Intraday price jumps, market liquidity, and the magnet effect of circuit breakers[1]

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Abstract:

This paper studies the magnet effect of market-wide circuit breakers using high-frequency data from the Chinese stock index futures market. Unlike previous studies that mainly analyze the price trend and volatility, this paper is the first to consider intraday price jumps in studying the magnet effect. We find that when a market-wide trading halt is imminent, both the probability of a price decrease and the level of market volatility remain stable. However, the conditional probability of observing a price jump increases significantly, leading to a higher possibility of triggering market-wide circuit breakers, which is in support of the magnet effect hypothesis. 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 liquidity imbalance plays an important role in explaining the magnet effect.

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

JEL classification: G10; G12; G18

1. Introduction

As a market stabilization mechanism implemented in many securities exchanges around the world, circuit breakers are designed to prevent price movements from fluctuating excessively. When prices reach pre-specified levels, circuit breakers will halt trading on individual securities or the whole market.[3] Although circuit breakers are widely used in financial markets, the effectiveness of this mechanism remains an ongoing debate.[4] Much of the research on how circuit breakers affect the markets and participants' behavior has focused on the "magnet effect" suggested by Subrahmanyam (1994).

The magnet effect hypothesis states that circuit breakers may actually increase the price variability and exacerbate price movements when a price or an index is very close to the trigger level. This is because market participants want to avoid being constrained in market transaction, so 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 sub-optimally advance their trades to ensure their ability to trade. As a result, circuit breakers may exacerbate the very problem they were meant to address. In the existing literature, empirical studies on the magnet effect of circuit breakers provide mixed and inconsistent results among different financial markets. 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 the magnet effect (e.g., Holder, Ma, & Mallett, 2002; Belcher, Ma, & Mallett, 2003; Cho, Russell, Tiao, & Tsay, 2003; Hsieh, Kim, & Yang, 2009). Moreover, most of the previous studies (e.g., Cho et al., 2003; Abad & Pascual, 2007; Kim, Yagüe, & Yang, 2008; Du, Liu, & Rhee, 2009; Hsieh et al., 2009; Wong, Liu, & Zeng, 2009; Hautsch & Horvath, 2016) examine the magnet effect of single stock price limits rather than market-wide circuit breakers because it is rare to observe a market-wide trading halt triggered by a circuit breaker. One notable exception is the study by Goldstein and Kavajecz (2004), which empirically investigates market participants' trading

[3] 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.

[4] See Kim and Yang (2004) for a comprehensive review of the literature.

strategies at the New York Stock Exchange (NYSE) during the turbulent October of 1997 period and finds evidence consistent with the magnet effect of market-wide circuit breakers. Overall, the understanding of the influence of market-wide circuit breakers on financial markets (especially emerging financial markets) remains limited and insufficient.

To complement the existing literature, this paper studies the magnet effect of market-wide circuit breakers established in Chinese financial markets using high-frequency data. On January 1, 2016, Chinese regulators formally introduced the market-wide circuit breakers in the stock market and index futures market. 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; and the Level 2 breaker (a 7% change) halts trading for the rest of the day. The intention of this newly established market rule is to reduce the likelihood of a market crash and improve the stability of Chinese financial markets. However, within four trading days, both Level 1 and Level 2 breakers were triggered twice and the whole stock market lost more than 10% of its value. This led to the suspension of circuit breakers in China on January 8, 2016. Such a dramatic event provides a unique opportunity to study the market behavior with and without circuit breakers and presents clearer evidence of the magnet effect, if it exists. As China's financial markets have become more important among the global financial markets, the study of China's experience of market-wide circuit breakers is also meaningful for other financial markets.

Among the academic studies of the magnet effect hypothesis, most of them identify the magnet effect by measuring the price trend, market volatility, or trading activity. Although volatility is an important risk measure, it can only adequately represent risk in normal market circumstances (e.g., Gourieroux & Jasiak, 2001, p.427) and does not capture extreme market risk.[5] Moreover, circuit breakers may have a non-negligible effect on the frequency and severity of extreme price movements (e.g., Brogaard & Roshak, 2016). Given that large, adverse market movements are great concerns to practitioners and regulators (Hong, Liu, & Wang, 2009), this paper not only analyzes the characteristics of price trend and market volatility as most previous studies do, but also examines extreme market risk when studying the magnet effect. We use price

[5] 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 risk during volatile periods.

jump as a proxy for extreme market risk and apply the high-frequency jump test proposed by Christensen, Oomen and Podolskij (2014) to identify jumps.[6] To the best of our knowledge, our study is the first to consider high-frequency price jumps in the analysis of the magnet effect hypothesis.

Moreover, we examine the variation in market liquidity to shed light on the role of market liquidity in explaining the magnet effect. Inspired by Draus and Van Achter (2016), who emphasize that the effectiveness of a circuit breaker is closely related to the uncertainty about liquidity needs, we separately construct variables of liquidity demand, liquidity supply and overall market liquidity, and use a VARX model to investigate the dynamics of liquidity measures before the triggering of circuit breakers.[7] We have the following key findings.

First, when the CSI 300 index decreases and is very close to the breaker level, our model shows that both the probability of a price decrease and the level of 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 toward the breaker level, the probability of observing a price jump (especially a negative jump) increases significantly, 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 lagged return. This indicates that the magnet effect actually exists in the form of extreme market risk.

We also exploit a control sample period without circuit breakers to make inferences about the effect of circuit breakers. During the control sample period, the circuit breaker did not exist, but the CSI 300 index also experienced a large movement that would have triggered a trading halt had the circuit breakers been in force at the time. We find that the impact of the breaker distance on the probability of observing a price jump is significantly negative during the period with

[6] The jump detection methods have been improving in recent years, moving from low-frequency jump detection to high-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.

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

circuit breakers, while it is insignificant in the control period without circuit breakers.

Third, when a market-wide trading halt is imminent, the liquidity demand increases significantly; however, there is no significant change in the 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 plays an important role in explaining the magnet effect.[8]

The key contribution of this paper is to extend and examine possible forms of the magnet effect of circuit breakers by taking into account price jumps a proxy for extreme market risk. Our study shows that it is important and necessary to distinguish the continuous diffusive component and discontinuous jump component of a price process when analyzing the magnet effect hypothesis, and that the variation of market liquidity contributes to the understanding of the magnet effect. Our results provide valuable insights to better understand 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; Section 5 presents the methodology and empirical results; Section 6 conducts the robustness checks; Section 7 examines market liquidity ahead of a market-wide trading halt; Section 8 concludes the paper.

2. Institutional background

In this paper, we use high-frequency data from the Chinese stock index futures market to examine the magnet effect of market-wide circuit breakers. Traded on the China Financial Futures Exchange (CFFEX), Chinese stock index futures contracts are based on several stock market 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, and the contract month can be the current month, the next month, or the final months of the next two quarters.

Among the three stock index futures, the CSI 300 index futures is the first and most frequently traded in the exchange (it starts trading on April 16, 2010). The underlying index (CSI 300 index) represents about 70% of the total stock market capitalization in China. Moreover, the

[8] Jiang, Lo, and Verdelhan (2011) point out that liquidity shocks have a non-negligible predictive power for price jumps.

volume of the dominant contract (i.e., the most active futures contract among all futures contracts with different expiration dates for the same index futures) accounts for more than 80% of the total trading volume for each index futures during the period with circuit breakers. Therefore, we choose the dominant contract of the CSI 300 index futures as our main sample, and the dominant contracts of the SSE 50 index futures and the CSI 500 index futures are used as robustness checks. The three dominant contracts are sufficient to reveal the overall performance of the Chinese stock index futures market.

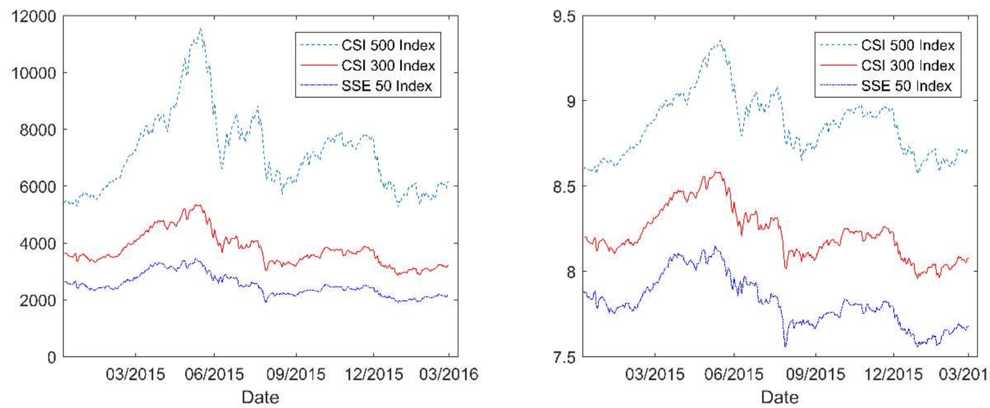

Figure 1. Price movements of three stock indexes from January 2015 to March 2016. The left chart shows the indexes without logarithmic adjustment and the right chart shows the indexes with logarithmic adjustment. The data of these stock indexes come from the Wind database.

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 decreased by 45% within three months (June to August, 2015). To restrain the risk of excessive price fluctuation and improve the stability of financial markets, China Securities Regulatory Commission (CSRC) sought public opinion on an index circuit breaker system from September 7, 2015 to September 21, 2015. On December 4, 2015, the CSRC formally announced that the market-wide circuit breakers in both the stock market and index futures market would come into effect on January 1, 2016. The Level 1 breaker (if the CSI 300 index is 5% below/above its previous close) would halt trading on the whole market for 15 minutes, and the Level 2 breaker (if there is a 7% change) would halt trading for the remainder of the trading day.[9]

However, contrary to the anticipation of market participants that this newly-established

[9] In a normal trading day, the market opens at 9:30 a.m. and closes at 3:00 p.m., and it has a lunchtime break from 11:30 a.m. to 1:00 p.m.

trading rule would help to stabilize jittery market sentiment and reduce investors' overreaction to asset price shocks, extreme price movements occurred more frequently in financial markets during the period with circuit breakers and both the 5% and 7% breakers were triggered two times in the first four trading days after the implementation of market-wide circuit breakers. Figure 2 shows that on January 4, the first trading day after implementation, the CSI 300 index decreased by 5% and triggered the Level 1 circuit breaker at 1:12 p.m. Less than 7 minutes after the resumption of trading, the index fell below 7% and triggered the Level 2 circuit breaker at 1:33 p.m. Similar but more drastic price movements were observed on January 7 as the CSI 300 index triggered the 5% downside circuit breaker at 9:42 a.m. and triggered the 7% downside circuit breaker at 9:58 a.m. In view of such excessive market movements, 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 collapses, Chinese regulators announced that, starting from January 8, 2016, the market-wide circuit breakers would be suspended in order to "smooth" trading operations. Therefore, this newly-established rule exists for only four trading days in China.

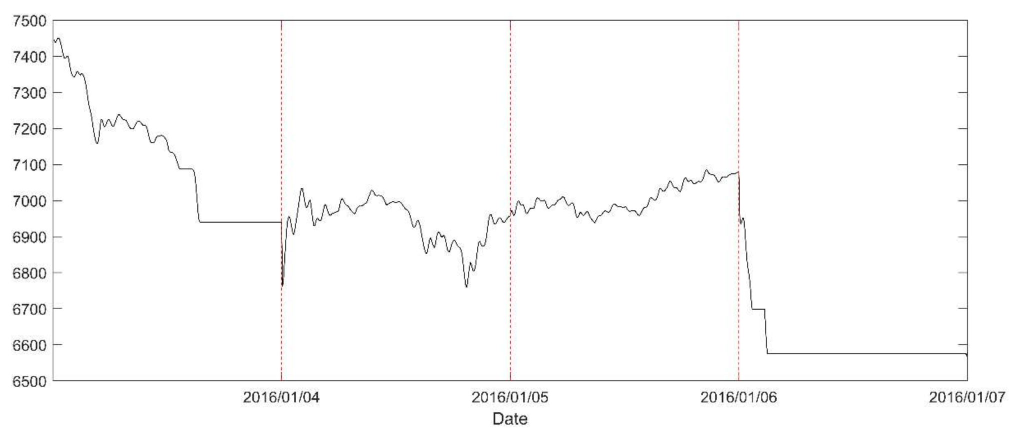

Figure 2. Intraday price movement of the CSI 300 index from January 4, 2016 to January 7, 2016 when the market-wide circuit breakers take effect.

During the period immediately before the implementation of market-wide circuit breakers (from October to December 2015), the price movements of stock indexes were relatively stable. During the period when the circuit breakers existed, there were no major macroeconomic shocks or news announcements about fundamentals in the financial markets. The most significant and important difference between the two periods is the new trading rule (i.e., circuit breakers).

Consequently, the changes of market microstructure due to the implementation of circuit breakers may have contributed to the observed large downward market movements.

3. Hypotheses of magnet effect

The proposed magnet effect hypotheses are based on the theoretical analysis conducted by Subrahmanyam (1994), who develops a two-period model to analyze the strategic trading decision of uninformed traders with exogenous needs to trade. Subrahmanyam (1994) concludes that uninformed traders will split their trades across time when there are no circuit breakers, and they will advance their trades if circuit breakers exist and the underlying price approaches the breaker limit, as investors try to avoid being constrained not to trade. As a result, the above-mentioned trading decision leads to an increase in both the ex-ante price variability and the probability of triggering a market-wide trading halt. In other words, the magnet effect of circuit breakers may exacerbate price movements and increase the probability of triggering a market-wide trading halt when the price is very close to the limit.

Unlike previous studies that merely examine the dynamic of price trend and market volatility, our magnet effect analysis further takes into account the dynamic of extreme market risk because circuit breakers are designed to prevent large price movements. 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 considered in previous studies (e.g., Hsieh et al., 2009), states that as the CSI 300 index falls and approaches the breaker level, the probability of an index futures price further decreasing would increase correspondingly. If the magnet effect exists, the distance between the CSI 300 index and the breaker level (i.e., the breaker distance) will be negatively correlated to the magnitude of magnet effect. Thus, we use the breaker distance as a proxy for magnet effect and construct a logit model to examine the impact of breaker distance on price trend. If the price acceleration hypothesis holds, the breaker distance is expected to have a significant negative impact on the probability of an index futures price further decreasing.

Second, the market volatility hypothesis states that as the CSI 300 index moves toward the breaker level, the volatility of an index futures contract will gradually increase. If the magnet effect exists, circuit breakers would exacerbate the market movements when a trading halt is imminent; that is, circuit breakers have a significant stimulating effect on market volatility. To eliminate the bias caused by price jumps, 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 significantly negative, which indicates that the smaller the distance between the CSI 300 index and the breaker level, the stronger the stimulating effect of circuit breakers on market volatility.

Third, the extreme market risk hypothesis, which has not been considered in previous magnet effect studies, states that the smaller the distance between the CSI 300 index and the breaker level, the greater the extreme market risk. The circuit breaker rules, especially the market-wide circuit breakers, are designed to take place under abnormal intraday price movements. These large price movements cannot be fully explained by the current level of market volatility and are more related to extreme market risk. Unlike previous studies that did not take extreme market risk into consideration when studying the magnet effect, we emphasize that extreme market risk is a non-negligible part of the analysis.

We use the price jump as a proxy for extreme market risk because both of them have a very low probability of occurrence and, when they do happen, the market is 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 price jump. If the extreme market risk hypothesis holds, the coefficient of breaker distance should be significantly negative, which indicates that as the distance between the CSI 300 index and the breaker level decreases, the probability of observing a price jump would increase, leading to a higher possibility of triggering a market-wide trading halt.

4. 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-second records of trading prices, trading size, best bid quote prices, bid depth (the number of shares displayed at the best bid quote price), best ask quote prices, and ask depth (the number of shares displayed at the best ask quote price). We look at all three stock index futures listed on CFFEX, namely the CSI 300 index futures, the CSI 500 index futures, and the SSE 50 index futures. We focus on the dominant contracts of each index futures because the dominant contracts are the most actively traded futures contracts and contain more information compared to other non-dominant contracts.[10]

We divide our data into two sub-periods: one is the last ten trading days prior to the implementation of market-wide circuit breakers (December 18 to December 31, 2015; Period 1), and the other is the four trading days when market-wide circuit breakers existed in the market (January 4 to January 7, 2016; Period 2).

The data is sampled at a frequency of one minute.[11] There are 2700 one-minute intervals during Period 1 when the circuit breakers did not exist. In Period 2, the CSI 300 index fell and triggered the Level 1 breaker (-5% change) and the Level 2 breaker (-7% change) twice, respectively. We exclude the intraday data after the Level 1 circuit breaker was triggered because the triggering of Level 2 circuit breaker is conditional on the Level 1 breaker being triggered and there is a 15-minute market-wide trading halt, which could lead to biased results. We also exclude the incomplete one-minute intervals (two of them) that are truncated by the triggering of Level 1 breaker. This leaves us with a sample of 624 one-minute intervals during Period 2 when the circuit breakers existed.

In a later section, we will make a comparison between these two sub-periods to examine the potential structural market changes due to the implementation of market-wide circuit breakers. Then we will use the data in Period 2 to test the three magnet effect hypotheses.

5. Methodology and empirical results

In this section, we will first construct different measures of market microstructure. Next, we will explain our jump detection method. Finally, we will report empirical results on the structural changes in the Chinese stock index futures market and the tests of three magnet effect hypotheses.

[10] The non-dominant contracts of the three index futures are infrequently traded compared to the dominant contracts. In particular, during the period when the CSI 300 index was close to the breaker level, there were no transactions for several minutes for some non-dominant contracts.

[11] Increasing the interval over which we construct measures of statistics reduces the number of observations in our sample. Hence, we focus on this relatively short interval. The choice of working with 1-minute frequency is also consistent with some of the existing studies, such as Locke and Sayers (1993), Taylor (2008), and Hou and Li (2020).

5.1. Measures of market microstructure

To examine potential structural changes in the stock index futures market due to the implementation of market-wide circuit breakers, we construct various microstructure variables (one-minute frequency) to capture intraday variations in price trend, market volatility, extreme market risk, and market liquidity.

A. Price trend

The logarithmic return in interval t $(Return_t)$ is the sum of one-second log returns in the interval:

$$Return_t = \sum_{i=2}^{T}[ln(P_{t,i}) - ln(P_{t,i-1})] \quad (1)$$

where $P_{t,i}$ is the i-th trading price in interval t, and the interval length $T = 60$.

B. Market Volatility

We not only construct a traditional, low-frequency volatility measure, the difference between the maximum and minimum log price in interval t $(Maxdiff_t)$, but also calculate a noise- and jump-robust realized volatility measure, the bi-power variation in interval t (BPV_t).

The variable $Maxdiff_t$ is defined as

$$Maxdiff_t = Max(ln(P_{t,i})) - Min(ln(P_{t,i})) \ , i = 1, \dots, T \quad (2)$$

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

Meanwhile, it is necessary to remove the effect of microstructure noise and price jumps when we calculate a volatility variable using high-frequency data. To get a noise- and jump-robust volatility variable in a one-minute interval t, we assume the instantaneous volatility remains invariable during an estimation window. We set the window size $W = 60$ and the estimation window consists of interval t and previous $W - 1$ intervals before interval t.

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

$$BPV_t = \left(\frac{N}{N-2K+2}\frac{1}{K\psi_K}\frac{\pi}{2}\sum_{t=0}^{N-2K+1}|r_{t,K}^*||r_{t+K,K}^*| - \frac{\omega^2}{\theta^2\psi_K}\right)/W \quad (3)$$

where $r_{t,K}^*$ stands for the pre-averaged return series, K is the size of the pre-average window, and W is the window size of instantaneous volatility estimation. The numerator of equation (3) is the BPV value of the whole estimation window.

C. Extreme Market Risk

The extreme market risk variable captures abnormal price movements such as market crashes or drastic price increases, which are very unlikely to occur but have a significant impact on the whole market whenever they happen. Therefore, the extreme market risk is a particular concern when regulators make decisions on market trading policies. To some extent, market-wide circuit breakers are more likely designed to mitigate extreme risk rather than volatility risk, because they only take effect during abnormal conditions.

In this paper, we identify price jumps to characterize extreme price movements in the index futures market. At the same time, we also need a continuous variable to capture the time-varying characteristic of extreme market risk under different trading mechanisms. Therefore, for each observation interval t, we calculate the 5% upper quantile of the distribution of one-second frequency absolute logarithmic return ($Quantile_t$) :

$$\Pr\left[\left|ln\left(P_{t,i}/P_{t,i-1}\right)\right| \leq Quantile_t\right] = 0.95,\ \mathrm{i} = 2, \dots, \mathrm{T} \tag{4}$$

A larger size of $Quantile_t$ indicates a more significant fat tail of the return distribution and a higher probability of observing extreme price movements during a short time interval.

D. Market Liquidity

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

First, the total number of transactions in interval t ($Volume_t$) is one of the most straightforward measure of trading intensity. Boudt and Petitjean (2014) state that trading volume can be viewed as the demand for immediate execution 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 $Volume_t$ as a proxy for liquidity demand, which is given by

$$Volume_t = \sum_{i=1}^{T} Trading\_volume_{t,i} \tag{5}$$

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

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

$$Depth_t = [\sum_{i=1}^{T}(Bid\_depth_{t,i} + Ask\_depth_{t,i})]/\mathrm{T} \tag{6}$$

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

A larger $Depth_t$ indicates a greater number of limit orders at the best bid and ask prices, but $Depth_t$ does not reveal the proportion of buy depth and sell depth. Therefore, we also calculate the order imbalance as follows:

$$OI_t = \left[\sum_{i=1}^{T}\frac{(Bid\_depth_{t,i} - Ask\_depth_{t,i})}{(Bid\_depth_{t,i} + Ask\_depth_{t,i})}\right]/T \tag{7}$$

OI_t captures the relative size of buy depth and sell depth, and may have a predictive power for future price movements.

Finally, we measure the overall market liquidity using bid-ask spread ($Spread_t$) and noise variance ($Noise_t$), which separately represent the size of trading cost and transaction friction. The bid-ask spread ($Spread_t$) 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 $Spread_t$ as the average bid-ask spread in interval t:

$$Spread_t = \sum_{i=1}^{T}(Best\_ask_{t,i} - Best\_bid_{t,i})/T \tag{8}$$

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

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

$$Noise_t = \frac{1}{2(T-1)} \sum_{i=2}^{T} (P_{t,i} - P_{t,i-1})^2 \quad (9)$$

Although equation (9) is similar to the function of realized volatility, the information captured by $Noise_t$ is different from the information captured by realized volatility measures. For example, the correlation coefficient between $Noise_t$ and BPV_t ranges from 0.3241 to 0.4651, which suggests that these two variables are not highly correlated and each of them contains different information about market microstructure.

5.2. Detection of asset price jumps

In the previous section, we construct a continuous variable of extreme market risk, $Quantile_t$. To better characterize extreme market risk, we now investigate the index futures price jumps (i.e., extreme price fluctuations). There exists an extensive literature on index return models that unanimously agrees that index prices "jump".[12] By their nature, jumps are large, discrete price movements. We use price jump as a proxy for extreme market risk because both of them have a very low probability of occurrence and, when they do happen, markets are greatly affected.

In this paper, we follow the noise-robust jump detection procedure proposed by Christensen et al. (2014). First, we make use of the pre-averaging approach introduced by Jacod, Li, Mykland, Podolskij, and Vetter (2009) and Podolskij and Vetter (2009a, b) to asymptotically remove the microstructure noise component in the observed price series. Second, we construct noise- and outlier-robust versions of realized variation (RV) and bi-power variation (BPV) to separate the jump component in price dynamics. Finally, we apply the Lee and Mykland (2008) rolling-based nonparametric test to detect price jumps.

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

[12] See Eraker (2004), Maheu and McCurdy (2004), and Zargar and Kumar (2020), among others.

observations. The conventional realized variation (RV) and bi-power variation (BPV) are defined as

$$RV_N = \sum_{t=1}^{N} r_t^2 \tag{10}$$

$$BPV_N = \frac{N}{N-1}\frac{\pi}{2}\sum_{t=2}^{N} |r_{t-1}||r_t| \tag{11}$$

where $r_t = \ln(P_t/P_{t-1})$ and P_t is the observed price at time t. It is well known (see Barndorff-Nielsen & Shephard, 2006) that $\text{plim}_{N\to\infty} RV_N = \int_0^1 \sigma_s^2 ds + \sum_{i=1}^{N_j} J_i^2$ and $\text{plim}_{N\to\infty} BPV_N = \int_0^1 \sigma_s^2 ds$, where the N_j is the number of jumps and J_i stands for the size of the ith 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 (10) and (11), the difference between the realized variation and the bi-power variation can be used to isolate the 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.,

$$r_{t,K}^* = \frac{1}{K}\left(\sum_{j=K/2}^{K-1} P_{(t+j)/N} - \sum_{j=0}^{K/2-1} P_{(t+j)/N}\right) \tag{12}$$

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

$$RV^* = \frac{N}{N-K+2}\frac{1}{K\psi_K}\sum_{t=0}^{N-K+1} |r_{t,K}^*|^2 - \frac{\widehat{\omega}^2}{\theta^2\psi_K} \tag{13}$$

$$BPV^* = \frac{N}{N-2K+2}\frac{1}{K\psi_K}\frac{\pi}{2}\sum_{t=0}^{N-2K+1} |r_{t,K}^*||r_{t+K,K}^*| - \frac{\widehat{\omega}^2}{\theta^2\psi_K} \tag{14}$$

where $\psi_K = (1+2K^{-2})/12$, and $\widehat{\omega}^2/\theta^2\psi_K$ is a bias-correction, which compensates for the residual microstructure noise that remains after pre-averaging.[13]

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

$$\mathcal{L}_t^* = \frac{r_{t,K}^*}{\sigma_{t,K}} \quad \text{where } {\sigma_{t,K}}^2 = \frac{1}{M-2}\frac{\pi}{2}\sum_{j=t-M+2}^{t-1} |r_{j,K}^*||r_{j-K,K}^*| \tag{15}$$

for $t = M-2+K,\ M-2+2K, \ldots$. M is the window size of volatility estimation, and is

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

chosen as recommended by Lee and Mykland (2008). $\mathcal{L}_t^*$ 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 $r_{t,K}^*$ if

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

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 $S_n = \frac{1}{(2\log n)^{0.5}}$. Following the empirical setting in Lee and Mykland (2008), we select the significance level α of jump detection at 5%. The window size of instantaneous volatility estimation is 60 minutes when we detect the price jump in each one-minute interval.[14]

Following the above-mentioned test procedure, we compare the price jumps before and after the implementation of market-wide circuit breakers. Taking the CSI 300 index futures dominant contract as an example, in Period 1, when circuit breakers did not exist, there are 2700 one-minute intervals and 13 jumps are detected.[15] The probability of detecting a jump is about 0.48% and the average absolute size of detected jumps is 0.08%. In Period 2, when circuit breakers existed, there are 624 one-minute intervals, and we find 10 jumps with an average absolute jump size of 0.21%. The probability of detecting a jump in Period 2 is 1.60%, which is about 3.33 times the probability in Period 1. Similar results are obtained in the CSI 500 index futures and SSE 50 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 increase significantly from Period 1 to Period 2. The probability rises from 0.44% to 1.76% for the CSI 500 index futures and from 0.59% to 1.44% for the SSE 50 index futures. The average absolute jump size increases from 0.10% to 0.20% for the CSI 500 index futures and from 0.08% to 0.16% for the SSE 50 index futures.

The jump detection results show that since the implementation of circuit breakers, both the jump frequency and the absolute size of index futures price jumps increase significantly. Therefore, extreme events occur more frequently and have a greater impact on the stock index

[14] We repeat our analysis using a wider or narrower window size. The results are similar.

[15] When we detect price jump in a one-minute interval, we also need the additional 59 minutes' data immediately before the current minute to estimate the 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.

futures market during the period with circuit breakers, indicating an increase in extreme market risk.

5.3. Structural changes in the Chinese stock index futures market

Before we test the magnet effect hypotheses of circuit breakers, a relevant question is whether the implementation of market-wide circuit breakers leads to structural changes in the Chinese stock index futures market. However, we do not observe the counterfactual, that is, what would have happened if market-wide circuit breakers had not been in place. Nevertheless, it is informative to see how measures of market microstructure differ immediately before and after the implementation of market-wide circuit breakers.

To examine the potential structural changes due to the implementation of market-wide circuit breakers, Table 1 shows the summary statistics of three index futures for different dimensions of market microstructure measures. The statistics are reported separately for Period 1 (without circuit breakers) and Period 2 (with circuit breakers).

As we can see in Table 1, the stock index futures prices move downward, the market becomes more volatile, and there is a lack of liquidity during the period with circuit breakers. Taking the CSI 300 index futures as an example, the average logarithmic return equals -0.0011% in Period 1 and -0.0097% in Period 2, indicating that the asset price decreases more rapidly when circuit breakers exist. The two market volatility measures become higher in Period 2, with the mean value of $Maxdiff_t$ increasing from 0.0010 to 0.0020 and the mean value of BPV_t rising from 5.6 to 22.3. Similarly, the extreme market risk measure ($Quantile$) in Period 2 is about two times that of Period 1. These results indicate that the market becomes more unstable when market-wide circuit breakers exist. In terms of market liquidity, the overall market liquidity becomes insufficient in Period 2 (the bid-ask spread increases from 1.08 to 1.59, the noise variance rises from 0.19 to 0.61). Moreover, the large increment in $Volume_t$ (rises from 52 contracts to 81 contracts per minute) indicates a sharp increase in liquidity demand in Period 2, but we do not find significant changes in liquidity supply, which is characterized by market depth and order imbalance. These results reveal that market liquidity deteriorates and trading cost increases after the implementation of circuit breakers, which are likely caused by an increase in liquidity demand instead of a decrease in liquidity supply.

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														
$Return_t$(%)	-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
$Maxdiff_t$	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_t(*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
$Quantile_t$	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
$Volume_t$	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
$Depth_t$	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_t	-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
$Spread_t$	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
$Noise_t$(*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														
$Return_t$(%)	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
$Maxdiff_t$	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_t(*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
$Quantile_t$	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
$Volume_t$	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
$Depth_t$	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_t	-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
$Spread_t$	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
$Noise_t$(*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														
$Return_t$(%)	-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
$Maxdiff_t$	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_t(*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
$Quantile_t$	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
$Volume_t$	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
$Depth_t$	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_t	-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
$Spread_t$	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
$Noise_t$(*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 the one-minute frequency. They are logarithm return ($Return_t$), maximum and minimum price difference ($Maxdiff_t$), bi-power variation (BPV_t), the 5% upper quantile of the absolute logarithmic return series ($Quantile_t$), transaction volume ($Volume_t$), total quote depth ($Depth_t$), order imbalance (OI_t), bid-ask spread ($Spread_t$), and noise variance ($Noise_t$).

Furthermore, we conduct an event study to pinpoint the effect of establishing market-wide circuit breakers on market microstructure measures. All the variables, including price trend ($Return_t$), market volatility ($Maxdiff_t$, BPV_t), extreme market risk ($Quantile_t$), and market liquidity ($Volume_t$, $Depth_t$, OI_t, $Spread_t$, $Noise_t$), are calculated at a one-minute frequency. To make all the variables comparable, we standardize these variables by subtracting the sample mean and dividing by the standard deviation.

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:

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

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 eight indicators as control variables.

Table 2

Effect of circuit breakers on market microstructure

Dependent Variable	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Return	-0.1696	(0.1035)	-0.1013	(0.0796)	-0.0182	(0.1120)
Maxdiff	0.5465***	(0.0999)	0.4269***	(0.0776)	0.4966***	(0.1176)
BPV	1.4309***	(0.1648)	1.3830***	(0.1838)	1.8211***	(0.1374)
Quantile	0.4654***	(0.0719)	0.3189***	(0.0848)	0.4137***	(0.1103)
Volume	0.3058**	(0.1229)	0.1643*	(0.0986)	0.3497**	(0.1729)
Depth	-0.0849	(0.0540)	-0.0775	(0.0886)	0.4550**	(0.2242)
OI	0.0278	(0.0768)	-0.0200	(0.0775)	-0.1981	(0.1365)
Spread	0.3303***	(0.0965)	0.4470***	(0.1056)	-0.0347	(0.1143)
Noise	0.4156***	(0.1095)	0.3669***	(0.0982)	0.4538***	(0.1346)

Note: For each index futures contract, we use the data 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 equation (16) and use the other indicators and the dummy variable $\mathrm{D(circuit\ breaker)}$ as explanatory variables. The $\mathrm{D(circuit\ breaker)}$ equals 1 when the circuit breakers take effect, and 0 otherwise. For brevity, we only report the coefficients (Newey-West standard errors are reported in brackets) 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 coefficients of $\mathrm{D}(circuit\ breaker)$ for each dependent variable. The effect of $\mathrm{D}(circuit\ breaker)$ on price trend, $Return$, is insignificant. However, $\mathrm{D}(circuit\ breaker)$ has significant positive effects on market volatility measures (*Maxdiff* and *BPV*) and extreme market risk measure (*Quantile*), which suggests that the market becomes more volatile and risky during Period 2. Moreover, the overall market liquidity is also significantly affected; the coefficients of $\mathrm{D}(circuit\ breaker)$ are significantly positive for both the bid-ask spread (except for the CSI 500 group) and noise variance, indicating that the overall market liquidity deteriorates when circuit breakers exist. Finally, 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*. The market becomes more volatile, actively-traded, and lack of liquidity when the market-wide circuit breakers exist. Thus, the existence of market-wide circuit breakers does not appear to stabilize the market.

5.4. 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 a perverse effect of exacerbating price fluctuations and market liquidity. The magnet effect of circuit breakers could offer a possible explanation for this phenomenon. As all the circuit breaker triggering events in China are caused by downward movements of the CSI 300 index, we focus on the downward Level 1 breaker to analyze the magnet effect in this paper.

Following Abad and Pascual (2007) and Hsieh et al. (2009), we use the breaker distance (the distance between the CSI 300 index and the breaker level) as a proxy variable for magnet effect. If the magnet effect of circuit breakers does exist, its magnitude will monotonously increase as the price gradually moves toward the breaker level, regardless of the form of magnet effect. Consequently, the breaker distance is a key explanatory variable for the tests of magnet effect hypotheses, and is defined as follows:

$$Distance_t = (Price_t - Lower\ level_t)/(Upper\ level_t - Lower\ level_t) \tag{17}$$

where $Lower\ level_t$ and $Upper\ level_t$ stand for the lower breaker level and upper breaker level of the CSI 300 index in interval t, and $Price_t$ is the average of the index opening price and closing price in interval t. The breaker distance variable 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

Similar to the magnet effect hypothesis proposed by Hsieh et al. (2009), the price acceleration hypothesis states that the probability of a price decrease is negatively related to the value of breaker distance. We run a logit regression for each index futures contract to test whether the breaker distance has predictive power for future price movements. If the magnet effect exists and attracts future prices to move toward the lower breaker level, the likelihood of a price decrease should relate inversely to the distance from the breaker level. That is, the closer the CSI 300 index moves toward its lower breaker level, the greater the probability that stock index futures prices will move downward in the near future.

In order to utilize data information adequately and validate our empirical analysis, our model not only considers the predictive power of breaker distance ($Distance_{t-1}$) on the price trend, but also takes into account the multiple-period explanatory power of several control variables. Specifically, the control variables contain two lags of the futures return, jump-robust volatility measure, and liquidity measures ($Return_{t-j}$, BPV_{t-j}, $Volume_{t-j}$, $Depth_{t-j}$, OI_{t-j}, $Spread_{t-j}$ and $Noise_{t-j}, j = 1,2$). The model is specified as follows:

$$\mathrm{P}(D(Return_t < 0) = 1|\mathrm{X}) = F(\beta_0 + \beta_1 Distance_{t-1} + \textstyle\sum_{i=1}^{7}\sum_{j=1}^{2}\beta_{i,j}Control_{i,t-j}) \quad (18)$$

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 index futures price decreases in interval t given a set of explanatory variables X, and $Control_{i,t-j}$ stands for the ith control variable with time lag j. $F(\cdot)$ is the CDF of logistic distribution function, which is given by

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

If the price acceleration hypothesis holds, the coefficients 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. For example, the coefficient of

$Distance_{t-1}$ in the CSI 300 group (–0.2543) is negative but statistically insignificant, indicating that the breaker distance does not have a significant impact on the probability of a price decrease for the CSI 300 index futures.[16] Meanwhile, the regression results in the SSE 50 and CSI 500 groups also reject the price acceleration hypothesis because the coefficients of $Distance_{t-1}$ are positive. This suggests that as the breaker distance becomes smaller, the probability of future price declines would decrease rather than increase.

Table 3
The effect of breaker distance on future price movements

Panel A. Estimation results	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
$Distance_{t-1}$	-0.2543	0.6437	0.6267	0.2226	0.9274	0.1396
$Return_{t-1}$	0.0790	0.1245	-0.0217	0.6839	0.0413	0.4218
$Return_{t-2}$	-0.0592	0.2367	0.0467	0.3782	0.0180	0.7368
$Volume_{t-1}$	-0.0585	0.5155	0.0506	0.5618	-0.0390	0.5787
$Volume_{t-2}$	-0.0344	0.6966	0.0386	0.6331	-0.0250	0.7213
BPV_{t-1}	0.6046	0.4375	0.6101	0.4333	0.1882	0.7761
BPV_{t-2}	-0.5609	0.4676	-0.6203	0.4228	-0.1634	0.8052
$Depth_{t-1}$	0.1455	0.2410	0.2647*	0.0959	-1.0767	0.1486
$Depth_{t-2}$	-0.0203	0.8663	-0.1231	0.4455	-0.5726	0.2898
OI_{t-1}	0.0997	0.2586	0.0885	0.3646	0.0851	0.3865
OI_{t-2}	-0.0334	0.7032	0.1393	0.1532	0.1602	0.1272
$Spread_{t-1}$	-0.0344	0.7547	0.3350***	0.0026	-0.0979	0.3234
$Spread_{t-2}$	-0.0177	0.8717	0.0052	0.9617	-0.0903	0.3588
$Noise_{t-1}$	0.0232	0.7689	-0.2043**	0.0156	0.0662	0.3760
$Noise_{t-2}$	-0.0963	0.2359	-0.1536*	0.0680	0.1193	0.1233
Panel B. Model adequacy						
$Pseudo\ R^2$	0.0135		0.0270		0.0647	
Sensitivity	63.58%		50.50%		68.42%	
Specificity	51.46%		61.37%		47.48%	

Notes: This table reports the estimation results of the logit model for each stock index futures contract. All the variables are sampled at the one-minute frequency over the period from January 4, 2016 to January 7, 2016 and the model is specified in equation (18). *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

Furthermore, we use a more straightforward way to validate our previous findings. The breaker distance is in the range [0, 1], which we divide into ten groups such that for the ith group,

[16] The average partial effect of $Distance_{t-1}$ for the CSI 300 group is -0.0624, which means that if the $Distance_{t-1}$ decreases by 0.1, the probability of future price declines would slightly increase by about 0.624%.

the breaker distance belongs to the interval $\left[\frac{i-1}{10},\frac{\mathrm{i}}{10}\right]$. As there is no observation with breaker distance greater than 0.7 in our sample, we end up with seven subgroups. For each subgroup, we calculate the proportion of observations with negative future returns, which reflects the probability of future price declines conditional on a given breaker distance range. The results for the CSI 300 index futures are plotted in Figure 3.

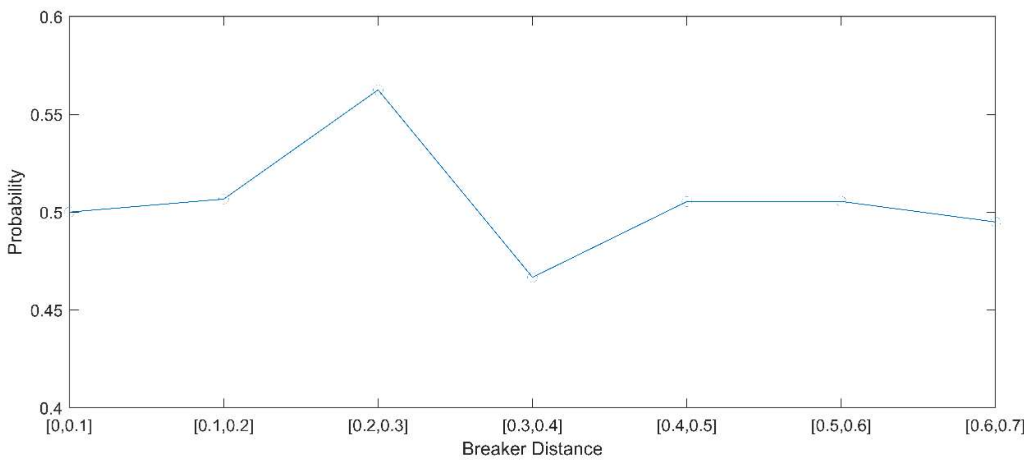

Figure 3. The probability of the CSI 300 index futures price decreases in each breaker distance interval.

We find that as the breaker distance decreases, the probability that the index futures price would 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 is still around 50%. Therefore, the price acceleration hypothesis is rejected by our analysis.

B. Market volatility hypothesis

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

To overcome the problem of data deficiency when we calculate the BPV in a one-minute interval t, we select a rolling window that contains interval t and additional 59 one-minute intervals immediately before t (i.e., a total of 60 minutes) for volatility estimation and assume that the instantaneous volatility during the estimation window remains constant. Note that the BPV series may be strongly autocorrelated when a rolling-based calculation method is used. Therefore, we construct an ARMA model to control for the autocorrelation of BPV and also take into account the effects of lagged return, extreme market risk, and market liquidity ($Return_{t-j}$, $Quantile_{t-j}$, $Volume_{t-j}$, $Depth_{t-j}$, OI_{t-j}, $Spread_{t-j}$ and $Noise_{t-j}, j = 1,2$). The model is specified as follows:

$$BPV_t = \beta_0 + \sum_{i=1}^{p} \alpha_{1,i} BPV_{t-i} + \sum_{i=1}^{q} \alpha_{2,i} \varepsilon_{t-i} + \beta_1 Distance_{t-1} + \sum_{i=1}^{7} \sum_{j=1}^{2} \beta_{i,j} Control_{i,t-j} \quad (19)$$

where p is the order of autoregressive (AR) part, q is the order of moving average (MA) part, ε_t is a white noise sequence, and $Control_{i,t-j}$ stands for the *i*th control variable with time lag j.

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
$Distance_{t-1}$	-0.0152	0.3881	-0.0441	0.3801	-0.0090	0.8834
$Return_{t-1}$	0.0006	0.7582	0.0035	0.1712	-0.0172***	0.0000
$Return_{t-2}$	-0.0016	0.5685	-0.0024	0.3075	-0.0113***	0.0000
$Quantile_{t-1}$	-0.0155**	0.0491	0.0096	0.2966	0.0062	0.3457
$Quantile_{t-2}$	0.0290***	0.0002	0.0149*	0.0731	0.0081	0.1883
$Volume_{t-1}$	0.0369***	0.0000	0.0263***	0.0000	0.0147***	0.0000
$Volume_{t-2}$	-0.0302***	0.0000	-0.0107*	0.0886	0.0111***	0.0014
$Spread_{t-1}$	-0.0047	0.5238	-0.0225***	0.0008	0.0001	0.9821
$Spread_{t-2}$	0.0022	0.7757	0.0120	0.1937	-0.0003	0.9647
$Noise_{t-1}$	0.0200***	0.0000	0.0158***	0.0034	0.0055	0.2670
$Noise_{t-2}$	-0.0231***	0.0000	-0.0157**	0.0200	-0.0006	0.9068
$Depth_{t-1}$	-0.0010	0.9047	-0.0062	0.6988	0.0025	0.8407
$Depth_{t-2}$	-0.0029	0.6847	0.0072	0.6212	0.0002	0.9836
OI_{t-1}	-0.0036	0.4944	0.0003	0.9722	0.0040	0.5166
OI_{t-2}	0.0041	0.4032	-0.0004	0.9577	-0.0020	0.7117

Notes: This table reports the estimation results of equation (19) for each stock index futures contract. The market volatility measure BPV captures the continuous diffusive component of realized volatility and is sampled at the one-minute frequency over the period from January 4, 2016 to January 7, 2016. For brevity, the coefficients of AR and MA terms are omitted. *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

If the market volatility hypothesis holds, the market volatility would increase as the CSI 300 index moves toward the breaker level. Thus, the breaker distance should have a significant negative effect on BPV. The estimation results of equation (19) for each index futures contract are reported in Table 4. We find that although the coefficients of breaker distance are negative (the first row in Table 4), none of them is statistically significant. For example, if the $Distance_{t-1}$ decrease by 0.1, the BPV_t of the CSI 300 index futures would slightly increase by 0.00152, which means that the market volatility risk would only slightly increase by about 0.10%. In other words, 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 shows that the coefficients of $Volume_{t-1}$ and $Noise_{t-1}$ 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 would become more volatile. Our results are consistent with Bao and Pan (2013), which shows that the illiquidity of the 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 observing a price jump will gradually increase as the breaker distance decreases. If this hypothesis holds, we would observe more jumps in stock index futures price movements when the CSI 300 index is close to the Level 1 breaker. A higher probability of price jumps indicates that extreme market events (i.e., price jumps) occur more frequently, leading to a higher level of extreme market risk and contributing to the triggering of circuit breakers. Therefore, the magnet effect of circuit breakers could also exist in a form of extreme market risk.

Similar to the model specification in the test of price acceleration hypothesis, we construct a logit model to examine the explanatory power of breaker distance on the probability of price jumps.[17] Our model is specified as follows:

$$\mathrm{P}(D(Jump\ occur_t) = 1|\mathrm{X}) = F(\beta_0 + \beta_1 Distance_{t-1} + \sum_{i=1}^{7}\sum_{j=1}^{2}\beta_{i,j} Control_{i,t-j}) \quad (20)$$

where the dummy variable $D(Jump\ occur_t)$ equals 1 if there is a price jump in interval t and 0

[17] In our analysis, the probability of a price jump is less than 2%. King and Zeng (2001) argue that logit regressions can underestimate the probability of rare events. Thus, we further conduct the rare event logit estimation (ReLogit) proposed by King and Zeng (2001). The ReLogit regression results are similar to the logit regression results reported in Table 5 below. The ReLogit regression results are not tabulated in this paper but are available from the authors upon request.

otherwise.[18] $F(\cdot)$ is the CDF of logistic distribution. The control variables are the same as before. We try to control for the effect of market liquidity on price jumps (Jiang et al., 2011; Boudt & Petitjean, 2014), the effect of volatility on price jumps (Boudt & Petitjean, 2014), and the effect of lagged return on price jumps.

Table 5

The impact of breaker distance on price jumps

	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
Panel A. Estimation results	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
$Distance_{t-1}$	-10.9390***	0.0037	-2.3234	0.3958	-5.9970**	0.0130
$Return_{t-1}$	0.0708	0.7007	0.0240	0.9159	-0.4336**	0.0228
$Return_{t-2}$	-0.4481	0.1282	-0.5337**	0.0268	-0.2904	0.1864
BPV_{t-1}	0.7798	0.8515	12.2417*	0.0554	-6.1258***	0.0065
BPV_{t-2}	-0.5955	0.8845	-15.6595**	0.0347	4.5836**	0.0324
$Volume_{t-1}$	0.2954	0.4123	0.1067	0.8067	0.3653**	0.0383
$Volume_{t-2}$	0.6012*	0.0837	0.1535	0.5860	0.1125	0.4022
$Depth_{t-1}$	0.0444	0.9387	-0.2964	0.7239	-18.2887**	0.0301
$Depth_{t-2}$	-0.9363	0.1643	0.8240	0.1081	-0.9879	0.2959
OI_{t-1}	-0.2051	0.6511	-0.5247	0.4248	1.2056	0.1336
OI_{t-2}	-0.6776	0.1894	0.6283	0.1671	-0.3780	0.4603
$Spread_{t-1}$	-1.5977**	0.0412	0.0848	0.8939	1.0686**	0.0209
$Spread_{t-2}$	-1.4921	0.1150	0.7456	0.2378	-1.0641**	0.0365
$Noise_{t-1}$	-0.1312	0.6671	-0.2096	0.7051	-0.4589	0.1561
$Noise_{t-2}$	-0.7527	0.4222	-0.9466**	0.0218	0.8090***	0.0052
Panel B. Model adequacy						
Pseudo R^2	0.4923		0.4024		0.4036	
Sensitivity	40.00%		25.00%		20.00%	
Specificity	99.84%		100.00%		100.00%	

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

To ensure the robustness of results obtained in this model, we separately use the data of each index futures to conduct the logit regression analysis and summarize these results 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. Taking the CSI 300 index futures as an

[18] The jump detection procedure is reported in section 5.2.

example, the coefficient of $Distance_{t-1}$ is –10.9390 and it is statistically significant at the 1% significance level. The average partial effect of $Distance_{t-1}$ is –0.1197, which indicates that as the breaker distance decreases by 0.1, the probability of observing a price jump increases by about 1.197%. It is worth noting that the increase of jump probability is non-negligible because the average probability of observing a price jump in the whole sample is about 1.60% for the CSI 300 index futures. As a result, this empirical result shows that as the CSI 300 index moves toward the breaker limit, extreme price movements (captured by price jumps) will occur more frequently in the CSI 300 index futures.

Similarly, the coefficients of the breaker distance for the SSE 50 index futures and the CSI 500 index futures are also negative, and the coefficient of the breaker distance for the CSI 500 index futures is significant at the 5% level. Meanwhile, the results of model adequacy tests are reported in Panel B, Table 5. We find that our model performs reasonably well. The pseudo R^2 values are higher than those in the test of price acceleration hypothesis. The true negative rates (specificity) are close to 100%, but the true positive rates (sensitivity) are lower and range from 20% to 40%, indicating that our model may not be sufficient to fully predict price jumps. This result is understandable due to the difficulty of predicting extreme price movements, especially at the intraday one-minute frequency. Overall, our results yield empirical evidence in favor of the extreme market risk hypothesis. The implementation of market-wide circuit breakers may have led to a higher level of extreme market risk in the Chinese stock index futures market.

Jiang et al. (2011) show that the liquidity shocks, such as changes in 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 consistent impact on the probability of price jumps. One possible explanation is that the magnet effect of circuit breakers, captured by breaker distance, may have weakened the explanatory power of liquidity variables for price jumps.

To summarize, in this section we examine whether the market-wide circuit breakers have a magnet effect from several perspectives (i.e., price trend, market volatility, and extreme market risk). Our regression results show that the breaker distance does not significantly exacerbate the price trend and price volatility. Both the absence of an acceleration in price change and the stability in instantaneous volatility are in support of the use of circuit breakers. However, the breaker distance has a significant explanatory power for the probability of future price jumps. In other words, when the CSI 300 index is very close to the breaker level, extreme price movements (captured by price jumps) occur more frequently in the stock index futures market, leading to a higher possibility of triggering the circuit breakers. Our study emphasizes 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 the previous section, we find that breaker distance has a significant impact on the probability of price jumps. When the CSI 300 index decreases and the breaker distance is close to 0, price jumps happen more frequently in the stock index futures market. Nonetheless, a price jump can be a positive jump or a negative jump, and only negative jumps contribute to the triggering of the downward Level 1 breaker. 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:

$$\mathrm{P}(D(Negative\ jump_t) = 1|\mathrm{X}) = F\left(\beta_0 + \beta_1 Distance_{t-1} + \sum_{i=1}^{7}\sum_{j=1}^{2}\beta_{i,j} Control_{i,t-j}\right) \quad (21)$$

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

Table 6 shows that the coefficients of $Distance_{t-1}$ remain negative for all three index futures contracts, and the impact of breaker distance becomes larger and more consistent compared with that in Table 5 where we use both positive and negative price jumps to test the extreme market risk hypothesis.[19] Taking the SSE 50 index futures as an example, the value of β_1 decreases from –2.3234 to –9.1960 and becomes statistically significant at the 10% significance level, indicating that the probability of detecting a negative jump is negatively related to the breaker distance. Moreover, its average partial effect also decreases from –0.0225 to –0.0451. This suggests that as the $Distance_{t-1}$ decreases by 0.1, the probability of a negative jump will

[19] Negative price jumps in our sample are rare events. We also check the robustness of our results by using the ReLogit method (King and Zeng, 2001). The ReLogit regression results are similar to those from the logit regressions reported in Table 6.

increase by about 0.451%, which is more than twice the increase of the probability of a price jump (0.225%).

Overall, our findings indicate that there exists a statistically significant negative relationship between the probability of negative price jumps and the breaker distance. When the CSI 300 index decreases and moves toward the breaker level, the price jumps (especially negative jumps) are more likely to occur in the Chinese stock index futures market. More extreme downward price movements (i.e., negative jumps) correspond to a higher level of extreme market risk and a higher probability of triggering the market-wide circuit breakers.

Table 6
The impact of breaker distance on negative price jumps

Panel A. Estimation results						
	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
$Distance_{t-1}$	-15.1797***	0.0071	-9.1960*	0.0764	-9.5089**	0.0166
$Return_{t-1}$	0.0965	0.7063	0.0613	0.7682	-0.5605**	0.0454
$Return_{t-2}$	-0.5733	0.1484	-0.2390	0.3509	-0.5486*	0.0837
BPV_{t-1}	1.9915	0.7149	8.5818	0.2969	-3.6542	0.3008
BPV_{t-2}	-1.4711	0.7830	-8.8503	0.2850	2.6339	0.4297
$Volume_{t-1}$	0.1672	0.7973	0.1105	0.8445	0.4677	0.1366
$Volume_{t-2}$	0.8854	0.1223	0.3943	0.1900	0.3599	0.1818
$Depth_{t-1}$	-0.7267	0.4437	0.3487	0.7956	-15.5840	0.2552
$Depth_{t-2}$	-1.8150*	0.0673	0.0995	0.9390	-1.6872	0.5458
OI_{t-1}	-0.1882	0.7672	0.2033	0.7913	1.0867	0.3405
OI_{t-2}	0.2358	0.7683	-0.6491	0.4488	-0.2831	0.7662
$Spread_{t-1}$	-2.3321**	0.0347	-0.7545	0.5613	1.4882*	0.0719
$Spread_{t-2}$	-1.5369	0.3289	0.6645	0.4389	-1.0955	0.2705
$Noise_{t-1}$	0.1274	0.7982	-0.5326	0.7247	-1.3426*	0.0663
$Noise_{t-2}$	-1.2711	0.4640	-0.5645	0.3616	0.0707	0.9242
Panel B. Model adequacy						
$Pseudo\ R^2$	0.5532		0.5504		0.5433	
Sensitivity	28.57%		40.00%		42.86%	
Specificity	99.84%		100.00%		100.00%	

Notes: This table reports the estimation results of equation (21) for each of the three stock index futures. Each variable is sampled 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 at 10%. *** (**, *) 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 in extreme market risk, measured by price jumps, may happen whenever there is a large decline in the CSI 300 index price, regardless of whether circuit breakers exist. To address this concern and make inferences about the effect of circuit breakers, we further examine stock index futures price jumps during a control period when the circuit breakers did not exist, but the CSI 300 index also fluctuated excessively so 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 (five trading days in total). In both the first and the last day of this control period, the CSI 300 index dropped more than 5% (i.e., it would have triggered the Level 1 breaker if the breakers were in place). The overall price movement in the control period is similar to the price movement in the period with circuit breakers (from January 4, 2016 to January 7, 2016).

Table 7
Robustness check of pseudo-breaker distance

Panel A. Estimation results						
	CSI 300 index futures		SSE 50 index futures		CSI 500 index futures	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
$PseDistance_{t-1}$	-4.8713	0.1408	-4.4890	0.2314	-0.3747	0.9456
$Return_{t-1}$	0.1480	0.6268	0.5581	0.1593	-0.3199	0.5282
$Return_{t-2}$	-0.1176	0.8302	-0.5405	0.4203	-1.4251	0.1798
BPV_{t-1}	1.8383	0.6634	0.3711	0.9418	20.1864	0.2141
BPV_{t-2}	-3.5716	0.4168	-4.4499	0.4397	-21.3942	0.1922
$Volume_{t-1}$	0.2166	0.7151	0.2624	0.6742	2.0902**	0.0371
$Volume_{t-2}$	-1.5987*	0.0664	-1.2511	0.2005	-2.9756**	0.0314
$Depth_{t-1}$	22.9515	0.7397	0.3483	0.4786	-125.4338	0.3907
$Depth_{t-2}$	59.4930	0.3833	-0.7608	0.3173	125.6438	0.1627
OI_{t-1}	0.3164	0.7047	0.0510	0.8955	0.9695	0.5257
OI_{t-2}	0.6057	0.4319	-0.0454	0.9048	-1.5276	0.2385
$Spread_{t-1}$	1.1004	0.2016	-0.1811	0.8421	-1.5254	0.2909
$Spread_{t-2}$	0.1107	0.9063	-0.7604	0.4497	0.3758	0.7720
$Noise_{t-1}$	0.1064	0.9292	1.8754	0.1659	-2.1957	0.3189
$Noise_{t-2}$	-0.1405	0.9255	0.4227	0.8375	0.4243	0.8381
Panel B. Model adequacy						
Pseudo R^2	0.1667		0.1770		0.3889	
Sensitivity	0.00%		0.00%		0.00%	
Specificity	100.00%		100.00%		100.00%	

Notes: This table reports the estimation results of equation (22) for each of the three stock index futures. Each variable is sampled at the one-minute frequency over the period from June 19, 2015 to June 26, 2015. ** (*) stands for statistically significant at the 5 (10) percent level.

Although the circuit breakers do not exist in the control period, we calculate the breaker distance at the one-minute frequency and rename it the pseudo-breaker distance. Following the same procedures as before, we also delete the intraday trading data after the CSI 300 index has decreased by 5% and calculate market microstructure variables at the one-minute frequency. The focus of this robustness check is to examine the impact of pseudo-breaker distance on price jumps. The logit model is specified as follows:

$$\mathrm{P}(D(Jump\ occur_t) = 1|\mathrm{X}) = F(\beta_0 + \beta_1 PseDistance_{t-1} + \sum_{i=1}^{7}\sum_{j=1}^{2}\beta_{i,j}Control_{i,t-j}) \qquad (22)$$

where $PseDistance_{t-1}$ stands for the value of the 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.[20]

According to the regression results, the coefficients of $PseDistance_{t-1}$ are all negative. Unlike the breaker distance, the pseudo-breaker distance, however, does not have a significant effect on the probability of price jumps. Moreover, the values of Pseudo R^2 and sensitivity are much lower than those in Table 5, where we conduct a similar exercise for the sample period with circuit breakers. These findings suggest that the constructed distance variable, $PseDistance_{t-1}$, is less informative about the future price jumps when the circuit breakers do not exist. Therefore, the explanatory power of the breaker distance on extreme market risk reported in Table 5 when using data in the period with circuit breakers is more likely due to the influence of market-wide circuit breakers.

7. Market liquidity dynamics ahead of a trading halt

Subrahmanyam (1994) develops a theoretical framework of circuit breakers and shows that as the price moves close to the breaker level, investors will suboptimally advance their trades and the current trading volume will increase significantly, leading to a perverse effect of exacerbating price

[20] We also test the validity of the estimations by using the ReLogit method. Our results are robust to this alternative model of estimation.

movements and increasing price variability. This suggests that a sudden increase in liquidity demand (i.e., the demand for immediate execution) may play an important role in understanding the magnet effect. Therefore, we further examine the variation in market liquidity ahead of a market-wide trading halt to uncover potential factors that influence the magnet effect.

Consistent with the previous variable selection, we use five liquidity indicators (volume, total quote depth, order imbalance, bid-ask spread, and noise variance) to capture the time-varying characteristics of liquidity demand, liquidity supply, and overall market liquidity. We construct a VARX model to take into account possible dynamic interactions between these liquidity variables:

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

where $Y_t = [Volume_t,\ Depth_t,\ OI_t,\ Spread_t,\ Noise_t]^T$ is the vector of liquidity variables in interval t, X_t stands for the value of the breaker distance ($Distance_t$), and p is the lag order. 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 impact of breaker distance for each liquidity variable. The coefficient matrix A_1 represents the dynamic correlations between liquidity variables. The regression results for the CSI 300 index futures are reported in Table 8.

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 presented in equation (23) using the data of the CSI 300 index futures. The coefficient vector B_1 represents the explanatory power of the breaker distance for liquidity variables and A_1 reflects the dynamic correlation between these liquidity variables. T-values are reported in parentheses. *** (**, *) stands for statistically significant at the 1 (5, 10) percent level.

As we can see in Table 8, the breaker distance is negatively related to bid-ask spread and noise variance. For example, the coefficient of $Distance_{t-1}$ on $Noise_t$ is -2.15, which is very significant. Therefore, when the CSI 300 index moves close to the breaker level, the bid-ask spread and noise variance become larger, leading to higher transaction costs and a more illiquid index futures market. However, it remains unclear whether the increase of overall market liquidity measures (bid-ask spread and market noise) is attributed to a decrease in liquidity supply or an increase in liquidity demand. Therefore, we further consider the variation of liquidity supply and liquidity demand separately before the triggering of circuit breakers.

Our results show that the coefficient of $Distance_{t-1}$ on $Volume_t$ is -1.11 and is statistically significant at the 1% level, but the coefficients of $Distance_{t-1}$ on $Depth_t$ and OI_t are statistically insignificant. These results suggest that as the breaker distance becomes smaller, the trading volume increases significantly (i.e., liquidity demand rises) while liquidity supply remains relatively stable as there are no significant changes in the order imbalance and market depth. Thus, the deterioration of overall market liquidity is more likely caused by an increase in liquidity demand instead of a decrease in liquidity supply. Our result is different from Goldstein and Kavajecz (2004), who find an increase in liquidity demand and a decrease in liquidity supply ahead of a market-wide trading halt at NYSE, but it is in line with the Subrahmanyam (1994) theoretical analysis and the recent empirical finding by Cui and Gozluklu (2016) that the triggering of circuit breakers is accompanied by a massive surge in volume and spread.

Overall, we find that the magnet effect of circuit breakers in the Chinese stock index futures market is associated with an 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. Previous studies by Jiang et al. (2011) and Christoffersen et al. (2016) have shown that liquidity shocks have significant predictive power for price jumps. We expect that the deterioration of market liquidity ahead of a market-wide trading halt will lead to more frequent price jumps and the stock index futures market will become more volatile and riskier.

8. Conclusion

Why do the market-wide circuit breakers established in the Chinese financial markets fail to improve market stability? Do market-wide circuit breakers have a magnet effect and what is the exact form of magnet effect, if it exists? How could we explain the existence of magnet effect? To shed light on these questions, this paper uses high-frequency data from the Chinese stock index futures market to examine the magnet effect of market-wide circuit breakers.

We first investigate the market structural changes due to the implementation of circuit breakers. We conduct an event study analysis to compare market microstructure characteristics in the periods with and without circuit breakers, and find that the stock index futures market becomes more volatile and lack of liquidity when the market-wide circuit breakers exist.

We then construct various econometric models to test three magnet effect hypotheses from the perspectives of price trend, market volatility, and extreme market risk. The estimation results show that no magnet effect is found in price trend and market volatility; that is, when the CSI 300 index decreases and moves toward the breaker level, neither the probability of a price decrease nor the level of market volatility will 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 a negative jump) in the stock index futures price movement, which indicates that extreme events occur more frequently and the circuit breakers are more likely to be triggered.

Finally, we examine the variation of market liquidity to explain the observed price jumps ahead of a market-wide trading halt. We construct a VARX model to analyze the interactions between liquidity variables when the CSI 300 index moved 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. Note that we do not have access to order book data on a high-frequency basis in that we are not able to follow order book dynamics by observing each order submission, cancellation, or execution on the market. The use of order book data would help better characterize the (im)balance between liquidity supply and demand. We leave this for future research.

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

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