The magnet effect of circuit breakers: A role of price jumps and market liquidity

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Abstract:

This paper investigates the magnet effect of market-wide circuit breakers using transaction data from the Chinese stock index futures market. It is the first to consider high-frequency price jump behavior in studying the magnet effect. We find that when a market-wide trading halt is imminent, the probability of future price moving toward the breaker level and the volatility of market remain stable. However, the conditional probability of price jumps increases significantly, leading to a higher possibility of triggering market-wide circuit breakers, in support of the magnet effect. In addition, we find a significant increase in liquidity demand, but no significant change in liquidity supply ahead of a market-wide trading halt, suggesting that the deterioration of market liquidity may play an important role in explaining the magnet effect.

Keywords: Magnet effect; Circuit breakers; Price jumps; Liquidity; Stock index futures

JEL classification: G10; G12; G18

1. Introduction

As a market stabilization mechanism implemented in many equity and futures exchanges around the world, circuit breakers are designed to prevent the markets from fluctuating excessively. When a price (or an index) reaches a pre-specified level, circuit breakers will halt trading on individual securities or the whole exchange.† Although circuit breakers are widely used, the effectiveness of this mechanism remains an ongoing debate.‡ Much of the research on how circuit breakers affect markets and market participants' behavior has focused on the "magnet effect" suggested by Subrahmanyam (1994).

The magnet effect states that circuit breakers may actually increase price variability and exacerbate price movements when a price/ an index is very close to the breaker trigger level. This is because market participants want to avoid being constrained not to trade, and they rush to submit orders even if these orders do not represent their optimal trading strategies. Thus, the magnet effect is an ex-ante self-fulfilling effect as investors advance their trades to ensure their ability to trade. As a result, circuit breakers may exacerbate the very problem they were meant to address. Using data from various countries and different financial markets, empirical studies on the magnet effect of circuit breakers provide mixed and inconsistent results. While some studies find no evidence of it (e.g., Berkman & Steenbeek, 1998; Hall & Kofman, 2001; Abad & Pascual, 2007), many other papers support the existence of magnet effect (e.g., Holder, Ma, & Mallett, 2002; Belcher, Ma, & Mallett, 2003; Cho, Russell, Tiao, & Tsay, 2003; Hsieh, Kim, & Yang, 2009).

As it is rare to observe a market-wide trading halt triggered by circuit breakers, most of previous studies examine the magnet effect of price limits for individual assets rather than market-wide circuit breakers. For example, Cho et al. (2003), Abad and Pascual (2007), Du, Liu, and Rhee (2009), Hsieh et al. (2009), Wong, Liu, and Zeng (2009), and Hautsch and Horvath (2016) all focus on the price limits in stock markets. One notable exception is Goldstein and Kavajecz (2004), which empirically investigates market participants' trading strategies at the New York Stock Exchange

† Although the specific rules of circuit breakers vary from market to market, they can be categorized into three different types: (1) price limits, (2) firm-specific trading halts, and (3) market-wide circuit breakers (Kim & Yang 2004). Price limits, which take into effect toward single asset price, restrict the intraday asset price within a limited range. Firm-specific trading halts stop trading on individual securities and are usually called by exchanges or security regulators, which often relate to news announcements. Finally, market-wide circuit breakers halt trading on the whole market for a pre-specified duration when the designated index reaches a pre-specified level.

‡ See Kim and Yang (2004) for a comprehensive review of the literature.

(NYSE) during the turbulent October 1997 period and finds evidence consistent with the magnet effect of the market-wide circuit breakers.

To complement the existing literature, this paper studies the magnet effect of market-wide circuit breakers using high-frequency data from the Chinese stock index futures market. Chinese regulators formally introduced the market-wide circuit breakers in stock markets and stock index futures market on January 1, 2016. There are two levels of breakers: the Level 1 breaker (a 5% change, either positive or negative, of the CSI 300 stock index compared to its previous close) triggers a 15-minute trading halt for the whole market, while the Level 2 breaker (a 7% change) halts trading for the rest of the day. The intention of this newly established rule is to reduce the likelihood of market crash events and improve the stability of Chinese financial markets. However, within four trading days, both Level 1 and Level 2 breakers were triggered for two times, and the whole stock market lost more than 10% of its value. This leads to the suspension of circuit breakers in China on January 8, 2016. Such a dramatic event provides a unique opportunity to study market behavior with and without circuit breakers and present clearer evidence of the magnet effect, if there is any. As China's financial markets have become more influential in global financial markets, the study of Chinese experience of market-wide circuit breakers is also meaningful for market participants and regulators in other financial markets.

Previous studies identify the magnet effect normally by measuring price trend, market volatility and trading activity. Although volatility is an important risk measure in finance and macroeconomics, it can only adequately represent small risks in practice (e.g., Gourieroux & Jasiak, 2001, p. 427),[§] and does not capture the extreme market risk ahead of the triggering of circuit breakers. Given that the large adverse market movement is a great concern to practitioners and regulators (e.g., Hong, Liu, & Wang, 2009), in this paper we not only analyze the characteristics of price trend and market volatility as most of previous studies do, but also investigate the extreme market risk when we examine the magnet effect. We use price jump behavior as a proxy for the extreme market risk and apply a high-frequency jump test proposed by Christensen, Oomen, and Podolskij (2014) to identify jumps.[**] To the best of our knowledge, our study is the first to consider

§ Volatility alone cannot satisfactorily capture risk in scenarios of occasionally occurring extreme market movements. For example, Longin (2000) and Bali (2000) point out that volatility measures based on asset return distributions cannot produce accurate estimates of market risks during volatile period.

** The jump detection methods have been improving in recent years, moving from low-frequency jump detection to high-

high-frequency price jump behavior in the analysis of the magnet effect of circuit breakers.

We further examine the variation in market liquidity to shed light on the role of market liquidity in explaining the magnet effect. We separately construct variables of liquidity demand, liquidity supply, and overall market liquidity, and use a VARX model to investigate the dynamics of market liquidity before the triggering of circuit breakers.[††] We have the following key findings.

First, when the CSI 300 index drops and is very close to the breaker level, our model shows that the probability of future price decline and the market volatility remain relatively stable. That is, no magnet effect is found in price trend or market volatility behavior.

Second, as the CSI 300 index falls and moves closer to the breaker level, the probability of price jumps (especially negative jumps) increases, which indicates that the circuit breakers become more likely to be triggered.[‡‡] The distance between the CSI 300 index and the breaker level (i.e., breaker distance) remains significant in predicting jumps even after we control for the effects of liquidity, volatility and return. This indicates that the magnet effect actually exists in the form of price jumps. We also exploit a control sample period without circuit breakers to make inference about the effect of circuit breakers. During the control sample period, circuit breaker did not exist, but the stock index experienced a large movement that it would have triggered a trading halt had the circuit breakers been in force at the time. We find that the impact of breaker distance on the probability of index futures price jump is significantly negative during the period with circuit breakers, while it is insignificant in the control period without circuit breakers.

Third, when a market-wide trading halt is imminent, liquidity demand increases significantly, while there is no significant change in liquidity supply measured by total quote depth and limit order imbalance. This suggests a significant deterioration of market liquidity ahead of a market-wide trading halt, which may play an important role in explaining the magnet effect.[§§]

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frequency jump detection. Barndorff-Nielsen and Shephard (2004, 2006) propose a jump-robust bipower variation (BPV) measure to separate the jump variance and the diffusive variance. Lee and Mykland (2008) exploit the property of BPV and develop a rolling-based nonparametric test of jumps. Jiang and Oomen (2008) take high-frequency microstructure noise into consideration and propose a "swap variance" jump detection approach. In this paper, we apply a high-frequency jump detection technique proposed by Christensen et al. (2014). This jump test makes use of a pre-averaging approach to remove the microstructure noise component, and the pre-averaged price series can then be used to construct consistent measures of the diffusive component and jump component of the price movement.

[††] Goldstein and Kavajecz (2004) and Du et al. (2009) also look at market liquidity, but they do not control the potential interaction between different liquidity measures.

[‡‡] All returns are calculated at one-minute frequency. For the CSI 300 index futures, the mean absolute jump size (one-minute interval) is 0.22%, which is about 7 times of the mean absolute return in all one-minute intervals.

[§§] Jiang, Lo, and Verdelhan, (2011) point out that liquidity shocks have a non-negligible impact on price jumps.

The key contribution of this paper is to extend and test the possible forms of the magnet effect of circuit breakers by taking into account the price jump behavior, a proxy for the extreme market risk. Our study shows the importance of distinguishing the continuous diffusive component and the discontinuous jump component of the price process in analyzing the magnet effect. It also points to the importance of market liquidity in explaining the magnet effect. Our results provide valuable insights in better understanding the impact of market-wide circuit breakers in financial markets.

The rest of the paper is organized as follows. Section 2 provides the institutional background. Section 3 develops our hypotheses. Section 4 describes the data and methodology. Section 5 presents our empirical findings. Section 6 conducts the robustness checks. Section 7 examines market liquidity ahead of a market-wide trading halt, and Section 8 concludes.

2. Institutional background

In this paper, we use transaction data from the Chinese stock index futures market to examine the magnet effect of market-wide circuit breakers. Traded in China Financial Futures Exchange (CFFEX), Chinese stock index futures contracts are based on several stock indexes. Up to now, there are three stock index futures, namely the CSI 300 index futures, the SSE 50 index futures, and the CSI 500 index futures. The expiration date of these index futures is the third Friday of the contract month. The contract month can be the current month, the next month, and the final months of the next two quarters.

Of the three stock index futures, the CSI 300 index futures is the first to be traded in the exchange, starting on April 16, 2010. It is also the most frequently traded stock index futures in China. The underlying index (the CSI 300 index) represents about 70% of the total market capitalization of both Shanghai and Shenzhen stock exchanges. Thus, we mainly focus on the CSI 300 index futures in this study. During the period with circuit breakers, the volume of the dominant contract (i.e. the most active futures contract among all futures contracts with different expiration date for the same index futures) accounts for more than 80% of the total trading volume for each index futures. Therefore, we choose the dominant contract of the CSI 300 index futures as our main sample. The dominant contracts of the SSE 50 index futures and the CSI 500 index futures are also used. The price behavior of the three dominant contracts should be sufficient to reveal the overall performance of Chinese stock index futures market.

As we can see from Figure 1, Chinese stock market experienced a turbulent period in 2015. There was a huge run up in early 2015, which was followed by a market crash. The CSI 300 index dropped 45% within three months (June – August, 2015). Many investors, including both institutional investors and retail investors, suffered enormous loss. To restrain the risk of excessive price fluctuation and improve the stability of financial markets, China Securities Regulatory Commission (CSRC) introduced market-wide circuit breakers in stock markets and stock index futures market on January 1, 2016. The Level 1 breaker (if the CSI 300 index is 5% below/above its previous close) will halt trading on the whole market for 15 minutes, and the Level 2 breaker (if there is a 7% change) will halt trading for the remainder of the trading day.***

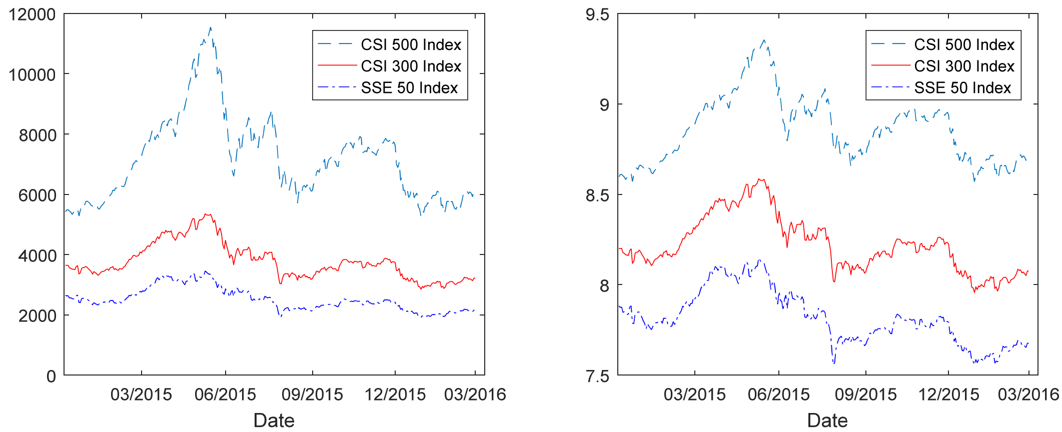

Fig. 1. Three stock indexes in China from January 2015 to March 2016. The left chart shows the indexes without logarithmic adjustment, and the right chart with logarithmic adjustment. The daily data of the stock indexes come from the Wind database.

Since the implementation of market-wide circuit breakers on January 4, 2016 (markets were closed from January 1, 2016 to January 3, 2016 due to holidays), both the 5% and 7% breakers were triggered on January 4 and January 7, 2016. Many commentators and market participants believe that the existence of circuit breakers exacerbates investor panic and leads to the instability of financial markets. To avoid further stock price collapse, Chinese regulators announced that starting from January 8, 2016 market-wide circuit breakers would be suspended in order to "smooth" trading operations. Thus, this newly established rule exists for only four trading days in China.

*** In a normal trading day, the market opens at 9:30 am and closes at 3:00 pm.

In the period immediately before the introduction of market-wide circuit breakers (i.e., from October to December 2015), stock indices in China were relatively stable. During the period when circuit breakers exist, there were no major macro-economic shocks or major news about fundamentals in the financial markets. The most important difference between the two periods is the new trading rule (i.e., circuit breakers). Consequently, the changes of market microstructure caused by circuit breakers may have contributed to the observed large downside market movement.

3. Hypotheses of magnet effect

We develop three hypotheses in this paper based on the theoretical analysis of magnet effect in Subrahmanyam (1994), which develops a two-period model to analyze the strategic trading decision of uninformed traders with exogenous needs to trade. Without circuit breakers, the traders split their trades across time. With circuit breakers, they will advance their trades if the price is close to the breaker limit, as they try to avoid being constrained not to trade. The above-mentioned trading decision leads to an increase in the ex-ante price variability and the probability of the price hitting the circuit breaker bounds, i.e., the magnet effect. The three hypotheses developed in this paper illustrate the possible forms of magnet effect from the perspectives of price trend, market volatility, and extreme market risk.

First, the price acceleration hypothesis, which has been examined in past studies (e.g., Hsieh et al., 2009), states that as the CSI 300 index falls and moves toward the breaker level, the probability of the stock index futures price further moving toward the circuit breaker trigger level increases correspondingly. If circuit breakers have magnet effect, the distance between the CSI 300 index and the breaker level (i.e., breaker distance) will be negatively correlated with the magnitude of the magnet effect. Thus, we use the breaker distance as the proxy for the magnet effect. We construct a logit model to examine how the breaker distance influences the price trend. If the price acceleration hypothesis holds, we expect the breaker distance to have a significant negative impact on the probability of the stock index futures price further moving toward the breaker level.

Second, the market volatility hypothesis states that as the CSI 300 index moves toward the breaker level, the volatility of stock index futures price will gradually increase. Volatility is an important measure to evaluate the effectiveness of circuit breakers. If circuit breakers are an effective market-stabilization mechanism, they should have a "cool-off" effect on market volatility.

On the other hand, the magnet effect of circuit breakers exacerbates market movements when trading halt is imminent, that is to say, circuit breakers have significant stimulating effect on market volatility. In this paper, we construct a jump robust measure of realized volatility and analyze the explanatory power of the breaker distance for market volatility. If the market volatility hypothesis holds, the coefficient of breaker distance should also be negative, which indicates that the smaller the distance between the CSI 300 index and the breaker level, the stronger the stimulating effect of the circuit breakers on market volatility.

Third, market-wide trading halts take place under abnormal intraday price movements. The large movement of intraday price cannot be fully explained by the current level of market volatility. It is more likely related to the extreme market risk. However, previous studies do not take the extreme market risk into consideration when studying the magnet effect. We emphasize that the extreme market risk is a non-negligible part of the analysis. The extreme market risk hypothesis states that the smaller the distance between the CSI 300 index and the breaker level, the greater the extreme market risk. We use the price jump behavior as a proxy for the extreme market risk. This is because both of them have very low probability of occurrence, and when they do happen, the market would be greatly affected.[†††] Similar to the test of price acceleration hypothesis, we use a logit model with breaker distance as one of the explanatory variables to test whether circuit breakers have an impact on the futures price jump behavior. If the extreme market risk hypothesis holds, the coefficient of breaker distance should be significantly negative. Such a regression result would suggest that as the distance between the CSI 300 index and the breaker level decreases, the probability of a stock index futures price jump will increase, leading to a higher possibility that the index price movement will trigger circuit breakers.

4. Data and Methodology

4.1. Data

We obtain the Chinese stock index futures data from the Pyramid program trading software in China for the period from December 18, 2015 to January 7, 2016. The data contains second-by-

††† There exists an extensive literature on index return models, which unanimously agrees that index prices "jump", see Eraker (2004) and Maheu and McCurdy (2004), among others.

second records of trading price, trading size, best bid quote price, bid depth (i.e., the number of shares displayed at the best bid quote price), best ask quote price, and ask depth (i.e., the number of shares displayed at the best ask quote price). We look at all the three stock index futures listed in CFFEX, namely the CSI 300 index futures, the CSI 500 index futures, and the SSE 50 index futures. As the dominant contracts have the largest trading volume, we use the data of dominant contracts for the three index futures, with a focus on the CSI 300 index futures.[‡‡‡]

We divide our data into two sub-periods: one is the last 10 trading days prior to the introduction of market-wide circuit breakers (December 18, 2015 to December 31, 2015, Period 1), and the other is the 4 trading days when market-wide circuit breakers exist in the market (January 4, 2016 to 7 January 2016, Period 2). During the two sub-periods, there was no major news announcement about fundamentals. The major difference between the two sub-periods is the newly established circuit breaker rules.

The data are sampled at a frequency of one-minute. There are 2700 one-minute intervals during Period 1 when there are no circuit breakers. In Period 2, the CSI 300 index fell and triggered the Level 1 breaker (-5% change) for 2 times and the Level 2 breaker (-7% change) for 2 times. We exclude the intraday data after the Level 1 circuit breaker has been triggered. This is because the triggering of Level 2 circuit breaker is conditional on that the Level 1 breaker has been triggered and there is a 15-minute market-wide trading halt, which may lead to biased results. We also exclude the incomplete one-minute intervals (2 of them), which are truncated by the triggering of circuit breakers. This leaves us with a sample of 624 one-minute intervals in Period 2. In a latter section, we will first make a comparison between these two sub-periods to examine the structural changes in the stock index futures market due to market-wide circuit breakers. We then use the data in Period 2 to test the three hypotheses of the magnet effect.

4.2. Detection of asset price jump

To investigate the index futures price jump behavior using second-to-second price data, it is critical to use a noise-robust test to detect jumps. In this paper, we follow the jump detection procedures proposed by Christensen et al. (2014): First, we make use of the pre-averaging approach

[‡‡‡] The non-dominant contracts of the three index futures are infrequently-traded compared with the dominant contracts. In particular, during the period when the index price is near the breaker level, there were no transactions for several minutes for some non-dominant contracts.

introduced by Jacod, Li, Mykland, Podolskij, and Vetter (2009) and Podolskij and Vetter (2009a, b) to asymptotically remove the microstructure noise component in observed price series; Second, we construct noise- and outlier-robust versions of the realized variation (RV) and bi-power variation (BPV) to separate the jump component in price series; Finally, we apply the Lee and Mykland (2008) rolling-based nonparametric test to detect jumps in price series, which have been pre-averaged.

Throughout the paper, we assume the stock index futures prices are observed at a regular time interval $\delta = 1/\mathrm{N}$ over a given unit time interval $[0,1]$, where N is the number of observations. Then the conventional realized variation (RV) and bi-power variation (BPV) can be defined as

$$RV_N = \sum_{i=1}^{N} r_{\mathrm{i}}^2 \tag{1}$$

$$BPV_N = \frac{N}{N-1}\frac{\pi}{2}\sum_{i=2}^{N} |r_{i-1}||r_i| \tag{2}$$

where $r_i = \ln(P_i/P_{i-1})$ and P_i is the observed price at time i. It is well known (see Barndorff-Nielsen & Shephard, 2006) that $\mathrm{plim}_{N\to\infty} RV_N = \int_0^1 \sigma_s^2 ds + \sum_{i=1}^{N_j} J_i^2$ and $\mathrm{plim}_{N\to\infty} BPV_N = \int_0^1 \sigma_s^2 ds$, where the N_j is the number of jumps and J_i stands for the size of the i-th jump. In other words, RV is a consistent estimator of the total variance, including both the continuous diffusive component (σ_s^2) and the discontinuous jump component (J_i^2), while BPV only captures the diffusive component. Using equation (1) and (2), the difference between realized variation and bi-power variation can be used to isolate jump variation (JV).

However, the high-frequency microstructure noise invalidates the conventional RV and BPV measures described above. Thus, we use the pre-averaging approach to remove asymptotically the influence of microstructure noise. First, we calculate returns on a price series that is pre-averaged in a local neighborhood of K observations, i.e.,

$$r_{i,K}^* = \frac{1}{K}\left(\sum_{j=K/2}^{K-1} P_{(i+j)/N} - \sum_{j=0}^{\frac{K}{2}-1} P_{(i+j)/N}\right) \tag{3}$$

where K is an even number greater than 2. Based on the pre-averaged return series, Christensen et al. (2014) propose noise- and outlier-robust versions of RV and BPV as

$$RV^* = \frac{N}{N-K+2}\frac{1}{K\psi_K}\sum_{i=0}^{N-K+1} |r_{i,K}^*|^2 - \frac{\widehat{\omega}^2}{\theta^2\psi_K} \tag{4}$$

$$BPV^* = \frac{N}{N-2K+2}\frac{1}{K\psi_K}\frac{\pi}{2}\sum_{i=0}^{N-2K+1} |r_{i,K}^*||r_{i+K,K}^*| - \frac{\widehat{\omega}^2}{\theta^2\psi_K} \tag{5}$$

where $\psi_K = (1+2K^{-2})/12$, and $\hat{\omega}^2/\theta^2\psi_K$ is a bias-correction, which compensates for the residual microstructure noise that remains after pre-averaging. [§§§]

The associated test statistics for jumps in $r_{i,K}^*$ is the return standardized with a jump-robust instantaneous volatility estimate, i.e.,

$$\mathcal{L}_{\mathrm{i}}^* = \frac{r_{i,K}^*}{\sigma_{\mathrm{i,k}}} \quad \text{where } {\sigma_{\mathrm{i,k}}}^2 = \frac{1}{M-2}\frac{\pi}{2}\sum_{j=i-M+2}^{i-1} |r_{j,K}^*||r_{j-K,K}^*| \tag{6}$$

for $i = M-2+K, M-2+2K, \ldots$. M is the window size for volatility estimation, and is chosen as recommended by Lee and Mykland (2008). $\mathcal{L}_{\mathrm{i}}^*$ follows approximately a standard normal distribution in the absence of jumps and its sample absolute maximum is Gumbel-distributed. Lee and Mykland (2008) propose to reject the null hypothesis of no jump effect on $r_{i,K}^*$ if:

$$|\mathcal{L}_{\mathrm{i}}^*| > G^{-1}(1-\alpha)S_n + C_n$$

where $G^{-1}(1-\alpha)$ is the $(1-\alpha)$ quantile function of the standard Gumbel distribution, n is the total number of pre-averaged returns, $C_n = (2\log n)^{0.5} - \frac{\log(\pi)+\log(\log n)}{2(2\log n)^{0.5}}$, and $S_n = \frac{1}{(2\log n)^{0.5}}$. In the empirical analysis of the Chinese stock index futures for our sample period, we set $\alpha = 0.01$ and sample pre-averaged returns at the one-minute frequency. The window size of estimating instantaneous volatility is 60 minutes when we examine the jump behavior in each one-minute interval.

Using the jump detection method, we can compare the jump intensity in the stock index futures price series before and after the introduction of market-wide circuit breakers. Taking the CSI 300 index futures dominant contract as an example, in Period 1 when circuit breakers do not exist, there are 2700 one-minute intervals and 5 jumps are detected. [****] The probability of detecting a jump is about 0.19% and the average absolute size of jump is 0.09%. In Period 2 when circuit breakers exist, there are 624 one-minute intervals, and we find 8 jumps with an average absolute jump size of 0.22%. The probability of detecting a jump in Period 2 is 1.28%, which is about 6.7 times of the probability in Period 1. Since the introduction of circuit breakers, both the jump frequency and the absolute jump size of stock index futures price have risen significantly,

§§§ See Christensen et al. (2014) for more details about the finite-sample bias correction.

**** When we detect the price jump in a one-minute interval, we also need the additional 59 minutes' data immediately before the current minute to estimate instantaneous volatility. When we identify the presence of jumps within 60 minutes of opening time, we use part of last trading day's final data to conduct the jump test.

indicating an increase in extreme market risk.

We further apply the same procedure to test the jump behavior of the CSI 500 index futures and the SSE 50 index futures. Similar to the CSI 300 index futures, the probability of a price jump and the average absolute jump size for the CSI 500 index futures and the SSE 50 index futures also increased significantly from Period 1 to Period 2. The probability rises from 0.19% to 0.64% for the CSI 500 index futures and from 0.22% to 0.64% for the SSE 50 index futures. The average absolute jump size increases from 0.11% to 0.26% for the CSI 500 index futures and from 0.10% to 0.23% for the SSE 50 index futures.

5. Empirical procedures and results

5.1. Measures of market microstructure

Before testing the three hypotheses of magnet effect proposed above, we first consider the structural changes of stock index futures market after the introduction of market-wide circuit breakers. We construct various measures of market microstructure, which capture the intraday variations in price trend, market volatility, extreme market risk and market liquidity. All variables are calculated at one-minute frequency.

A. Price Trend

The stock index futures return in interval i ($Return_i$) is the sum of the per second log returns in the interval:

$$Return_i = \sum_{t=1}^{T} [ln(P_{t,i}) - ln(P_{t-1,i})] = ln(P_{T,i}) - ln(P_{0,i}) \tag{7}$$

where $P_{t,i}$ is the tth trading price in interval i, and the interval length $T = 60$. For the dominant contracts of the three index futures, we separately calculate the one-minute return series, and the sample length of each series is 3324. The first 2700 observations are returns in the 10 trading days immediately before the introduction of circuit breakers (December 18, 2015 to December 31, 2015). The latter 624 observations are returns during the period when the circuit breakers exist (January 4, 2016 to January 7, 2016).

B. Market Volatility

In this study, we not only construct a traditional low-frequency volatility measure, the difference between the maximum and minimum log price in interval i ($Maxdiff_i$), but also calculate a noise- and jump-robust realized volatility measure, the bi-power variation in interval i (BPV_i).

The variable $Maxdiff_i$ is defined as

$$Maxdiff_i = Max(ln(P_i)) - Min(\ln(P_i)),\ i = 0,1,\dots,T \quad (8)$$

In a fixed time interval (one minute), a larger $Maxdiff_i$ indicates a more unstable price movement during the period under consideration. Both the continuous diffusive component and the discontinuous jump component in the price process have an impact on the size of $Maxdiff_i$.

Meanwhile, when we use high frequency price series to calculate the volatility of stock index future, it is necessary to remove the effect of microstructure noise. To get a noise- and jump-robust volatility variable in interval i, we set the window size of instantaneous volatility estimation $W = 60$. That is, the estimation window consists of the previous $W-1$ intervals before interval i and interval i itself. We assume the instantaneous volatility remains unchanged during the estimation window.

Based on the settings above, we use Function (10) in Christensen et al. (2014) to calculate the BPV of the instantaneous volatility estimation window, and the BPV of interval i is given by:

$$BPV_i = \left(\frac{N}{N-2K+2}\frac{1}{K\psi_K}\frac{\pi}{2}\sum_{i=0}^{N-2K+1}\left|r_{i,K}^*\right|\left|r_{i+K,K}^*\right| - \frac{\omega^2}{\theta^2\psi_K}\right)/W \quad (9)$$

where the $r_{i,K}^*$ is the pre-averaged return in interval i, K is the size of pre-average window, and W is the size of instantaneous volatility estimation window. The numerator of (9) is the BPV of the instantaneous volatility estimation window.

C. Extreme Market Risk

The extreme market risk variable captures extraordinary market movements such as the Flash crash and Black Monday in U.S. stock markets, which are very unlikely to occur but have a significant impact on the whole market whenever they happen. The extreme market risk is a particular concern when market regulators make decisions on trading rules. To some extent, the market-wide circuit breakers are likely designed to mitigate the extreme market risk rather than the volatility risk, because they only take effect during extraordinary conditions.

In this paper, we use the price jump behavior as a proxy for the extreme market risk. In addition, we also need a continuous variable of extreme market risk to capture the time-varying characteristic of stock index futures market under different trading mechanism. Therefore, for each observation interval i, we calculate the absolute logarithmic return per second, and the 5% upper quantile of the absolute logarithmic return series ($Quantile_i$) can be regarded as an extreme market risk measure of the observation interval:

$$Quantile_i = |log(P_i) - log(P_{i-1})|_{0.95}, \quad i = 1,2,\dots,T \tag{10}$$

A larger size of $Quantile_i$ indicates a more significant fat tail of the return distribution and that the probability of stock index futures price decreasing or increasing sharply during a short time interval rises correspondingly.

D. Market Liquidity

Market liquidity describes the capacity in which an asset can be quickly bought or sold in the market without causing drastic change in the asset's price. As there is no single indicator that can capture all the features of market liquidity, we construct several measures to reflect the liquidity demand, liquidity supply, and overall market liquidity, respectively.

The total number of transactions in interval i ($Volume_i$) is one of the most straightforward measures of market trading intensity. As in Boudt and Petitjean (2014), trading volume can be viewed as the demand for immediate execution during interval i, because an increase in trading volume indicates that investors prefer to submit market orders rather than limit orders when implementing their trading strategies. Hence, we use $Volume_i$ as a proxy for liquidity demand, which is given by

$$Volume_i = \sum_{t=1}^{T} Trading\_volume_{i,t} \tag{11}$$

where $Trading\_volume_{i,t}$ is the number of shares for trade in the tth second of interval i.

We capture the characteristics of liquidity supply using two variables: total quote depth ($Depth_i$) and order imbalance (OI_i). Total quote depth is the volume of pending orders on both sides of the bid and ask, which shows the ability for the market to absorb buy and sell orders without moving the asset price dramatically in either direction. We calculate $Depth_i$ by averaging the total depth per second in interval i:

$$Depth_i = [\sum_{t=1}^{T}(Bid\_depth_{i,t} + Ask\_depth_{i,t})]/\mathrm{T} \tag{12}$$

where $Bid\_depth_{i,t}$ and $Ask\_depth_{i,t}$ are the bid depth (i.e., the number of shares displayed at the best bid quote price) and ask depth (i.e., the number of shares displayed at the best offer quote price) for the tth best bid and ask quote in interval i.

$Depth_i$ reveals the quantitative characteristic of market liquidity supply. Because a large value of $Depth_i$ indicate that there are a great number of limit orders at the best bid and ask prices. But $Depth_i$ does not reveal the proportion of buy depth and sell depth. We thus introduce the order imbalance, which is defined as:

$$OI_i = \left[\sum_{t=1}^{T} \frac{(Bid\_depth_{i,t} - Ask\_depth_{i,t})}{(Bid\_depth_{i,t} + Ask\_depth_{i,t})}\right] / T \tag{13}$$

This measure captures the relative size of buy depth and sell depth, and may have a predictive power for future price movement.

Finally, we measure the overall market liquidity by bid-ask spread ($Spread_i$) and noise variance ($Noise_i$), which represent the size of trading cost and transaction friction, respectively. The bid-ask spread ($Spread_i$) captures the difference between the highest price that a buyer is willing to pay for an asset and the lowest price at which a seller is willing to sell it. We define $Spread_i$ as the average bid-ask spread in interval i :

$$Spread_i = \sum_{t=1}^{T} (Best\_ask_{i,t} - Best\_bid_{i,t}) / T \tag{14}$$

where $Best\_ask_{i,t}$ and $Best\_bid_{i,t}$ represent the best offer quote price and best bid quote price in time t of interval i. The bid-ask spread reflects the degree of overall market liquidity and is influenced by both liquidity demand and liquidity supply. An increase of liquidity demand or a decrease of liquidity supply would reduce the overall market liquidity, which can be reflected as a larger size of bid-ask spread.

According to market microstructure theory, microstructure noise is the deviation between the trading price and the fundamental value due to market imperfections, such as tick size, bid-ask bounce, etc. In our study, we follow Zhang, Mykland, and Aït-Sahalia (2005) to calculate noise variance ($Noise_i$) in each one-minute interval. This measure can be used to reflect the market quality, and it is defined as

$$Noise_i = \frac{1}{2T} \sum_{i=1}^{T} (P_i - P_{i-1})^2 \tag{15}$$

5.2. Structural changes in Chinese stock index futures market

This section examines the structural changes in the Chinese stock index futures market due to the implementation of circuit breakers. Table 1 shows the summary statistics of the three index futures for all microstructure variables described above. The statistics are reported separately for both period 1 (without circuit breakers) and period 2 (with circuit breakers).

Comparing the trading volumes of the three stock index futures, the CSI 300 index futures contract has the highest trading volume, which is about the sum of the other two index futures contracts (the CSI 500 index futures and the SSE 50 index futures). After the introduction of market-wide circuit breakers, the trading intensity of the Chinese stock index futures market increases dramatically. The one-minute average trading volume of the CSI 300 index futures rises from 52 contracts to 81 contracts, and the volumes of the SSE 50 index futures and the CSI 500 index futures also change from 22 contracts to 30 contracts and from 29 contracts to 43 contracts, respectively. Overall, the trading volume has increased about 50%。

From the logarithmic returns, we find that the market prices are relatively stable in Period 1. There seems no obvious upward or downward trend, as the one-minute average returns of the three index futures contracts are all around 0. But in Period 2, when the market-wide circuit breakers take effect in the market, the one-minute average returns of all three index futures are lower than in Period 1, ranging from -0.0097% to -0.0039% per minute. These correspond to a daily loss of 0.936% to 2.328% in Period 2. Thus, there seems to be a downward trend in the stock index futures price after the introduction of market-wide circuit breakers. The negative values of skewness also provide support for this observation.

The market volatility and extreme market risk measures also show crucial differences between the two periods. Taking the CSI 300 index futures as an example, the average size of price fluctuation range ($Maxdiff$) increases from 0.0010 in Period 1 to 0.0020 in Period 2, and the BPV measure has a more prominent increase, rising from 5.6 to 22.3. The extreme market risk measure ($Quantile_i$) in Period 2 is two times of that in Period 1. Thus, the market becomes more unstable when the market-wide circuit breakers exist.

In terms of market liquidity, we obtain divergent results for different variables. For example, the overall market liquidity becomes insufficient in Period 2 for the CSI 300 index futures (the bid-ask spread increases from 1.08 in Period 1 to 1.59 in Period 2, and the noise variance jumps from 0.19 to 0.61). The large increase in the volume indicates a sharp increase in liquidity demand in Period 2. However, the liquidity supply variables (market depth and order imbalance) do not change much between the two periods for the CSI 300 index futures.

Table 1

Summary Statistics of Stock Index Futures Market Activities

Variable	Mean		Median		Std.Dev		Max.		Min.		Skewness		Kurtosis	
	Period1	Period2	Period1	Period2	Period1	Period2	Period1	Period2	Period1	Period2	Period1	Period2	Period1	Period2
CSI 300 Index Futures														
$Return_i$(%)	-0.0011	-0.0097	0.0000	-0.0056	0.0773	0.1813	0.3760	0.6793	-0.3805	-1.4612	-0.0270	-1.3649	4.5142	13.5527
$Maxdiff_i$	0.0010	0.0020	0.0009	0.0016	0.0006	0.0014	0.0061	0.0162	0.0001	0.0003	1.8897	3.5138	9.6831	25.6415
BPV_i(*1e7)	5.6234	22.3194	5.2294	16.3941	2.3875	13.7651	12.3939	52.8061	1.6394	5.5953	0.6236	0.7997	2.6334	2.2346
$Quantile_i$	0.0003	0.0006	0.0003	0.0005	0.0001	0.0003	0.0016	0.0026	0.0000	0.0001	1.4263	1.9374	8.4546	9.8768
$Volume_i$	52.1859	81.0593	43.0000	61.0000	35.2821	74.8757	510.0000	934.0000	4.0000	11.0000	3.2366	4.4619	24.1088	36.7200
$Depth_i$	3.6704	3.6023	3.3090	3.3377	1.5647	1.1537	40.2593	13.8400	2.0000	2.0000	8.1498	2.7313	140.1266	16.8347
OI_i	-0.0130	-0.0045	-0.0106	-0.0018	0.1299	0.1232	0.5600	0.3433	-0.5579	-0.4502	-0.1040	-0.1923	3.9371	3.5401
$Spread_i$	1.0850	1.5916	1.0528	1.5125	0.3223	0.5596	3.3238	4.3191	0.3647	0.4882	0.7016	0.8997	4.1814	4.2317
$Noise_i$(*1e7)	0.1932	0.6120	0.1538	0.4210	0.1582	0.6679	2.0332	8.2688	0.0069	0.0263	3.0642	4.7465	21.2943	40.2733
SSE 50 Index Futures														
$Return_i$(%)	0.0004	-0.0039	0.0000	0.0000	0.0774	0.1619	0.4711	0.7901	-0.4191	-1.0343	0.1875	-0.5831	5.4176	9.4691
$Maxdiff_i$	0.0010	0.0018	0.0009	0.0014	0.0006	0.0014	0.0047	0.0125	0.0000	0.0000	1.6140	2.8828	7.4794	16.4313
BPV_i(*1e7)	5.8610	20.8984	5.2625	16.0329	2.5591	15.5379	13.9178	68.8489	2.4363	5.2085	0.9518	1.8196	3.1420	5.7934
$Quantile_i$	0.0003	0.0006	0.0003	0.0005	0.0002	0.0004	0.0018	0.0054	0.0000	0.0000	1.3053	3.4587	6.4552	30.4770
$Volume_i$	21.7107	30.4904	18.0000	23.0000	15.0188	30.8124	144.0000	310.0000	1.0000	1.0000	2.1170	4.1831	10.5112	28.3613
$Depth_i$	3.1499	3.1460	2.8571	2.8509	2.2942	1.2263	77.2500	15.1818	0.0000	2.0000	16.0280	4.0557	450.4760	27.6156
OI_i	-0.0049	0.0015	0.0000	0.0000	0.1607	0.1342	0.6825	0.4375	-0.6858	-0.5756	0.0741	-0.1393	4.6667	4.3859
$Spread_i$	1.0959	1.5963	1.0857	1.4857	0.4610	0.6361	4.0375	4.4316	0.0000	0.3667	0.2905	0.8888	5.4826	3.9108
$Noise_i$(*1e7)	0.4138	1.0499	0.2949	0.6426	0.4223	1.3895	5.9018	20.4926	0.0000	0.0000	3.8921	6.1460	31.9703	69.6865
CSI 500 Index Futures														
$Return_i$(%)	-0.0014	-0.0089	0.0000	0.0000	0.0815	0.1709	0.4008	0.5017	-0.5447	-1.4457	-0.2003	-1.6082	5.3271	14.3938
$Maxdiff_i$	0.0010	0.0019	0.0009	0.0016	0.0006	0.0015	0.0057	0.0166	0.0000	0.0000	1.9443	3.2767	10.0845	25.8119
BPV_i(*1e7)	6.4292	21.9666	5.8656	19.5898	2.4383	9.9717	14.0903	49.2050	2.8433	8.2474	0.8458	1.1889	3.0818	3.5922
$Quantile_i$	0.0003	0.0006	0.0003	0.0005	0.0002	0.0004	0.0021	0.0030	0.0000	0.0000	1.1642	1.6849	7.6623	8.6575
$Volume_i$	29.1748	43.4503	24.0000	32.0000	19.4767	45.6839	153.0000	600.0000	0.0000	0.0000	2.0630	5.1531	9.6764	48.2588
$Depth_i$	3.2093	11.4054	2.8636	3.0000	1.2053	49.4458	14.6000	444.0000	0.0000	0.0000	2.7073	7.2077	14.9072	56.0045
OI_i	-0.0081	-0.0463	0.0000	-0.0040	0.1498	0.2510	0.6694	0.6387	-0.6860	-1.0000	-0.2119	-2.1827	4.5561	9.9086
$Spread_i$	3.1842	4.6397	3.1000	3.9388	1.0526	13.5126	10.3212	337.8533	0.0000	-1.0000	0.6975	24.0880	4.5880	594.4987
$Noise_i$(*1e7)	0.3730	0.9912	0.2831	0.6612	0.3862	1.2128	8.7114	10.7822	0.0000	0.0000	7.1906	3.8676	114.3597	24.4547

Notes: Table 1 reports the summary statistics of three stock index futures dominant contracts in Period 1 (without circuit breaker rules) and Period 2 (with circuit breaker rules). All the variables are calculated at one-minute frequency. They are logarithm return ($Return_i$), maximum and minimum price difference ($Maxdiff_i$), bi-power variation (BPV_i), the 5% upper quantile of the absolute logarithmic return series ($Quantile_i$), transaction volume ($Volume_i$), total quote depth ($Depth_i$), order imbalance (OI_i), bid-ask spread ($Spread_i$), and noise variance ($Noise_i$).

To pinpoint the effect of introducing the market-wide circuit breakers on market microstructure measures, we next conduct the event study for each variable. Again, the price trend ($Return_i$), market volatility ($Maxdiff_i$, BPV_i), extreme market risk ($Quantile_i$), and market liquidity ($Volume_i$, $Depth_i$, OI_i, $Spread_i$, $Noise_i$) are all at one-minute frequency. To make all the variables comparable, we standardize all the variables by subtracting the sample mean and dividing by the sample variance. Following the model specification of Abad and Pascual (2007), we estimate the following regression using ordinary least squares with HAC standard errors for each variable:

$$y_t = \beta_0 + \beta_1 \mathrm{D}(circuit\ \ breakers)_t + \sum_{i=2}^{9} \beta_i\, Control_{t-1} + \varepsilon_t \tag{16}$$

where the dummy variable $\mathrm{D}(circuit\ breakers)_t$ equals 1 when the market-wide circuit breakers exist at time t and 0 otherwise. For each variable, we use the other 8 indicators as control variables.

Table 2

Effect of circuit breakers on market microstructure

	D(circuit breaker)			
Dependent Variable	Coefficient	Standard Error	t-statistic	p-value
Return	-0.1696	0.1035	-1.6386	0.1014
Maxdiff	0.5465***	0.0999	5.4705	0.0000
BPV	1.4309***	0.1648	8.6826	0.0000
Quantile	0.4654***	0.0719	6.4729	0.0000
Volume	0.3058**	0.1229	2.4882	0.0129
Depth	-0.0849	0.0540	-1.5722	0.1160
OI	0.0278	0.0768	0.3620	0.7174
Spread	0.3303***	0.0965	3.4228	0.0006
Noise	0.4156***	0.1095	3.7954	0.0002

Note: We use the data of the CSI 300 index futures from December 18, 2015 to January 7, 2016, which include a trading period without market-wide circuit breakers (Period 1) and a period with market-wide circuit breakers (Period 2), to calculate one-minute frequency market microstructure variables including logarithmic return (*Return*), noise-robust bi-power variation (*BPV*), price fluctuation range (*Maxdiff*), extreme market risk (*Quantile*), trading volume (*Volume*), bid-ask spread (*Spread*), total depth (*Depth*), order imbalance (*OI*), and noise variance (*Noise*). For each variable, we estimate the equation (16) and use the other indicators and the dummy variable $\mathrm{D}(\mathrm{circuit\ \ breaker})$ as explanatory variables. The $\mathrm{D}(circuit\ breaker)$ equals 1 when the circuit breakers take effect, and 0 otherwise. Newey-West standard errors are computed. For brevity, we only report the coefficients of the dummy variable $\mathrm{D}(circuit\ breaker)$, which stand for the impacts of circuit breakers on market microstructure measures. *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

Table 2 reports the estimated coefficient of $\mathrm{D}(circuit\ breaker)$ for each dependent variable using the data of the CSI 300 index futures. The effect of the circuit breaker dummy variable on the return measure is negative, but the magnitude is small and the impact is not statistically significant. On the other hand, $\mathrm{D}(circuit\ breaker)$ has a significant positive effect on market volatility (*Maxdiff* and *BPV*) and the extreme market risk measure (*Quantile*). The overall market liquidity is also significantly affected. The coefficient of $\mathrm{D}(circuit\ breaker)$ is significantly positive for both the bid-ask spread and noise variance, indicating that the overall market liquidity deteriorates when circuit breakers exist. The existence of circuit breakers is associated with a higher liquidity demand (i.e., the trading volume increases), while it does not have much impact on the liquidity supply measured by *Depth* and *OI*.

5.3. Tests of magnet effect hypotheses

The event study results suggest that the market-wide circuit breakers are not associated with a lower market volatility. It actually has the perverse effect of exacerbating the market volatility and the liquidity risk of stock index futures market. The magnet effect of circuit breakers could offer a possible explanation for this phenomenon. As all the Chinese circuit breaker triggering events are caused by the CSI 300 index moving downward to the breaker level, we focus on the downward Level 1 breaker to analyze the magnet effect in this paper.

If the magnet effect of circuit breakers does exist, its magnitude will monotonously increase as the price gradually moves to the breaker level, regardless of the form of the magnet effect. Consequently, the distance between the CSI 300 index and the breaker level (i.e. breaker distance) can be regarded as a proxy variable for the magnet effect (Abad & Pascual, 2007; Hsieh et al., 2009). Hence, breaker distance is a key explanatory variable for the test of magnet effect, and it can be defined as follows:

$$Distance_i = (Price_i - Lower\ level_i)/(Upper\ level_i - Lower\ level_i) \tag{17}$$

where $Lower\ level_i$ and $Upper\ level_i$ stand for the lower breaker level and upper breaker level of CSI 300 index in interval i, and $Price_i$ is the average of index opening price and closing price in interval i. The breaker distance is also calculated at one-minute frequency, and there are 624 observations of breaker distance in the sample period with circuit breakers.

A. price acceleration hypothesis

In this subsection, we follow the model specification of Hsieh et al. (2009) and examine how breaker distance influences the future price trend of stock index futures. We run a logit regression for each stock index futures dominant contract to test whether the breaker distance has predictive power for future price movement. If the circuit breakers have magnet effect and cause price to move toward the lower breaker level, we should find that the likelihood of future price decline relates inversely to the distance from the breaker level. That is, the closer the CSI 300 index gets to its lower breaker level, the greater is the probability that stock index futures prices will move downward in the future. The model is specified as follows:

$$\mathrm{P}(D(Return_t < 0) = 1|\mathrm{X}) = F(\beta_0 + \beta_1 Distance_{t-1} + \beta_2 Return_{t-1} + \beta_3 BPV_{t-1} + \beta_4 Volume_{t-1} + \beta_5 Depth_{t-1} + \beta_6 OI_{t-1} + \beta_7 Spread_{t-1} + \beta_8 Noise_{t-1}) \quad (18)$$

where $D(Return_t < 0)$ equals 1 if $Return_t < 0$ and 0 otherwise. $\mathrm{P}(D(Return_t < 0) = 1|\mathrm{X})$ is the response probability that the stock index futures price decreases in interval t given a set of explanatory variables X, which includes breaker distance ($Distance$), past return ($Return$), bi-power variation (BPV), trading volume ($Volume$), total depth ($Depth$), order imbalance (OI), bid-ask spread ($Spread$), and noise variance ($Noise$). That is, to capture the effect of breaker distance on future price trend, we also incorporate the effects of market liquidity and volatility, as well as the autocorrelation of return series. All explanatory variables are included with a one-minute time lag. $F(\cdot)$ is the CDF of the logistic distribution function, which is given by

$$F(x) = \frac{1}{1 + e^{-x}}$$

If the price acceleration hypothesis holds, the coefficient of breaker distance should be significantly negative. However, according to the regression results listed in Table 3, there is no evidence supporting the price acceleration hypothesis. Although the breaker distance has a negative effect on the CSI 300 index futures price movement, the effect is small and statistically insignificant. When the CSI 300 index is very close to the breaker level (i.e. the breaker distance is near 0), the probability that the CSI 300 index futures price continues to drop only increases slightly comparing with a more stable situation (i.e., a situation with a larger breaker distance).[14] For the SSE 50 index futures and the CSI 500 index futures, the effect of the breaker distance is positive. This suggests that the probability of future price decline decreases as the breaker distance becomes smaller, inconsistent with the price acceleration hypothesis.

Table 3

The effect of breaker distance on future price movement

	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Distance	-0.1859	0.7273	0.6922	0.1711	1.3867**	0.0178
Return	0.0654	0.1893	-0.0328	0.5235	0.0323	0.5229
BPV	0.0196	0.7388	-0.0131	0.7944	0.0596	0.4167
Volume	-0.0764	0.2535	0.0390	0.5322	-0.0215	0.7106
Depth	0.1409	0.2443	0.2114	0.1602	-0.9315	0.1169
OI	0.0953	0.2678	0.1201	0.2016	0.1372	0.1371
Spread	-0.0606	0.5676	0.2824***	0.0063	-0.0559	0.5456
Noise	0.0187	0.8118	-0.2029**	0.0147	0.0565	0.4324

Notes: This table reports the estimation results of the logit model for each of the three stock index futures prices at the one-minute frequency over the period from January 4, 2016 to January 7, 2016. The model specification is function (18). *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

Furthermore, we use a more straightforward way to validate our finding. The breaker distance is in the range [0, 1], which we divide into 10 groups such that for the ith group, the breaker distance belongs to the interval $\left[\frac{i-1}{10}, \frac{i}{10}\right]$. As there is no observation with breaker distance greater than 0.7 for our sample, we end up with 7 groups. For each group, we calculate the proportion of observations with negative future returns. This proportion reflects the probability of future price decline in a given breaker distance range. The results for the CSI 300 index futures are plotted in

[14] For example, when the breaker distance drops from 0.5 to near zero, the probability that the CSI 300 index futures price continues to drop increases less than 2.32%.

Figure 2.

We find that, as the breaker distance decreases, the probability that the index futures price will continue to fall and move toward the breaker level does not significantly increase. Even in the sub-sample with a breaker distance less than 0.1, the probability still be around 50%. The price acceleration hypothesis is rejected by our analysis.

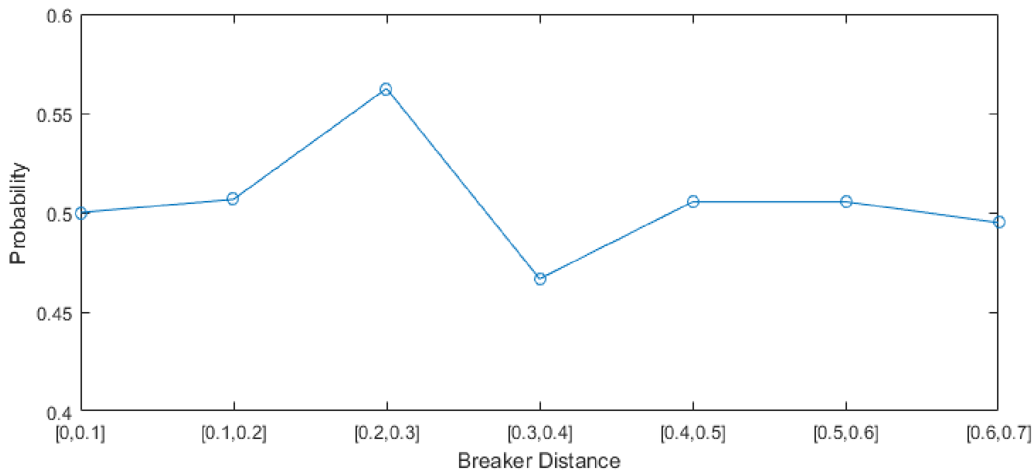

Fig. 2. The probability of future price decline in each breaker distance interval. The data are for the CSI 300 index futures over the period January 4-7, 2016

B. Market volatility hypothesis

By studying the explanatory power of the breaker distance with respect to market volatility, one can infer whether market-wide circuit breakers have "cool-off effect" or "magnet effect" on stock index futures market. In order to eliminate the bias caused by the jump component in price process, we use a noise- and jump-robust realized volatility measure, BPV, for this analysis.

When we calculate the BPV in an one-minute interval i, we assume that the instantaneous volatility during the estimation window remains constant, and the estimation window contains interval i and additional 59 one-minute intervals immediately before i (i.e., a total of 60 minutes). Note that when we use a rolling-based method to calculate the BPV variable for each minute, the BPV series may be strongly autocorrelated. Therefore, we construct an ARMA model to control for the autocorrelation of BPV, and also take into account the effects of liquidity, return, and extreme market risk. The model specification is as follows:

$$BPV_t = \beta_0 + \sum_{i=1}^{p} \alpha_1 BPV_{t-i} + \sum_{i=1}^{q} \alpha_2 \varepsilon_{t-i} + \beta_1 Distance_{t-1} + \beta_2 Return_{t-1} + \beta_3 Quantile_{t-1} + \beta_4 Volume_{t-1} + \beta_5 Depth_{t-1} + \beta_6 OI_{t-1} + \beta_7 Spread_{t-1} + \beta_8 Noise_{t-1} \quad (19)$$

where ε_t is a white noise sequence, p is the order of autoregressive (AR) part, and q is the order of moving average (MA) part.

Table 4 reports the estimation results of the ARMA model using the BPV series of the three index futures. If the market volatility hypothesis holds, the breaker distance should have a significant negative effect on BPV. Although the coefficients of breaker distance in the regressions are negative (the first row in Table 4), none of them is statistically significant. In other words, the circuit breakers do not have a significant impact on the continuous variation of stock index futures prices. Our empirical results do not support the market volatility hypothesis.

Table 4

Breaker distance and market volatility

	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Distance	-0.0502	0.2199	-0.0631	0.3306	-0.0010	0.9637
Return	0.0019	0.3446	0.0051**	0.0420	-0.0146***	0.0000
Quantile	-0.0209***	0.0067	0.0115	0.1792	0.0066	0.1133
Volume	0.0361***	0.0000	0.0209***	0.0000	0.0102***	0.0000
Depth	-0.0003	0.9736	-0.0071	0.6652	0.0010	0.7952
OI	0.0005	0.9191	-0.0030	0.7083	0.0021	0.6227
Spread	-0.0014	0.8369	-0.0159**	0.0109	-0.0017	0.7764
Noise	0.0253***	0.0000	0.0104**	0.0338	0.0026	0.5167

Notes: This table reports the estimation results of the ARMA model for each of the three stock index futures BPV series at the one-minute frequency over the period from January 4, 2016 to January 7, 2016. The model specification is equation (19). For brevity, the coefficients of AR and MA terms are omitted. *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

For the liquidity variables, the coefficients of volume and noise variance are positive and statistically significant. This implies that when the demand for immediate execution increases or the market transaction friction rises, the stock index futures market becomes more volatile. Our results are consistent with Bao and Pan (2013), which shows that the illiquidity of market will significantly influence market volatility.

C. Extreme market risk hypothesis

In this subsection, we examine the extreme market risk hypothesis of magnet effect: the probability of a jump in stock index futures price will gradually increase as the breaker distance of the CSI 300 index decreases. If this hypothesis holds, we would observe more jumps in stock index futures prices when the CSI 300 index falls and moves toward the Level 1 breaker. The increase in the probability of price jumps indicates a higher level of market extreme risk, which may contribute to the triggering of circuit breakers. Thus, the variation of price jump behavior could also be a potential form of the magnet effect.

Similar to the model specification in the test of price acceleration hypothesis, we examine the explanatory ability of breaker distance on the probability of price jumps using a logit model as follows:

$$\mathrm{P}(D(Jump\ \ occur_t) = 1|\mathrm{X}) = F(\beta_0 + \beta_1 Distance_{t-1} + \beta_2 Return_{t-1} + \beta_3 BPV_{t-1} + \beta_4 Volume_{t-1} + \beta_5 Depth_{t-1} + \beta_6 OI_{t-1} + \beta_7 Spread_{t-1} + \beta_8 Noise_{t-1}) \quad (20)$$

where the dummy variable $D(Jump\ \ occur_t)$ equals 1 if there is a price jump in interval t and 0 otherwise.[15] $F(\cdot)$ is the CDF of the logistic distribution function. The control variables are the same as before. We try to control for the effect of market liquidity on jump behavior (Jiang et al., 2011; Boudt & Petitjean, 2014), the effect of volatility on jump (Boudt & Petitjean, 2014), and the effect of lagged return on jump.

To ensure the robustness of model estimations, we separately use the data of each index futures to conduct the logit regression in equation (20), and the results are provided in Table 5. After controlling for the influence of liquidity, volatility, and return, the breaker distance still has a significant effect on the probability of price jumps. For the CSI 300 index futures, the coefficient of the breaker distance is negative and statistically significant at 5% level. This suggests that, as

[15] See section 4.2 for the method used to detect the jumps.

the CSI 300 index moves toward the breaker level, the price jump behavior of CSI 300 index futures occurs more frequently.

Similarly, the coefficients of the breaker distance for the SSE 50 index futures and the CSI 500 index futures are negative, and the effect on the CSI 500 index futures is also significant at 5% level. These results thus yield empirical evidence in favor of the extreme market risk hypothesis. The introduction of market-wide circuit breakers may have led to a higher level of extreme market risk in the Chinese stock index futures market.

Table 5

Breaker distance and price jump behavior

	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Distance	-5.8877**	0.0469	-4.5966	0.1537	-6.9590**	0.0296
Return	-0.1749	0.2895	-0.0586	0.7338	-0.3597*	0.0724
BPV	-0.4958	0.4130	-0.3614	0.4936	-1.1542	0.1264
Volume	0.8238***	0.0007	0.4207**	0.0130	0.2079	0.3116
Depth	-0.1638	0.7891	0.3730	0.6426	-6.5817	0.5389
OI	-1.0373*	0.0674	-0.3498	0.5999	-0.0062	0.9944
Spread	-1.0791	0.1205	0.5342	0.3284	0.4707	0.3762
Noise	-0.7174*	0.0670	-0.2863	0.3162	-0.2153	0.4945

Notes: This table reports the estimation results of the logit model for each of the three stock index futures price series at the one-minute frequency over the period from January 4, 2016 to January 7, 2016. The model specification is equation (20). *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

Jiang et al. (2011) show that the liquidity shocks, such as changes in the bid-ask spread and market depth, have significant predictive power for jumps in the U.S. Treasury market. In our analysis, however, the bid-ask spread and market depth do not have a significant impact on the probability of price jumps. One possible explanation is that the magnet effect of circuit breakers, captured by the breaker distance, may have weakened the explanatory power of liquidity variables for price jump behavior.

To summarize, in this section we examine whether the market-wide circuit breakers have a magnet effect from several perspectives (i.e., the price acceleration hypothesis, the market volatility hypothesis, and the extreme market risk hypothesis). The regression results show that the breaker distance does not significantly exacerbate price trend and price volatility, but it has a significant explanatory power for the probability of future price jumps. When the CSI 300 index is very close to the breaker level, the probability of a stock index futures price jump increases significantly, leading to a higher possibility of triggering the circuit breakers. Our study thus shows the necessity of distinguishing the continuous diffusive component and the discontinuous jump component of the price process in analyzing the magnet effect of circuit breakers.

6. Robustness checks

6.1. Breaker distance and negative jumps

In last section, we find that breaker distance has a significant impact on the probability of price jumps. When the CSI 300 index drops and the breaker distance is near 0, price jumps in stock index futures happen more frequently. Nonetheless, a price jump can be a positive jump or a negative jump, only negative jump will contribute to the triggering of circuit breakers. To correct the possible bias caused by the positive jumps, we replicate the test of extreme market risk hypothesis by only taking negative jumps into consideration. The model specification is as follows:

$$\mathrm{P}(D(Negative\ \ jump_t) = 1|\mathrm{X}) = F(\beta_0 + \beta_1 Distance_{t-1} + \beta_2 Return_{t-1} + \beta_3 BPV_{t-1} + \beta_4 Volume_{t-1} + \beta_5 Depth_{t-1} + \beta_6 OI_{t-1} + \beta_7 Spread_{t-1} + \beta_8 Noise_{t-1}) \quad (21)$$

where $D(Negative\ \ jump_t)$ equals 1 when we detect a negative jump in interval t and 0 otherwise. The other model settings are with the same as in equation (20). The regression results are presented in Table 6.

Our interest is the effect of breaker distance on the probability of negative price jumps. Table 6 shows that the coefficients of breaker distance for all the three index futures are negative. The impact of the breaker distance becomes larger and more significant compared with that in Table 5 where we use both positive and negative price jumps to test the extreme market risk hypothesis. For example, for the CSI 300 index futures, the effect is now significant at the 1% level, while it is significant at the 5% level in Table 5. Besides, the magnitude of the effect also becomes larger. Overall, our findings indicate that there is a statistically significant negative relationship between the intensity of negative price jumps and the breaker distance. When the CSI 300 index decreases and is near the circuit breaker trigger level, the index futures price jumps, especially negative jumps, are more likely to occur. A more frequent negative price jumps increase the extreme market risk and the probability of triggering the market-wide circuit breakers.

Table 6

Breaker distance and negative price jump

	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Distance	-8.6613***	0.0018	-83.1287*	0.0918	-8.2383***	0.0087
Return	0.0386	0.8044	1.2838	0.1414	-0.3725**	0.0381
BPV	-0.0833	0.8439	2.7963	0.2203	-0.7180	0.1049
Volume	0.6585***	0.0023	4.3995	0.1013	0.6116**	0.0182
Depth	-0.9392	0.2227	-21.8289	0.1497	-13.1942	0.1965
OI	-0.4755	0.4460	3.5073	0.1638	0.8700	0.3302
Spread	-1.0972*	0.0777	-4.5917	0.2736	0.8728	0.1150
Noise	-0.2813	0.2634	-1.2270	0.3420	-1.0397*	0.0957

Notes: This table reports the estimation results of the logit model for each of the three stock index futures price negative jumps at the one-minute frequency over the period from January 4, 2016 to January 7, 2016. To ensure the sufficiency of jump observations, we set the significant level of jump detection equals to 5%. The model specification is equation (21). *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

6.2. The effect of pseudo-breaker distance on price jumps

One may argue that the increase of extreme market risk, measured by price jumps, may happen whenever there is a large movement in market index prices regardless of the circuit breakers. To address this concern and make inference about the effect of circuit breakers, we next examine a control sample period during which circuit breakers did not exist, but the stock index experienced a large movement that it would have triggered a market-wide trading halt had the circuit breakers been in force at the time.

We select the control sample period from June 19, 2015 to June 26, 2015 (in total 5 trading days). In both the first and the last days of the control period, the CSI 300 index dropped more than

5% (i.e., it would have triggered the Level 1 breaker if the breaker were in place). The overall price movement in the control period when circuit breakers do not exist is similar to the price movement in the period with circuit breakers (from January 4, 2016 to January 7, 2016). We use the same method of computing the breaker distance to construct a pseudo-breaker distance variable for the control sample period. Following the same procedures as before, we also delete the intraday trading data after the CSI 300 index dropped 5% and calculate market microstructure variables at one-minute frequency. The focus of this robustness check is to examine the impact of the pseudo-breaker distance on the price jump behavior of stock index futures. The logit regression is as following:

$$\mathrm{P}(D(Jump\ \ occur_t) = 1|\mathrm{X}) = F(\beta_0 + \beta_1 Pseudo\ \ Distance_{t-1} + \beta_2 Return_{t-1} + \beta_3 BPV_{t-1} + \beta_4 Volume_{t-1} + \beta_5 Depth_{t-1} + \beta_6 OI_{t-1} + \beta_7 Spread_{t-1} + \beta_8 Noise_{t-1}) \tag{22}$$

where $Pseudo\ \ Distance_{t-1}$ represents the value of pseudo-breaker distance in interval $t-1$. The other model settings are the same as in equation (20). Our empirical results are presented in Table 7.

Table 7

Robustness check of pseudo-breaker distance

	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Pseudo-Distance	-5.8944	0.3478	-0.5565	0.8927	-0.8862	0.8643
Return	-0.7757	0.2630	0.5097	0.3275	-0.9873	0.1810
BPV	-2.5789	0.2858	-4.8807	0.1323	-0.4367	0.7180
Volume	-0.4341	0.6571	0.8843	0.2807	1.5129	0.1482
Depth	176.8834	0.1062	-1.0232	0.2698	-37.8783	0.7468
OI	-0.1854	0.9063	0.1406	0.7850	-0.0919	0.9550
Spread	4.4858*	0.0558	-0.1339	0.8994	-0.5585	0.6956
Noise	-2.4714	0.1890	0.8705	0.5374	-1.6491	0.4319

Notes: This table reports the estimation results of the logit model for each of the three stock index futures price jumps at the one-minute frequency over the period from June 19, 2015 to June 26, 2015. The model specification is equation (22). * stands for statistically significant at the 10 percent level.

According to the regression results, the coefficients of Pseudo Distance are negative for all the three index futures. Compared with those in Table 5 where we conduct a similar exercise for the sample period with circuit breakers, the effect of the Pseudo Distance on the probability of price jumps is much smaller for the SSE 50 index futures and the CSI 500 index futures. The magnitude of the impact for the CSI 300 index futures is similar, but the impact is not statistically significant in the control period. On the other hand, in the period with circuit breakers the breaker distance is negatively correlated with the probability of price jumps and the effect of breaker distance is statistically significant for the CSI 300 index futures. Our analysis provides evidence that the explanatory power of the breaker distance on the extreme market risk is more likely due to the influence of market-wide circuit breakers.

7. Market liquidity dynamics ahead of a trading halt

In the theoretical analysis, Subrahmanyam (1994) shows that as the price moves close to the breaker level, investors will advance their trading strategy and the current trading volume will increase, leading to the perverse effect of exacerbating price movements and increasing price variability. This suggests that a sudden increase in liquidity demand may play a significant role for the magnet effect. We next move to systematically examine the variation in market liquidity ahead of a market-wide trading halt.

We use the five liquidity indicators (volume, total quote depth, order imbalance, bid-ask spread, noise variance) mentioned above to capture the time-varying characteristics of liquidity demand, liquidity supply and overall market liquidity. Considering the possible dynamic interaction between these liquidity variables, we construct the following VARX model:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} A_i Y_{t-i} + B_1 X_{t-1} + U_t \tag{23}$$

where $Y_t = [Volume_t,\ Depth_t,\ OI_t,\ Spread_t,\ Noise_t]^T$ is the vector of endogenous liquidity variables in interval t, X_t stands for the value of the exogenous breaker distance ($Distance$), and p is the lag order. For $\mathrm{i} = 1{:}\,\mathrm{p}$, A_i is a 5×5 coefficient matrix. B_1 is a 5×1 column vector, and U_t stand for the 5×1 error vector.

According to the rules of AIC and BIC, we select the lag order $p = 1$. Each element of the coefficient vector B_1 corresponds to the explanatory power of breaker distance for a liquidity variable. The coefficient matrix of A_1 represents the dynamic correlation between the liquidity variables. The regression results for the CSI 300 index futures are reported in Table 8.

We find that the coefficient of breaker distance is significantly negative for the bid-ask spread and noise variance. This implies that, as the CSI 300 index moves toward the breaker level, the bid-ask spread and noise variance increase significantly. Among all the liquidity indicators, bid-ask spread and noise variance can be regarded as measures of overall market liquidity. They reflect the imbalance between liquidity supply and liquidity demand. The increase in the bid-ask spread and noise variance can be attributed to a decrease in the liquidity supply or an increase in liquidity demand. Therefore, we need to consider the variation of liquidity supply and liquidity demand separately before the triggering of circuit breakers.

Table 8

Breaker distance and market liquidity

Dependent variables	Intercept	A_i					B_1
Volume	0.85**	0.63**	-0.17*	0.01	-0.03	0.03	-1.11**
	(5.06)	(16.00)	(-2.87)	(0.31)	(-0.55)	(0.45)	(-3.59)
Depth	0.10	0.05	-0.07*	0.03	-0.01	0.18**	-0.25
	(0.97)	(1.96)	(-1.99)	(1.19)	(-0.36)	(4.10)	(-1.29)
OI	0.26	-0.04	-0.02	0.00	0.19**	-0.07	-0.40
	(1.93)	(-1.16)	(-0.46)	(0.12)	(4.81)	(-1.23)	(-1.62)
Spread	1.21**	-0.09*	0.39**	0.05	-0.01	0.08	-1.35**
	(7.52)	(-2.30)	(6.90)	(1.19)	(-0.20)	(1.24)	(-4.58)
Noise	1.58**	0.06	0.17*	0.17**	-0.06	0.09	-2.15**
	(6.53)	(1.05)	(2.02)	(2.73)	(-0.78)	(0.89)	(-4.84)

Notes: This table reports the estimation results of the VARX model using the data of the CSI 300 index futures. The coefficients of exogenous variables, B_1, represent the explanatory power of the breaker distance on the liquidity variables. A_1 reflects the dynamic correlation between the liquidity variables. T-values are reported in parentheses. The model specification is equation (23). *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

Table 8 shows that the breaker distance has a significant effect on the trading volume. As the breaker distance becomes smaller, the trading volume increases (i.e., liquidity demand rises). However, it does not have a significant impact on either total quote depth or order imbalance, which suggests that when a trading halt is imminent, the limit order strategy of market investors remains nearly unchanged, and the market liquidity supply keeps stable. Our result is different from Goldstein and Kavajecz (2004), which finds an increase in liquidity demand and a decrease in liquidity supply ahead of a market-wide trading halt at NYSE, but is more in line with Subrahmanyam (1994).

Overall, we find that the magnet effect of the circuit breakers in the Chinese stock index futures market is more likely due to the increased demand for immediate execution, rather than the reluctance of investors to provide liquidity. As the CSI 300 index moves toward the breaker level, the liquidity demand increases prominently and the overall market liquidity deteriorates. According to Jiang et al. (2011) and Christoffersen, Feunou, Jeon, and Ornthanalai (2016), the deterioration of market liquidity ahead of the circuit breaker trigger will leads to more frequent price jumps, which indicates that stock index futures market becomes more volatile and risky.

8. Conclusion

Why do the market-wide circuit breakers established in Chinese financial markets fail to improve the market stability? Do market-wide circuit breakers have a magnet effect? If yes, in what form? What explains the existence of the magnet effect? To shed light on these questions, this paper uses transaction data from the Chinese stock index futures market to examine the magnet effect of market-wide circuit breakers.

We first investigate the changes in market microstructure caused by the introduction of circuit breakers. We select two sample periods where Period 1 is the period immediately before the introduction of circuit breakers and Period 2 is the period with circuit breakers. We compare the market microstructure characteristics in these two periods and find that the stock index futures market becomes more volatile and there is a lack of liquidity when the market-wide circuit breakers exist.

We then construct various econometric models to test three hypotheses of magnet effect from the perspectives of price trend, market volatility, and the extreme market risk. We apply a high frequency noise-robust jump detection method in the analysis. The estimation results show that no magnet effect is found in price trend and market volatility, that is, when the CSI 300 index drops and moves toward the breaker level, the probability of future price decline and the market volatility do not increase significantly. However, our analysis provides support for the extreme market risk hypothesis. We find that when the CSI 300 index is close to the breaker level, it is more likely to detect a price jump (particularly negative jump) in stock index futures, which indicates that the circuit breakers become more likely to be triggered.

Finally, we examine the variation of market liquidity to explain the observed price jump behavior ahead of a market-wide trading halt. We construct a VARX model with the breaker distance as an exogenous variable to analyze the interaction of liquidity variables when the CSI 300 index moves toward the breaker level. Our empirical results show that when a trading halt is imminent, the liquidity demand increases significantly and the liquidity supply remains stable, leading to a shortage of market liquidity. As a result, the probability of price jumps increases significantly, resulting in a higher possibility of triggering the circuit breakers.

This paper is the first to consider the price jump behavior in analyzing magnet effect. Our findings show the importance of distinguishing the jump variation and diffusive variation in the price movement. As it is rare to observe a market-wide trading halt triggered by circuit breakers, our study contributes to a better understanding of the impact of market-wide circuit breakers.

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