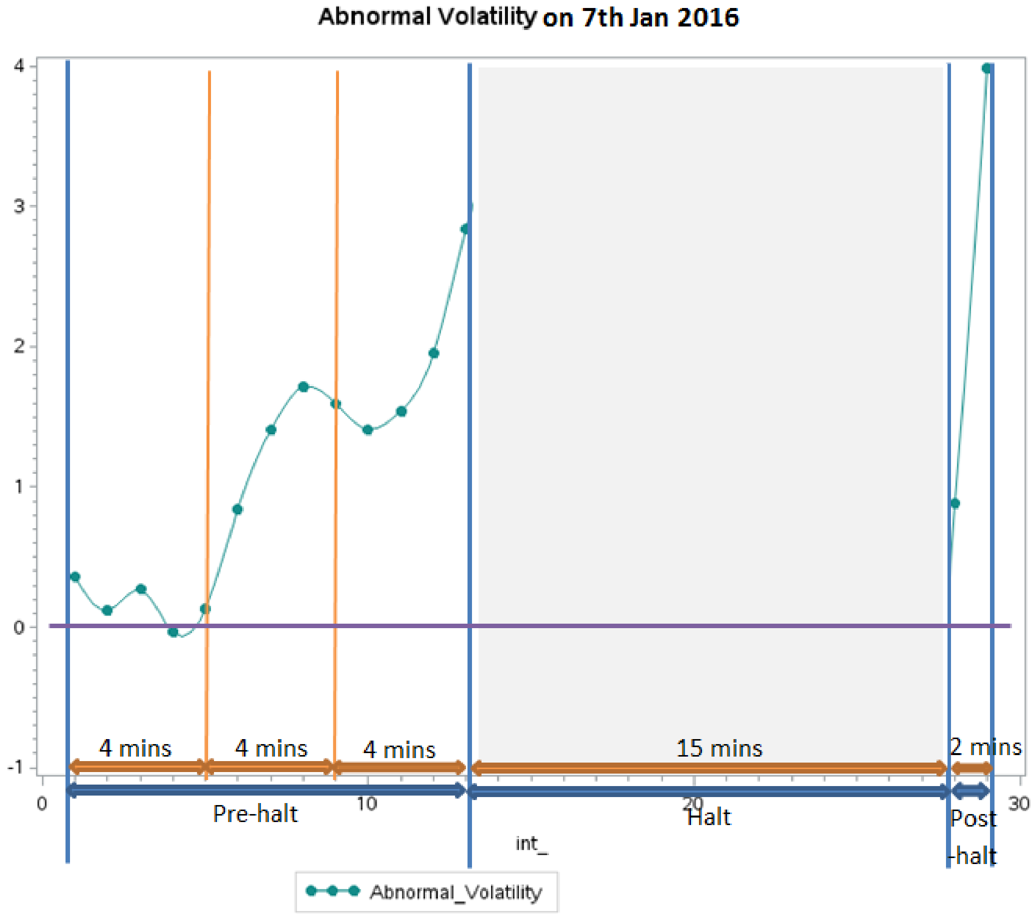
This figure presents the patterns of 1-minute interval data on the abnormal volatility, abnormal volume, abnormal bid size, abnormal ask size, abnormal market depth and abnormal effective bid-ask spread of the constituent stocks for the first and second events (4th and 7th of January 2016). We analyse three 15-minute (4-minute) periods on the first (second) event day before the 5% threshold is reached, triggering a 15-minute trading halt. We calculate the abnormal measures on the event days relative to non-event days, for example, the abnormal volatility of stock j for interval i on the event day is computed as:

$$100 * \left[\frac{Volatility\ on\ the\ Event\ Day - Mean\ Volatility\ on\ the\ Non-event\ Day}{Mean\ Volatility\ on\ the\ Non-event\ Day}\right] \quad (6)$$

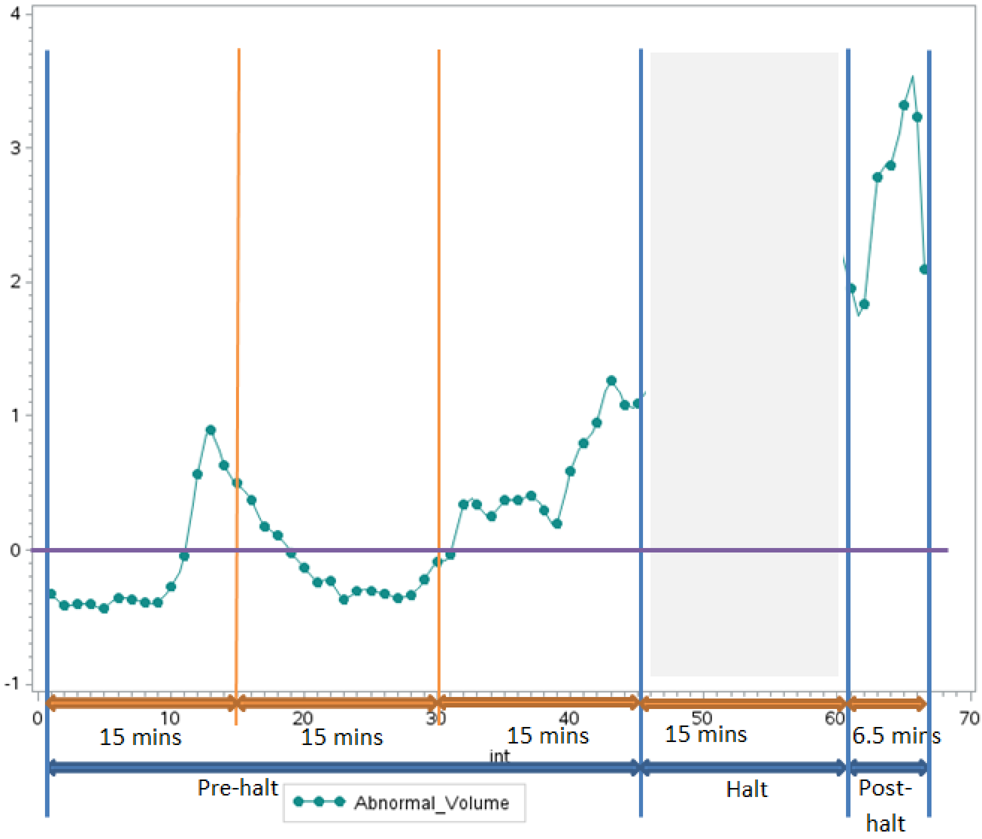
Volatility is computed as the difference between the high and low prices during each interval; market depth is calculated as the sum of bid and ask sizes; and effective bid-ask spread is computed as twice the difference between actual execution price and the mid-point market quote at the time of order entry. Panel A shows the patterns of abnormal volatility on the event days relative to non-event days. Panel B shows the patterns of abnormal volume on the event days relative to non-event days. Panel C shows the patterns of abnormal bid size on the event days relative to non-event days. Panel D shows the patterns of abnormal ask size on the event days relative to non-event days. Panel E shows the patterns of abnormal market depth on the event days relative to non-event days. Panel F shows the patterns of abnormal effective bid-ask spread on the event days relative to non-event days.

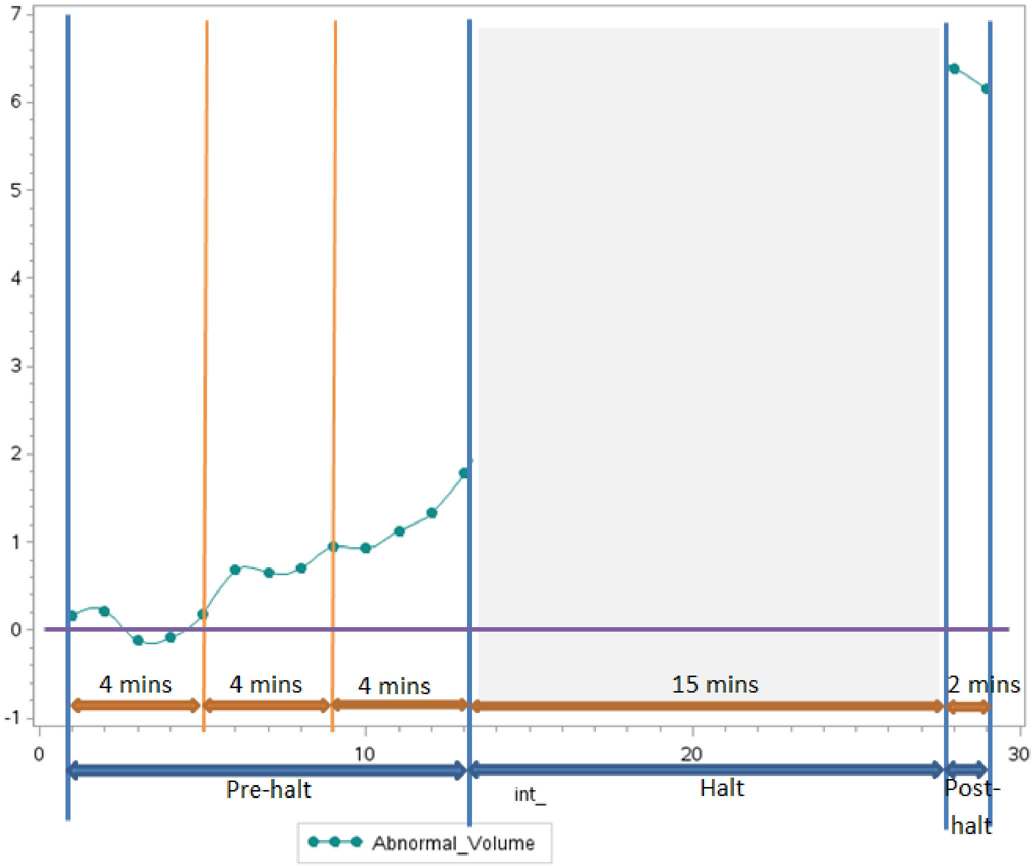
Panel A: Abnormal Volatility on the Event Days Relative to Non-event Days





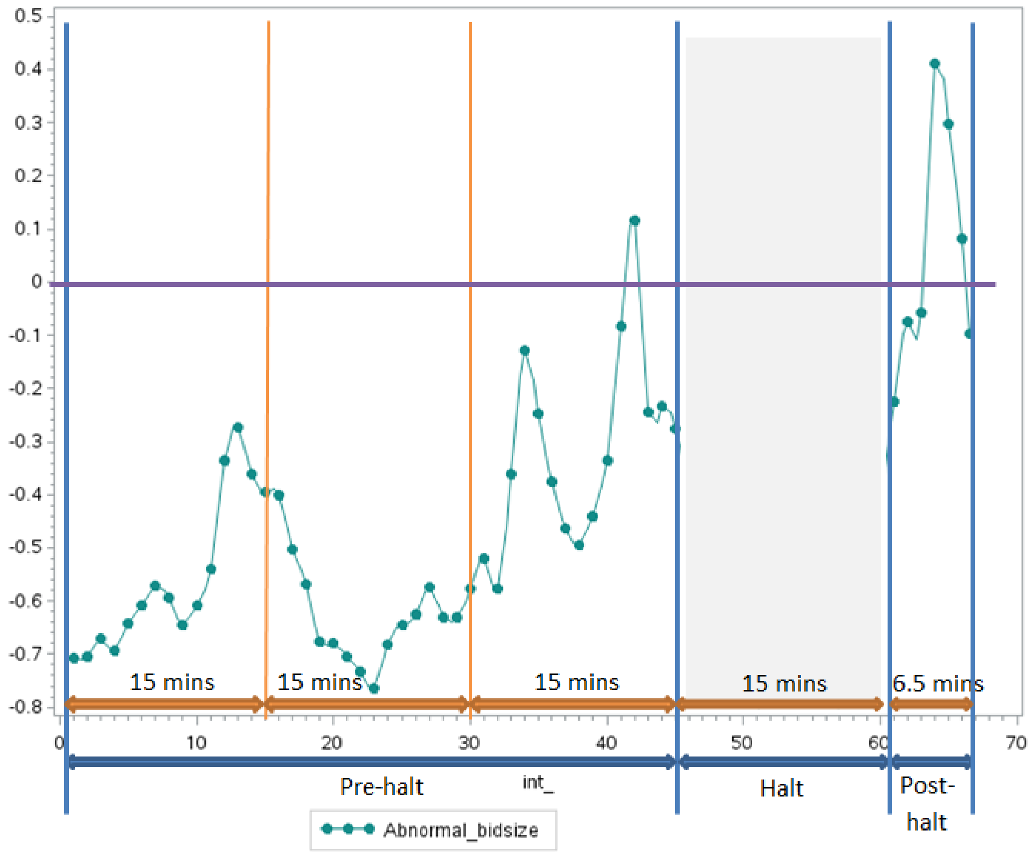
Panel B: Abnormal Volume on the Event Days Relative to Non-event Days


Abnormal Volume on 4th Jan 2016

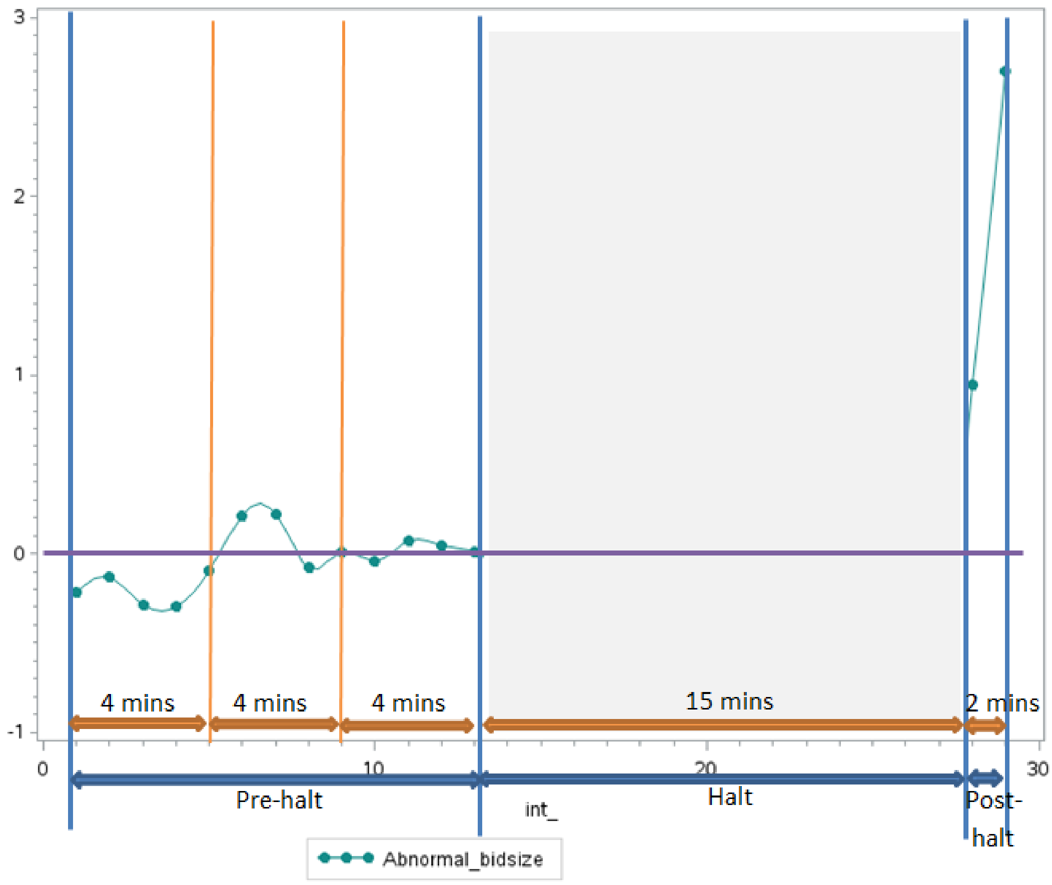

Abnormal Volume on 7th Jan 2016

Panel C: Abnormal Bid Size on the Event Days Relative to Non-event Days

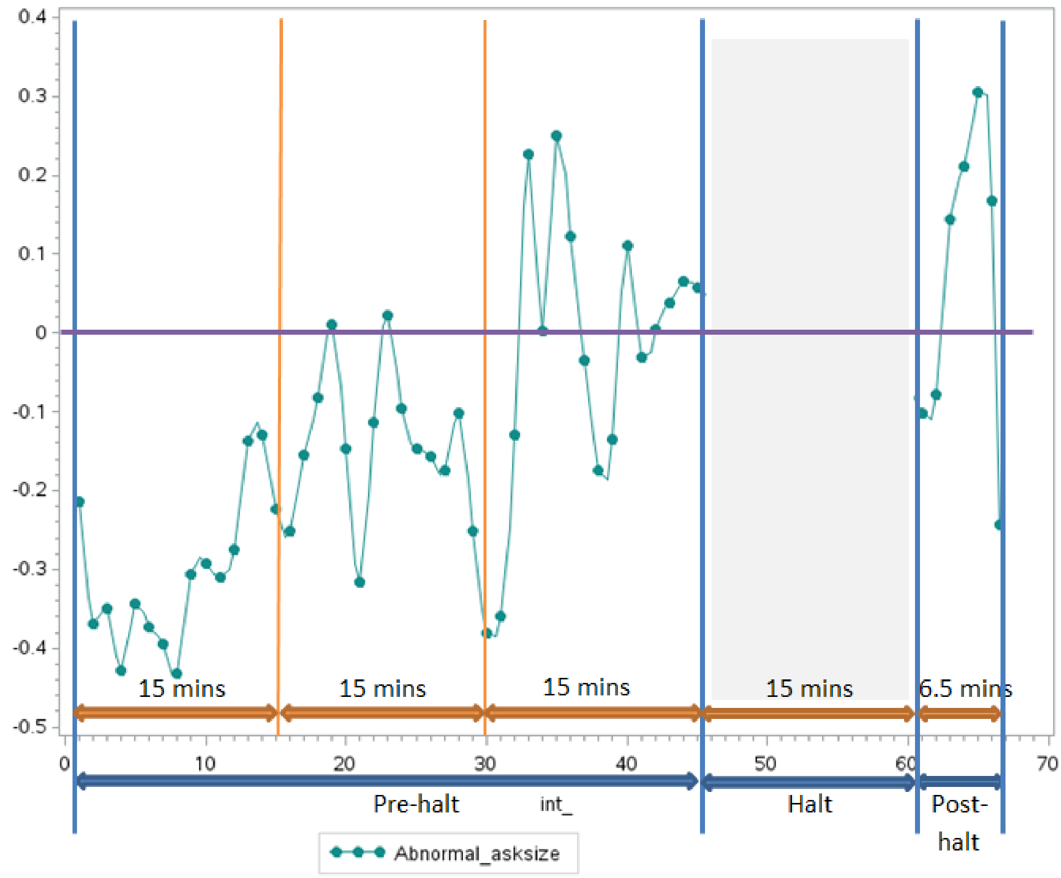
Abnormal Bid Size on 4th Jan 2016

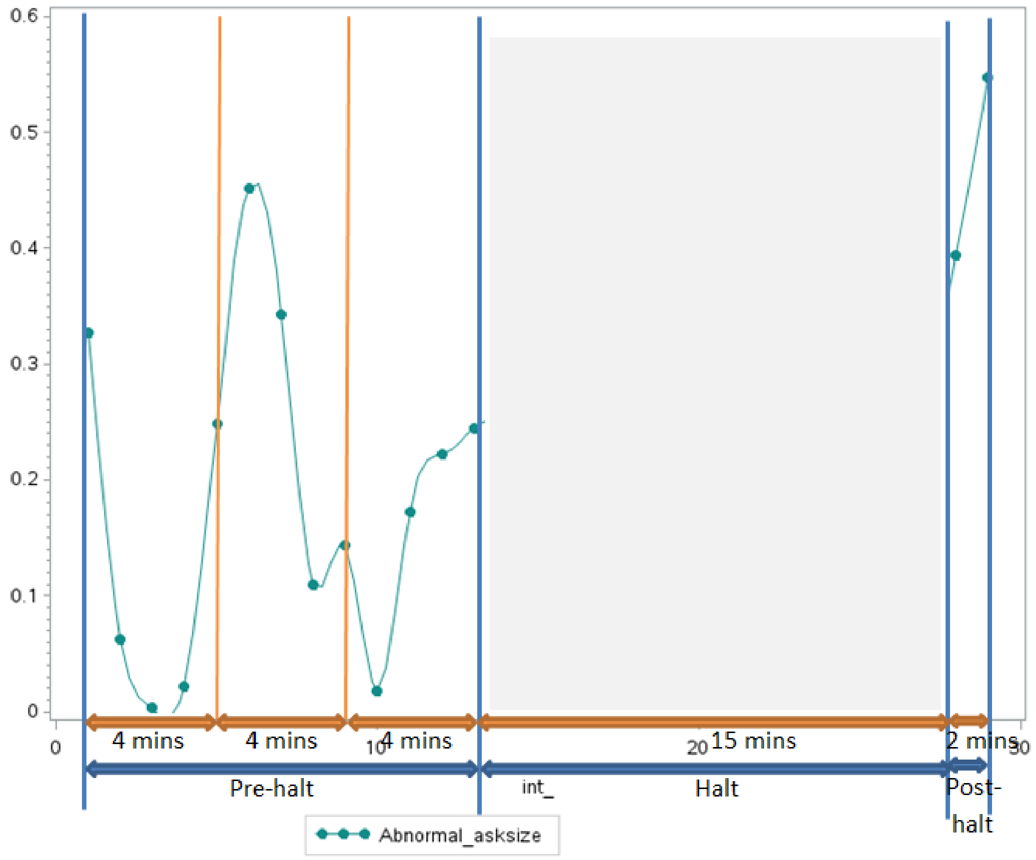


Abnormal Bid Size on 7th Jan 2016



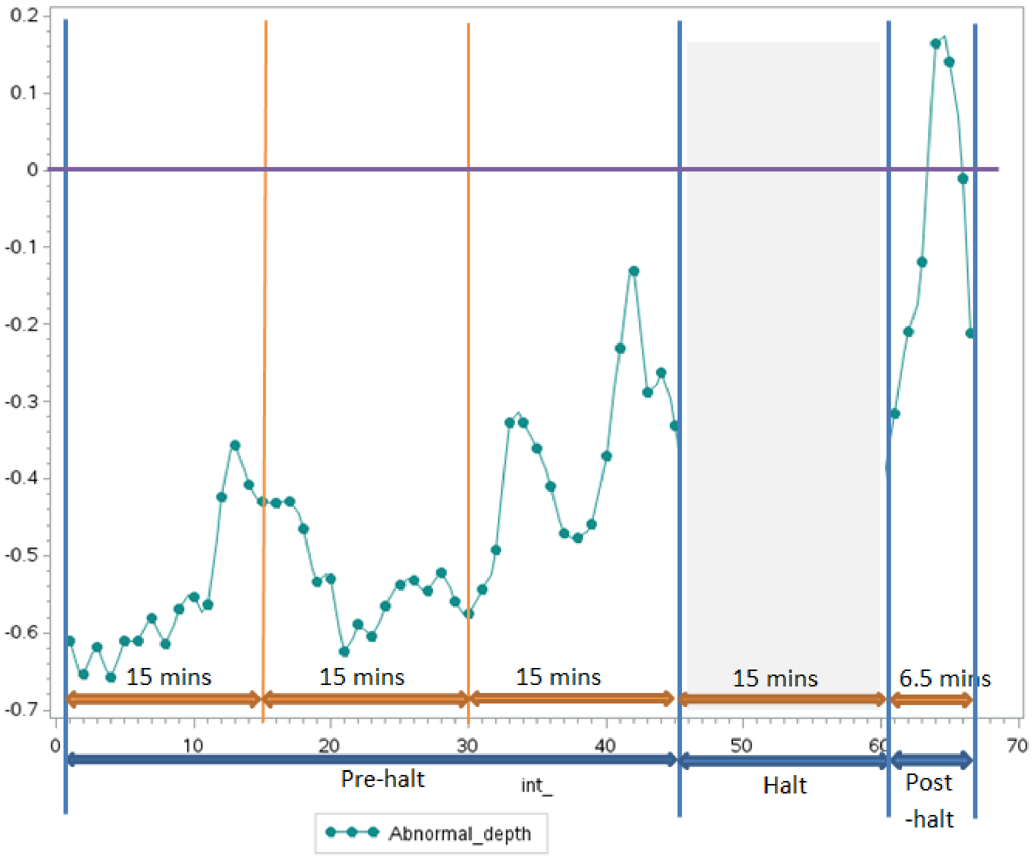
Panel D: Abnormal Ask Size on the Event Days Relative to Non-event Days


Abnormal Ask Size on 4th Jan 2016

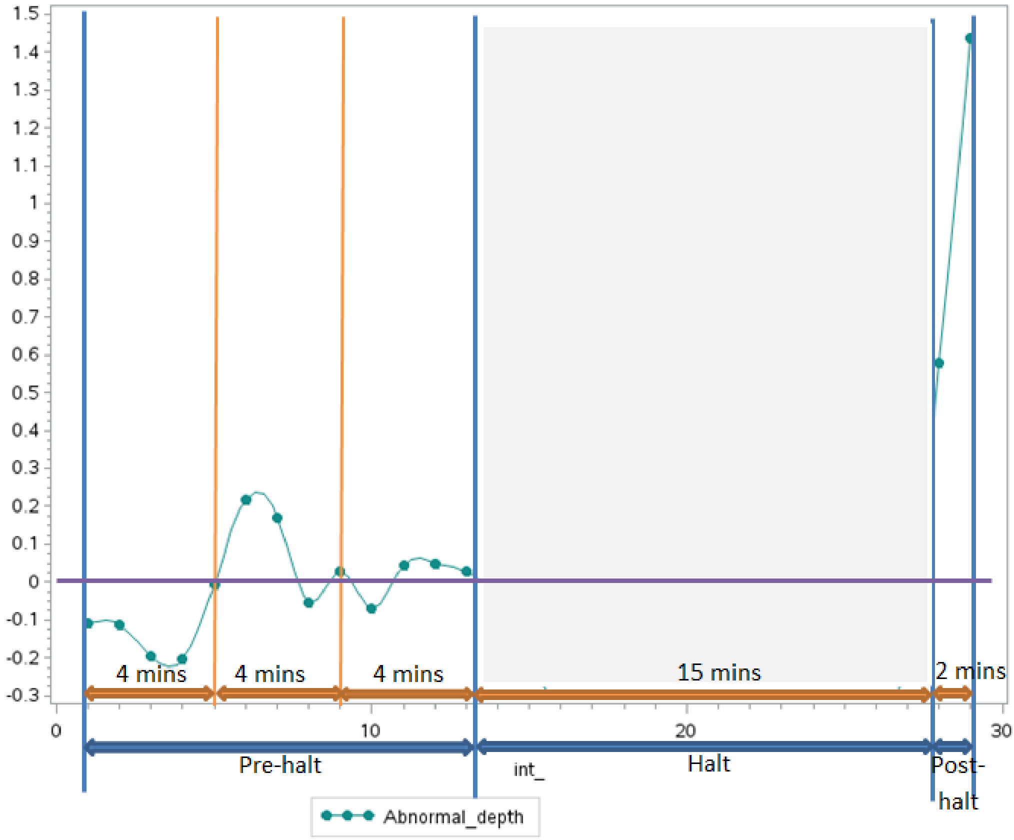

Abnormal Ask Size on 7th Jan 2016

Panel E: Abnormal Market Depth on the Event Days Relative to Non-event Days

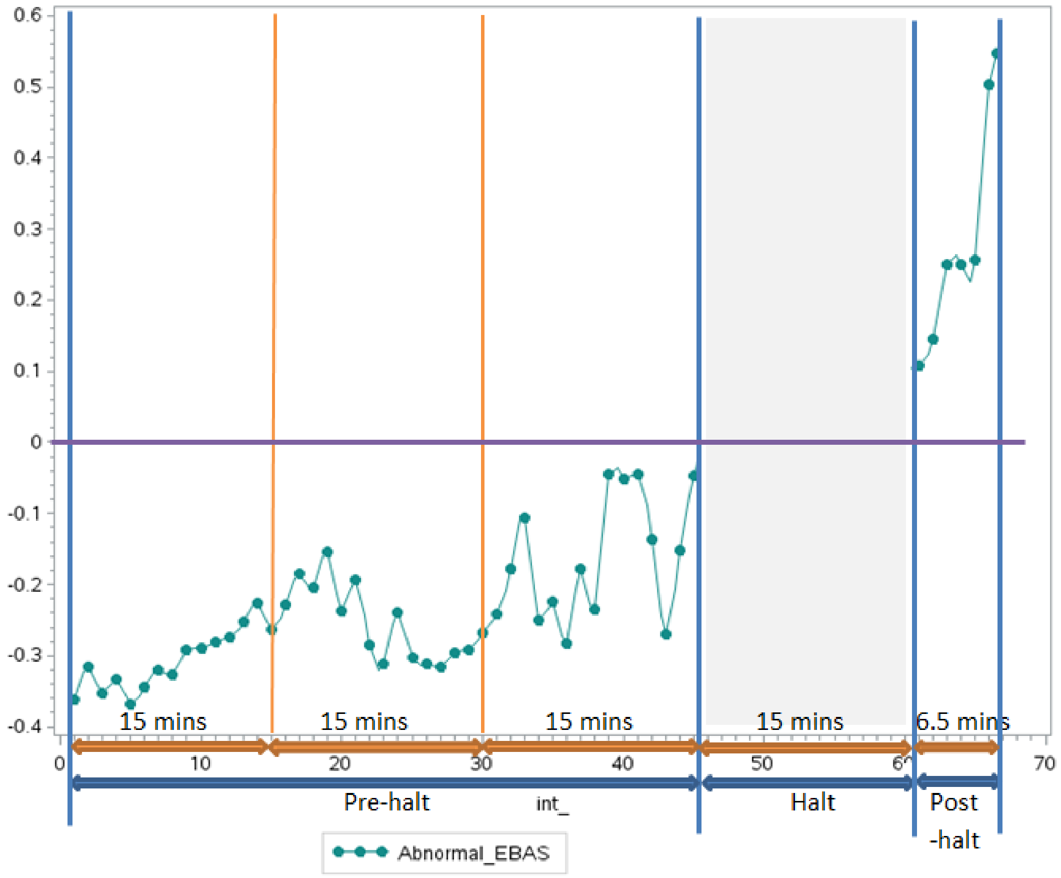
Abnormal Depth on 4th Jan 2016



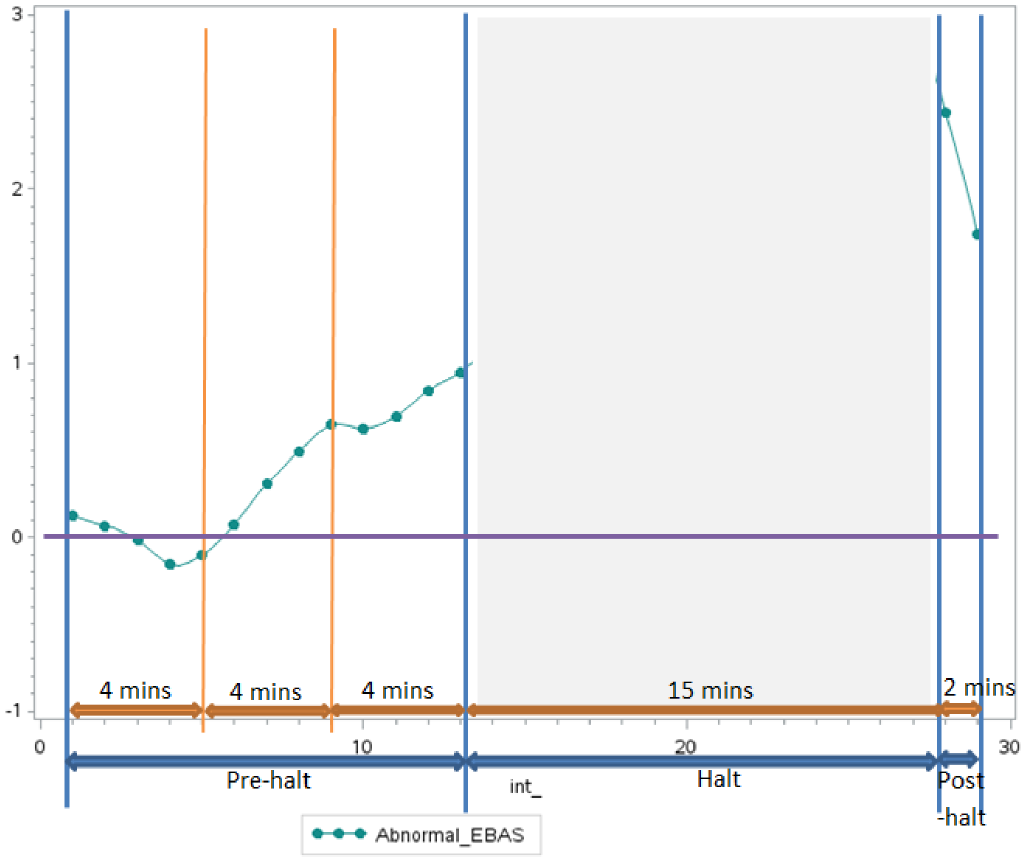
Abnormal Depth on 7th Jan 2016



Panel F: Abnormal Effective Bid-ask Spread on the Event Days Relative to Non-event Days



Abnormal Effective Bid-ask Spread on 4th Jan 2016



Abnormal Effective Bid-ask Spread on 7th Jan 2016

Figure 3

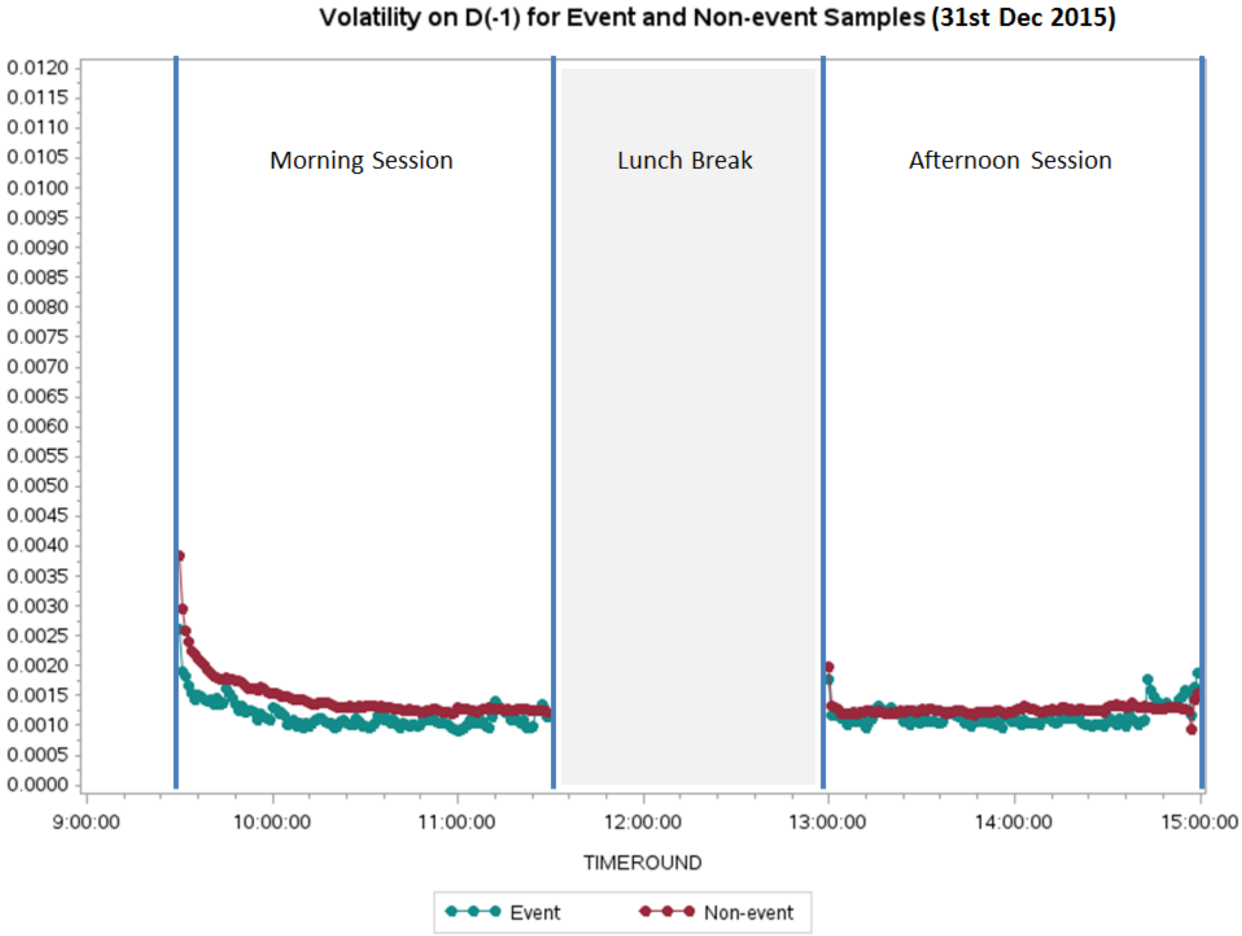
Patterns of Volatility around Event Day

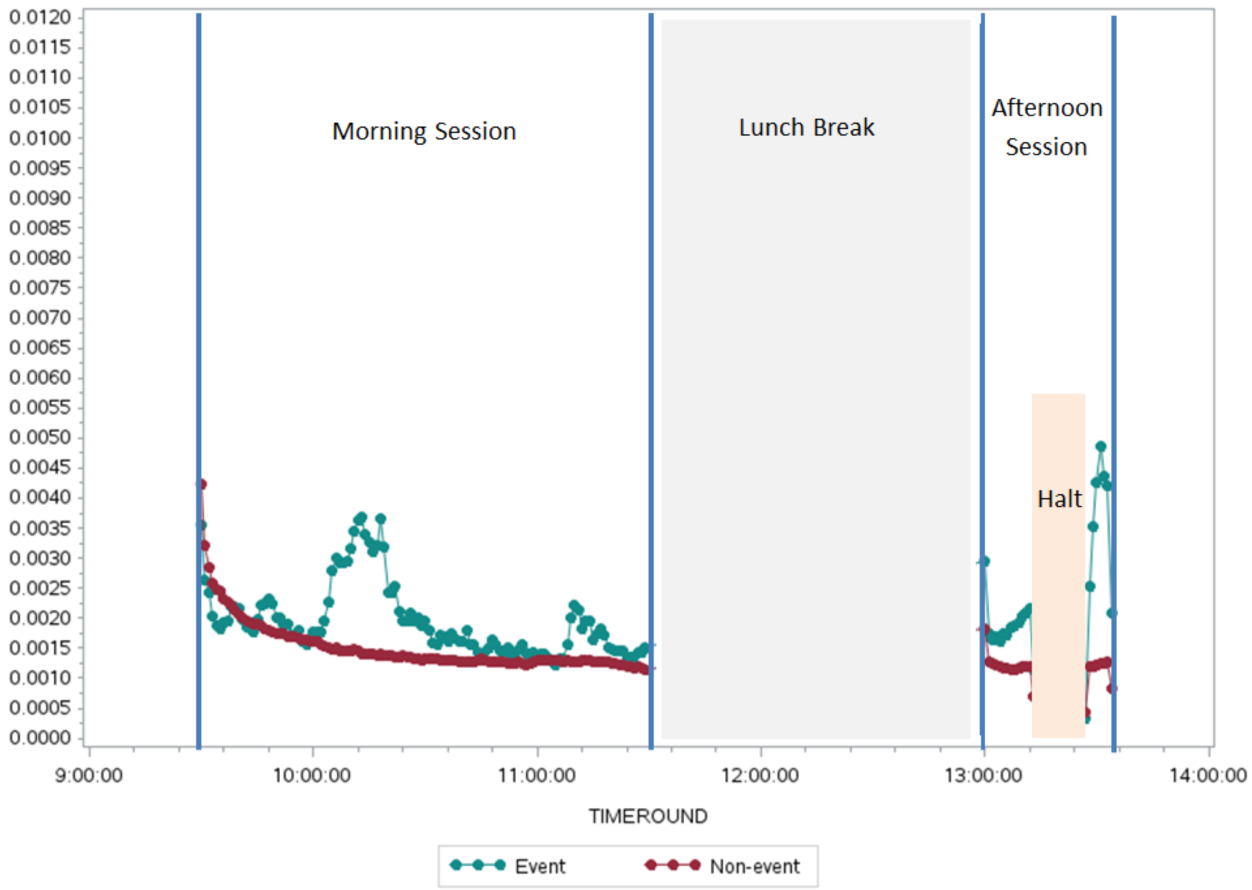
This figure presents the volatility pattern of the constituent stocks of the CSI300 index on the event day (D_0) and a day before and after the event day (D_{-1}, D_{+1}). We calculate the intraday range-based volatility on minute-by-minute basis as follows:

$$\sigma^2_{i,t,j} = \frac{[\ln(H_{i,t,j}) - [\ln(L_{i,t,j})]^2}{4ln2} \tag{9}$$

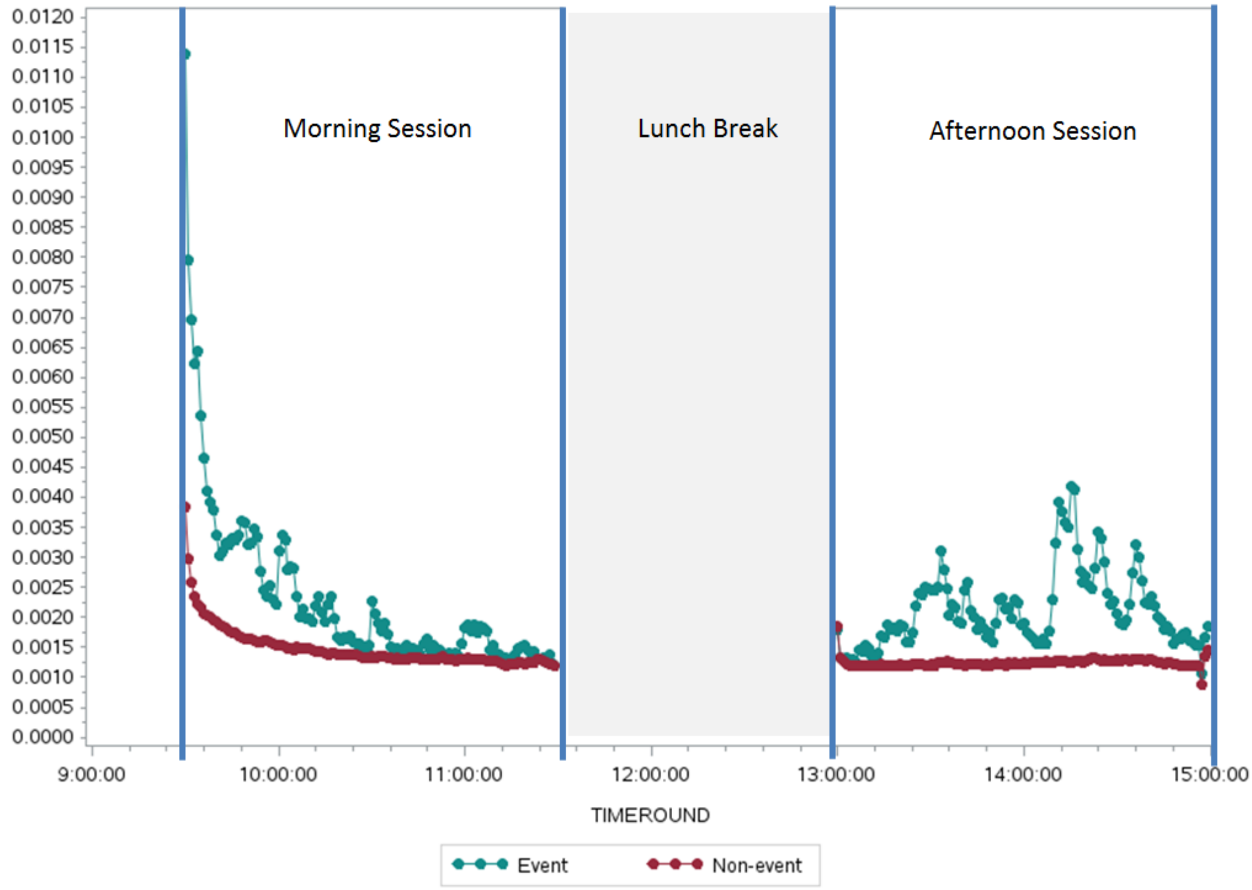
where $\sigma^2_{i,t,j}$ is the variance of stock j for interval i on day t; $H_{i,t,j}$ is the highest trade price of stock j for interval i on day t; $L_{i,t,j}$ is the lowest trade price of stock j for interval i on day t. We also calculate intraday volatility for all non-event days to examine the abnormal volatility on the event days relative to non-event days. Panel A shows the patterns of volatility for event and non-event samples on D_{-1}, D_0, D_{+1} regarding the first event, while Panel B shows the patterns of volatility for event and non-event samples on D_{-1}, D_0, D_{+1} regarding the second event.

Panel A: Volatility Pattern around the First Event



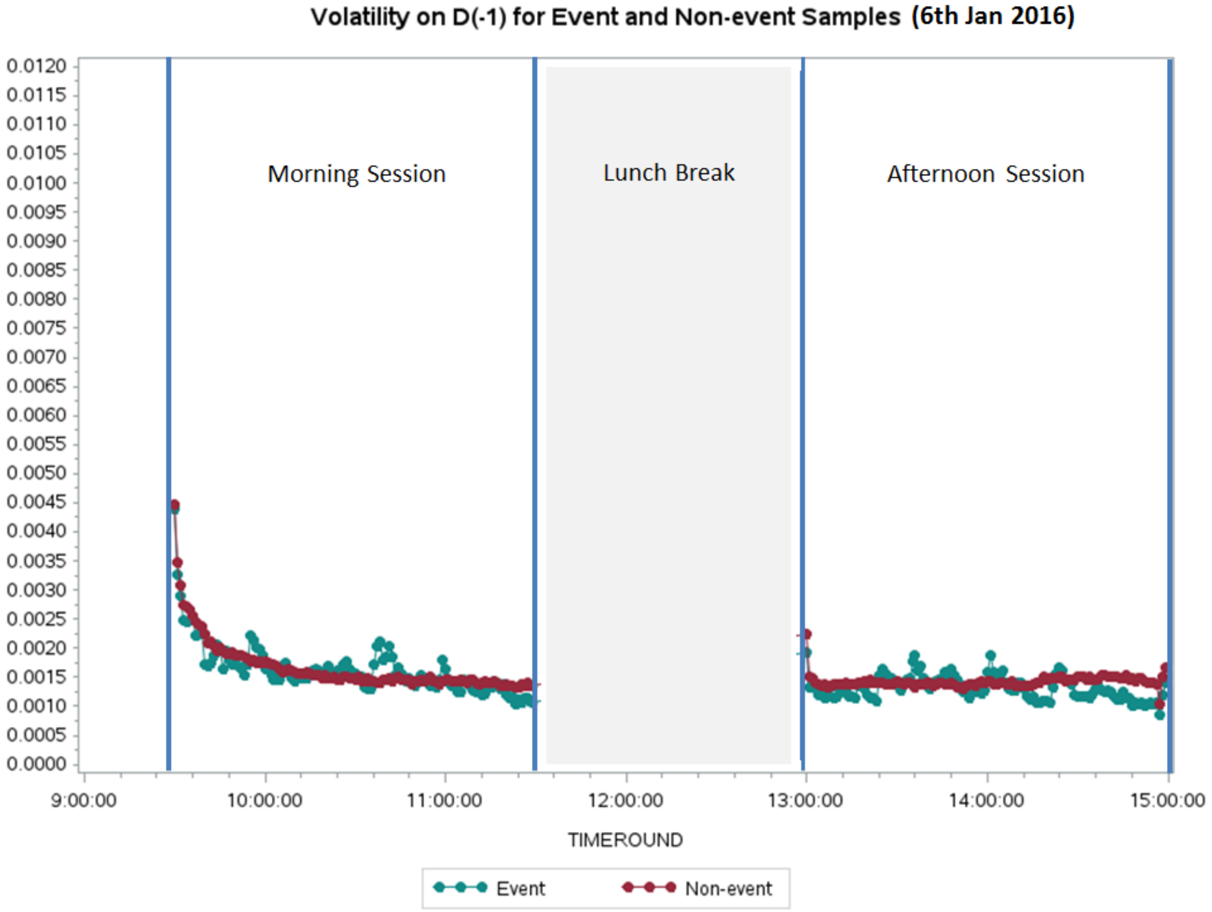


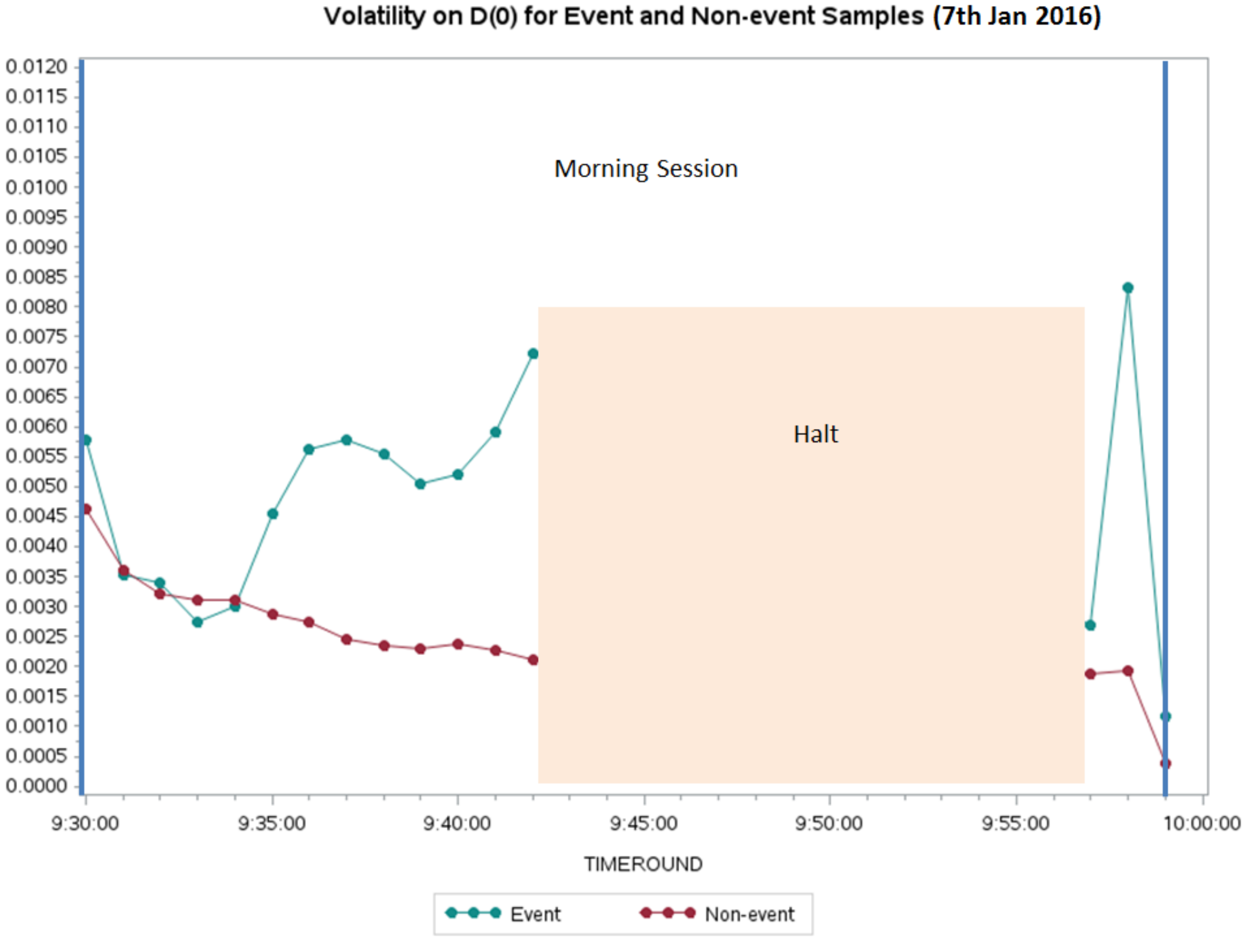
Volatility on D(0) for Event and Non-event Samples (4th Jan 2016)



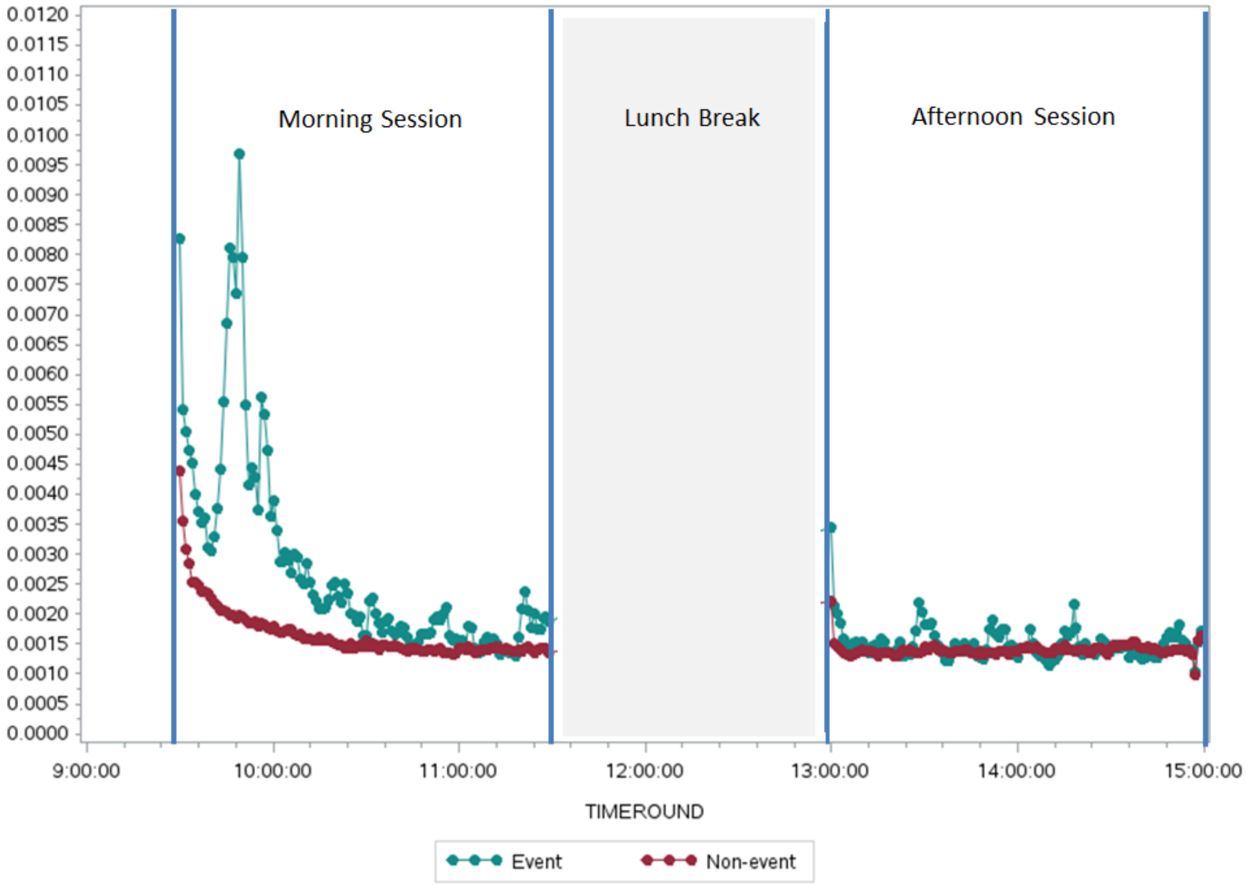
Volatility on D(+1) for Event and Non-event Samples on 5th Jan 2016

Panel B: Volatility Pattern around the Second Event





Volatility on D(+1) for Event and Non-event Samples (7th Jan 2016)



Appendix

Appendix A

A-shares Code	Corresponding B-shares Code	Constituent Name (English)	Exchange
000413	200413	Dongxu Optoelectronic Technology Co., Ltd.	Shenzhen
000539	200539	Guangdong Electric Power Development Co., Ltd.	Shenzhen
000581	200581	Weifu High-Technology Group Co. Ltd.	Shenzhen
000625	200625	Chongqing Changan Automobile Co. Ltd.	Shenzhen
000725	200725	BOE Technology Group Co. Ltd.	Shenzhen
600221	900945	Hainan Airlines Co. Ltd.	Shanghai
600663	900932	Shanghai Lujiazui Finance and Trade Zone Development Co., Ltd.	Shanghai
600827	900923	Shanghai Bailian Group Co., Ltd.	Shanghai

Appendix B

Abnormal Measures on 4th Jan 2016

	Volatility		Volume		EBAS		Bid Size		Ask Size		Depth	
Interval	Mean	P-value	Mean	P-value	Mean	P-value	Mean	P-value	Mean	P-value	Mean	P-value
1	0.0686	0.2477	-0.3274	<.0001	-0.3625	<.0001	-0.707	<.0001	-0.2143	<.0001	-0.6097	<.0001
2	0.0962	0.4827	-0.4128	<.0001	-0.3155	<.0001	-0.7056	<.0001	-0.3682	<.0001	-0.6532	<.0001
3	0.0927	0.6028	-0.4087	<.0001	-0.3535	<.0001	-0.671	<.0001	-0.3502	<.0001	-0.6179	<.0001
4	0.1193	0.4341	-0.408	<.0001	-0.334	<.0001	-0.6944	<.0001	-0.4282	<.0001	-0.6583	<.0001
5	0.0898	0.7817	-0.4398	<.0001	-0.3672	<.0001	-0.6409	<.0001	-0.3436	<.0001	-0.6106	<.0001
6	0.0418	0.3326	-0.3591	<.0001	-0.3446	<.0001	-0.6086	<.0001	-0.3724	<.0001	-0.6109	<.0001
7	0.0185	0.0094	-0.3686	<.0001	-0.321	<.0001	-0.5714	<.0001	-0.3946	<.0001	-0.5809	<.0001
8	0.0255	0.0716	-0.3882	<.0001	-0.3264	<.0001	-0.5952	<.0001	-0.4323	<.0001	-0.6143	<.0001
9	0.0257	0.0723	-0.3945	<.0001	-0.2927	<.0001	-0.6438	<.0001	-0.3057	<.0001	-0.5693	<.0001
10	0.106	0.7305	-0.2763	<.0001	-0.2901	<.0001	-0.6078	<.0001	-0.2922	<.0001	-0.5542	<.0001
11	0.3135	<.0001	-0.0437	<.0001	-0.2816	<.0001	-0.5408	<.0001	-0.3104	<.0001	-0.5634	<.0001
12	0.7218	<.0001	0.5647	<.0001	-0.2747	<.0001	-0.334	<.0001	-0.2749	<.0001	-0.4242	<.0001
13	0.8014	<.0001	0.8983	<.0001	-0.2525	<.0001	-0.2743	<.0001	-0.1376	<.0001	-0.3573	<.0001
14	0.5841	<.0001	0.6288	<.0001	-0.2263	<.0001	-0.3616	<.0001	-0.1287	<.0001	-0.4088	<.0001
15	0.4733	<.0001	0.5027	<.0001	-0.2643	<.0001	-0.3957	<.0001	-0.2241	<.0001	-0.4299	<.0001
16	0.5394	<.0001	0.3685	0.0004	-0.2272	<.0001	-0.4005	<.0001	-0.2509	<.0001	-0.4312	<.0001
17	0.5032	<.0001	0.1713	0.6982	-0.1852	<.0001	-0.5023	<.0001	-0.1544	<.0001	-0.4299	<.0001
18	0.3371	<.0001	0.1116	0.0498	-0.205	<.0001	-0.5674	<.0001	-0.0819	<.0001	-0.4643	<.0001
19	0.4475	<.0001	-0.0213	<.0001	-0.1535	<.0001	-0.6775	<.0001	0.0113	<.0001	-0.5333	<.0001
20	0.4757	<.0001	-0.1306	<.0001	-0.2377	<.0001	-0.6799	<.0001	-0.1472	<.0001	-0.5305	<.0001
21	0.3136	<.0001	-0.235	<.0001	-0.1933	<.0001	-0.704	<.0001	-0.3169	<.0001	-0.6248	<.0001
22	0.2488	<.0001	-0.2302	<.0001	-0.2843	<.0001	-0.7342	<.0001	-0.1144	<.0001	-0.5893	<.0001
23	0.2111	0.0192	-0.3736	<.0001	-0.3118	<.0001	-0.7648	<.0001	0.0231	<.0001	-0.6037	<.0001
24	0.2293	0.0068	-0.304	<.0001	-0.2396	<.0001	-0.6824	<.0001	-0.096	<.0001	-0.5653	<.0001
25	0.2096	0.0012	-0.3027	<.0001	-0.3032	<.0001	-0.6456	<.0001	-0.1478	<.0001	-0.537	<.0001
26	0.1691	0.219	-0.3309	<.0001	-0.3111	<.0001	-0.6258	<.0001	-0.1574	<.0001	-0.5322	<.0001

27	0.13	0.2512	-0.3564	<.0001	-0.3158	<.0001	-0.5728	<.0001	-0.175	<.0001	-0.5464	<.0001
28	0.11	0.9266	-0.3361	<.0001	-0.295	<.0001	-0.6306	<.0001	-0.1026	<.0001	-0.5226	<.0001
29	0.1643	0.4678	-0.2182	<.0001	-0.2911	<.0001	-0.6294	<.0001	-0.2517	<.0001	-0.5583	<.0001
30	0.1886	0.0165	-0.0923	<.0001	-0.2686	<.0001	-0.5769	<.0001	-0.3804	<.0001	-0.5753	<.0001
31	0.3357	<.0001	-0.03	<.0001	-0.2413	<.0001	-0.5202	<.0001	-0.3598	<.0001	-0.5444	<.0001
32	0.5885	<.0001	0.3403	0.012	-0.1772	<.0001	-0.5779	<.0001	-0.1296	<.0001	-0.493	<.0001
33	0.686	<.0001	0.3428	0.2869	-0.1065	<.0001	-0.3615	<.0001	0.2263	<.0001	-0.3278	<.0001
34	0.3903	<.0001	0.2532	0.5949	-0.2491	<.0001	-0.1293	<.0001	0.00324	<.0001	-0.3266	<.0001
35	0.356	<.0001	0.3678	0.0585	-0.2241	<.0001	-0.2476	<.0001	0.25	<.0001	-0.361	<.0001
36	0.4113	<.0001	0.3665	0.1977	-0.2822	<.0001	-0.3753	<.0001	0.1227	<.0001	-0.4089	<.0001
37	0.4383	<.0001	0.4028	0.0875	-0.1791	<.0001	-0.4644	<.0001	-0.034	<.0001	-0.4715	<.0001
38	0.5598	<.0001	0.296	0.2574	-0.2346	<.0001	-0.4949	<.0001	-0.1737	<.0001	-0.476	<.0001
39	0.5754	<.0001	0.194	0.8906	-0.0446	<.0001	-0.4398	<.0001	-0.1352	<.0001	-0.4582	<.0001
40	0.7859	<.0001	0.5904	<.0001	-0.0523	<.0001	-0.3351	<.0001	0.1096	<.0001	-0.3705	<.0001
41	0.7625	<.0001	0.7964	<.0001	-0.0455	<.0001	-0.0828	<.0001	-0.0309	<.0001	-0.2304	<.0001
42	0.6861	<.0001	0.954	<.0001	-0.1369	<.0001	0.115	<.0001	0.00496	<.0001	-0.1316	<.0001
43	0.8155	<.0001	1.2658	<.0001	-0.2691	<.0001	-0.245	<.0001	0.0381	<.0001	-0.2878	<.0001
44	0.8006	<.0001	1.0867	<.0001	-0.151	<.0001	-0.2327	<.0001	0.0654	0.0008	-0.2631	<.0001
45	0.8053	<.0001	1.0957	<.0001	-0.0475	<.0001	-0.2767	<.0001	0.0578	<.0001	-0.3319	<.0001
						15-minute Trading Halt						
61	0.9841	<.0001	1.9553	<.0001	0.1086	<.0001	-0.2239	<.0001	-0.1009	<.0001	-0.3149	<.0001
62	2.0327	<.0001	1.8318	<.0001	0.1453	0.0009	-0.0731	<.0001	-0.0772	<.0001	-0.2103	<.0001
63	2.7047	<.0001	2.7882	<.0001	0.2496	0.0002	-0.0584	<.0001	0.1441	0.0299	-0.1197	<.0001
64	3.0748	<.0001	2.8737	<.0001	0.2496	<.0001	0.411	<.0001	0.2118	0.0119	0.1648	<.0001
65	2.7095	<.0001	3.3247	<.0001	0.2569	0.015	0.2965	<.0001	0.3054	0.175	0.1413	0.0017
66	2.4239	<.0001	3.2314	<.0001	0.5038	0.0825	0.0821	<.0001	0.1666	0.0242	-0.0116	<.0001
66.5	1.9207	<.0001	2.0978	<.0001	0.5466	0.7173	-0.0966	<.0001	-0.2423	<.0001	-0.2117	<.0001

Abnormal Measures on 7th Jan 2016

	Volatility		Volume		EBAS		Bid Size		Ask Size		Depth	
Interval	Mean	P-value	Mean	P-value	Mean	P-value	Mean	P-value	Mean	P-value	Mean	P-value
1	0.356	<.0001	0.1599	<.0001	0.1209	0.3348	-0.2206	<.0001	0.3269	0.0499	-0.1095	<.0001
2	0.1179	0.9016	0.2236	<.0001	0.0644	0.0013	-0.1313	<.0001	0.0621	0.0025	-0.1125	<.0001
3	0.2685	0.0095	-0.1222	<.0001	-0.0141	<.0001	-0.2867	<.0001	0.00308	<.0001	-0.1964	<.0001
4	-0.0325	<.0001	-0.0878	<.0001	-0.1561	<.0001	-0.2973	<.0001	0.0221	<.0001	-0.205	<.0001
5	0.1283	0.2739	0.1855	0.0058	-0.1037	<.0001	-0.0976	<.0001	0.248	0.5088	-0.00496	<.0001
6	0.8439	<.0001	0.6805	<.0001	0.0684	0.1607	0.2109	0.0278	0.4522	0.1092	0.2163	0.63
7	1.4064	<.0001	0.6599	<.0001	0.3077	<.0001	0.223	0.0002	0.3433	0.2308	0.1705	0.2227
8	1.7111	<.0001	0.7014	<.0001	0.49	<.0001	-0.0812	<.0001	0.1097	0.0071	-0.0546	<.0001
9	1.5919	<.0001	0.9479	<.0001	0.6456	<.0001	0.0116	<.0001	0.1437	0.0336	0.0303	<.0001
10	1.4112	<.0001	0.9271	<.0001	0.6216	<.0001	-0.0411	<.0001	0.0178	<.0001	-0.0701	<.0001
11	1.5423	<.0001	1.1188	<.0001	0.6954	<.0001	0.0676	<.0001	0.1721	0.0231	0.0445	0.0008
12	1.959	<.0001	1.3336	<.0001	0.8396	<.0001	0.0476	<.0001	0.2222	0.4344	0.0496	0.0217
13	2.8442	<.0001	1.7878	<.0001	0.9478	<.0001	0.00853	<.0001	0.244	0.6634	0.0273	0.0529
15-minute Trading Halt												
28	0.8827	0.5466	6.3827	<.0001	2.4416	<.0001	0.9458	0.0938	0.3941	<.0001	0.5776	0.0449
29	3.9834	<.0001	6.152	<.0001	1.7407	<.0001	2.7013	<.0001	0.5469	0.0078	1.4359	<.0001