WFE RESEARCH WORKING PAPER NO. 3

CIRCUIT BREAKERS AND MARKET QUALITY

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APRIL 2022

WORLD FEDERATION OF EXCHANGES

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April 2022

Abstract In March 2020, the U.S. security market experienced heightened volatility induced by the COVID-19 pandemic, and market-wide circuit breakers were triggered on four occasions. Relying on high-frequency intraday trade and quote data, we investigate the market conditions around these trading halts to shed light on the effectiveness of circuit breakers. We find that, on average, stock returns stabilize, trading cost reduces, selling pressure resolves, and prices become more informative after trading resumes from the market-wide trading halts. Moreover, we provide evidence that traders tend to hold back from aggressive trading right before the trading halts, which is inconsistent with the circuit breakers causing panic (the *magnet effect*). Overall, our findings point to the efficacy of the circuit breakers as a well-designed safeguarding mechanism employed by the exchanges.

Keywords: Circuit breakers, COVID-19, market quality, market-wide circuit breakers, Limit Up/Limit Down
JEL classification: G01, G10, G14

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Acknowledgements: We would like to thank Steven Poser, Heinrich Lutjens, Phil Mackintosh, Ed Knight, and the members of the WFE Emerging Markets Working Group for their feedback. Any errors are ours.

1 Introduction

Circuit breakers are safeguarding mechanisms that temporarily halt continuous trading when an indicator crosses a pre-specified threshold during volatile market conditions. Such halting mechanisms intend to provide market participants with a cool-down period to evaluate their trading strategies, assess information, adjust their positions, or modify submitted orders (Ackert (2012); Subrahmanyam (2017)). These actions are intended to alleviate the rapid deterioration in market quality that may occur during market turmoil. In general, the circuit breaker can stop the trading of the entire market (market-wide circuit breakers or MWCBs) or stop the trading of single securities (single-stock circuit breakers).[1]

In March 2020, the COVID-19 induced volatility led to multiple occurrences of market-wide trading halts, and the effectiveness of the circuit breakers re-entered the discussion among exchanges, regulators, and market participants. On the one hand, in the past, some theoretical studies have raised concerns about the effectiveness and benefits of circuit breakers arguing, for example, that circuit breakers could make more likely prices would reach the triggering threshold (the so-called *magnet effect*). On the other hand, the triggering of market-wide circuit breakers had been so rare that empirical research to test their impact has been limited or non-existent. Given the importance of ensuring an orderly market, especially in times of stress, it is critical to empirically assess the effectiveness of circuit breakers and the adequacy of their calibration.

The aim of this paper is to empirically study the effectiveness of the U.S market-wide circuit breakers by examining the market conditions around the trading halts experienced by that market in March 2020. In particular, we study their impact on market quality (e.g., liquidity conditions, price informativeness), on trading behavior (e.g., the magnet effect), and the differential between market-wide and single-instrument circuit breakers. We complement the analysis by comparing the effects on S&P500 firms with non-S&P500 firms. We use the intraday trades and quotes (TAQ) data provided by the NYSE of a selected and matched sample of 17 pairs of stocks, half at the bottom of the S&P500 index (ranked by market capitalization) and half with comparable market capitalization but which are not in the market index. Relying on this sample, we compute eleven trading characteristics and market quality measures in a volume clock setting, as outlined by Easley et al. (2021), who have shown that traditional market microstructure measures perform adequately under a high-frequency market environment.

The analysis consists of three parts. First, to study the impact on market quality, we conduct a before and after analysis around the four market-wide circuit breaker triggering events. We find that the market-wide trading halt is associated with increased stock return, lowered price impact (measured by the effective spread, realized spread, and the Goyenko et al. (2009) measure), reduced selling pressure (measured by order imbalance), and improved price informativeness (measured by VPIN as in Easley et al. (2012, 2016)). Such improvements suggest that market-wide circuit breakers could improve market quality during extreme volatility. Moreover, we also document that the quoted bid-ask spread widens by 7.1bps after trading resumes from the MWCBs, which implies that liquidity suppliers provide less liquidity in response to the trading halts. The wider spreads grant the liquidity suppliers protection and compensation against the increased risks, which include the increased adverse selection costs as shown by the increased VPIN measure. Our findings align with the Kyle (1988) theory model, which states that circuit breakers can decrease volatility and resolve order imbalances. Also, our results support the Greenwald and Stein (1991) model, which predicts that circuit breakers can reduce transactional costs and bring buyers' demand to the market.

Empirically, while there exist comprehensive studies on the single-security circuit breakers,[2] market-

[1] For a detailed review of the different types of circuit breakers and their characteristics, see the WFE report "Circuit Breakers and other safeguards" Alderighi et al. (2021)

[2] For example, studies that support the implementation of single security circuit breakers include Lauterbach and Ben-Zion (1993); Corwin and Lipson (2000); Zimmermann (2013); Goldstein (2015); Brogaard and Roshak (2016); Brugler et al. (2018); Guillaumie et al. (2020). Studies that do not support the single security circuit breakers include Santoni and Liu

wide circuit breakers have not been thoroughly investigated due to their infrequent occurrences. Li and Yao (2020) also study the MWCBs in the U.S. and claim that the market-wide trading halts result in market panics. They rely on the subsequent drop in the market index following the initial one, which triggered that trading halt, as the counterfactual observations to identify the causal effects. Although our paper does not intend to establish causality but rather association, we deem their approach unsuitable. The subsequent decrease in index price is conditional on the first drop, and therefore is not exogenous and might not be appropriate for a difference-in-differences setting.

Second, we investigate the holding back hypothesis and the magnet effect hypothesis. The holding back hypothesis states that the circuit breakers cause traders to trade less aggressively as the probability of a circuit breaker being triggered increases, and we therefore observe fewer extreme price movements. Whereas the magnet effect, first established by Subrahmanyam (1994), claims that the circuit breakers cause traders to trade more aggressively, leading to more extreme price movements as prices approach a triggering point. Consistent with the holding back hypothesis, we provide visual evidence that the deterioration of stock return, volatility, liquidity, and selling pressure slows down right before the trigger of the MWCBs. For instance, we find that the trend of stock return, while declining, switches from concave to convex right before the trading halt. Such a change in convexity signals the slowing of return decrease and suggests that traders tend to hold back and trade less aggressively as they become less willing to take position that they cannot lay off in anticipation of the MWCBs or to avoid triggering MWCBs. Other studies have also investigated these two hypotheses. Wang et al. (2019) and Wong et al. (2020) study the market-wide circuit breakers in China and show evidence of magnet effects. Goldstein and Kavajecz (2004) investigate the trading halt in the NYSE in October 1997 and find evidence of magnet effects. Such differences in results are in line with the intuition that the presence of hold back or of magnet effect will depend on market structure and on the design and calibration of circuit breakers. For example, markets with more institutional traders will tend to hold back, while markets with higher retail participation, may tend to show magnet effects. On the other hand, in October 1997, U.S. circuit breakers were designed using a point-based system tracking the Dow-Jones Industrial Average instead of the current design based on a percentage change system that tracks the S&P500 index.

Lastly, we complement the MWCB analysis by studying the differential effects of MWCB on S&P500 stocks and non-S&P500 stocks and the differential effects between market-wide trading halts and single stock trading halts by adding the corresponding interaction terms in the before and after analysis. We find that the MWCBs have no statistically different impacts on the trading of the stocks at the bottom of the S&P500 index and the stock just ranked outside the market index. Such results imply that index membership and index funds do not have a differential impact around MWCBs. In addition, we find that the liquidity suppliers tend to become more reluctant to provide liquidity after MWCBs than after single stock halts. Otherwise, there are no significant differences between these two types of trading halts.

Overall, our findings have important policy and market design implications. The improved market environment associated with the market-wide circuit breakers suggests that these trading halts could alleviate the deteriorating market conditions during surging volatility. Such improvement is more evident when we investigate the trend leading up to the triggers of the MWCBs, as we show that market deterioration slows down right before the commencement of the trading halts. Our results point to the adequacy of the current circuit breaker designs in the U.S. and the efficacy of the circuit breakers as an efficient safeguarding mechanism employed by the exchanges.

The remainder of the paper proceeds as follows. In Section 2, we provide more information about the circuit breakers. In Section 3, we describe the data samples and discuss the empirical design for our analyses. In Section 4, we present and discuss the empirical results. Finally, in Section 5, we conclude our paper.

(1993); Lee et al. (1994); Kim and Rhee (1997); Nath (2005); Cui and Gozluklu (2016). Also, Belcher et al. (2003); Aitken et al. (2015); Magnani and Munro (2020) report mixed findings.

2 Background and institutional details

Circuit breakers are safeguarding mechanisms employed by security exchanges that temporarily halt the continuous trading in one or more financial instruments or contracts. The market-wide circuit breakers (MWCB) halt the continuous trading of all securities in the market. In contrast, the single-stock circuit breakers only halt the trading of the security that triggers the halt. In the U.S., the market-wide circuit breaker was introduced in response to the market crash on October 19, 1987 (Black Monday). When the market becomes turbulent and volatile, such trading halts could provide market participants with the time and opportunity to absorb information and make better investment decisions. After the stock market flash crash on May 6, 2010, the SEC updated the circuit breaker system to include single-stock trading halts.[3] In May 2012, the SEC introduced the single-stock circuit breaker system as the Limit Up/Limit Down (LULD) plan, to prevent equity trading from taking place outside of specified price band. Nowadays, both market-wide circuit breakers and single-stock circuit breakers are widely used in the exchange industry as mechanisms to stabilize volatile market conditions. A recent survey by the World Federation of Exchanges (Alderighi et al. (2021)) indicates that a large majority (86%) of exchanges in the world have circuit breakers in place, although their design and calibration vary to answer the needs of different individual market structures.

Amid the COVID-19 pandemic, circuit breakers re-enter the regulatory debate after being triggered in multiple markets around the globe. For instance, in March 2020, market-wide circuit breakers were triggered four times in the U.S., twice in South Korea, six times in Brazil, and six times in Egypt. Moreover, the occurrence of single-stock circuit breakers also reached record levels. For example, the quarterly report of the LULD Plan[4] in the U.S. shows that the equity market experienced about 740 single stock trading halts in March 2020, compared with three times in January 2020 and five times in February 2020. This was not an isolated phenomenon: many other exchanges across the world observed in March 2020 significantly more frequent triggers of their single-stock circuit breakers (Alderighi et al. (2021)).

The turbulent market and the record high trigger of circuit breakers during March 2020 also prompted security exchanges and financial regulators to evaluate and revise the design of the trading halt mechanisms. For example, the Athens Stock Exchange (ATHEX) lengthened the duration of trading halts from two minutes to ten minutes. The Indonesia Stock Exchange (IDX) expanded the original single-tier circuit breaker system to a three-tier system to allow for multiple trading halts. The U.S. SEC also asked the national exchanges and FINRA to analyze the volatility events in March 2020 and the corresponding market-wide circuit breakers. The ensuing report concluded that the MWCB mechanism worked as intended during the March 2020 events.[5]

In the following section we provide further institutional details about the market-wide circuit breakers and the Limit Up/Limit Down plan in the U.S.

2.1 Market-wide circuit breaker institutional details

Under the current rule, the MWCB halts trading in the cash equity market and the equity options markets if the S&P500 index experiences a severe single-day decline with respect to the previous closing price. The triggers have three thresholds: 7% (Level 1), 13% (Level 2), and 20% (Level 3). If the index breaches the Level 1 or Level 2 thresholds between 9:30 a.m. and 3:25 p.m., the market-wide trading halts for 15 minutes. If these thresholds are reached after 3:25 p.m., no trading halts take place. A market decline

[3] For more information on Black Monday and the market-wide circuit breaker, see Brady et al. (1988). For information on the introduction of stock-by-stock circuit breakers, see https://www.sec.gov/news/press/2010/2010-98.htm.

[4] The LULD quarterly report is available at https://www.luldplan.com/studies.

[5] The Market-Wide Circuit Breaker Working Group report is available at https://www.nyse.com/publicdocs/nyse/markets/nyse/Report_of_the_Market-Wide_Circuit_Breaker_Working_Group.pdf.

triggering the Level 3 halts market-wide trading for the remainder of the trading day, regardless of the time of the trigger.

Before March 2020, the only occurrence of a MWCB in the U.S. was on October 27, 1997 (the "mini-crash"). However, in March 2020 market-wide trading halts were triggered four times due to concerns related to the COVID-19 pandemic. The Level 1 MWCB halt was triggered for these four occurrences, and market-wide trading halted for 15 minutes. Table 1 lists the date and time of the four MWCBs. The first two MWCBs happened at 9:34:13 a.m. and 9:35:44 a.m., a few minutes after the market opened. On March 16, 2020, the third MWCB halted trading at 9:30:01 a.m., and most of the stocks in the S&P 500 index did not complete their primary listing exchange opening auction before the market-wide trading halt. The last MWCB took place at 12:56:17 p.m. on March 18, 2020.

Table 1. The market-wide circuit breakers in March 2020

This table lists information on the four market-wide circuit breakers that took place in March 2020. The information is taken from FINRA.

Date	Time	MWCB Level
March 9, 2020 (Monday)	9:34:13 a.m.	Level 1
March 12, 2020 (Tuesday)	9:35:44 a.m.	Level 1
March 16, 2020 (Monday)	9:30:01 a.m.	Level 1
March 18, 2020 (Wednesday)	12:56:17 p.m.	Level 1

2.2 Limit Up/Limit Down single stock circuit breaker institutional details

The current single-stock circuit breaker in the US is the Limit Up/Limit Down (LULD) plan, which was approved by the SEC on April 11, 2019, as a permanent rule after being introduced as a pilot plan on May 31, 2012. The LULD prohibits trades from taking place outside specific price bands, which are determined as in the equation below.

$$Price\,Band = Reference\,Price \pm Reference\,Price \times Percentage\,Parameter \tag{1}$$

For each National Market System (NMS) stock, the reference price is the average transaction price over the proceeding five minutes. The first reference price of each trading day is the opening price or the previous closing price. The percentage parameter is set depending on the security's designation (Tier 1 or Tier 2 security) and the previous closing price, as shown in Table 7. The Tier 1 securities include all securities in the S&P500 index and the Russell 1000 index and selected ETPs. Tier 2 securities include other securities, not in Tier 1.

The security enters a Limit State when the National Best Bid is below the Lower Price Band, and the National Best Offer is above the Higher Price Band, and therefore inexecutable. If all Limit State Quotations are executed or canceled, trading exits the Limit State. Otherwise, trading halts for five minutes, and the halt can be extended for another five minutes.[6]

Based on the LULD 2020 Annual Report[7], Table 3 compares the LULD Pause during the 2020 volatile period with the non-volatile period[8] and reports the daily average number of Limit States and LULD Pauses. On average, during the non-volatile period, there were around 200 Limit States, and roughly 10%

[6]For more information about the Limit Up/Limit Down Plan, see https://www.luldplan.com.
[7]The LULD 2020 Annual Report is available at https://www.luldplan.com/studies.
[8]The LULD Annual Report identifies the 2020 volatile market period as February 24 to May 1, which differs from the period used in the paper (March 1 to March 31).

Table 2. Limit Up/Limit Down Percentage Parameter

This table lists the LULD parentage parameters for the U.S. securities. The information is taken from the LULD Plan (https://www.luldplan.com/).

Tier 1 Securities and Tier 2 Securities below $3.00		Tier 2 Securities above $3.00	
Previous Closing Price	**Percentage Parameter**	**Previous Closing Price**	**Percentage Parameter**
Greater than $3.00	5%	Greater than %3.00	10%
$0.75 up to including $3.00	20%		
Less than $0.75	Lesser of $0.15 or %75		

of the Limit States resulted in LULD pause. Such figures increased notably during the volatile market period. There were almost 1,000 occurrences of Limit States and about 18% of them ended up in a single stock trading halt.

Table 3. Limit Up/Limit Down 2020 summary

This table summarizes that the number of occurrences of the LULD pause and Limit State during the volatile market period and non-volatile period. The volatile period is from February 24th to May 1st, 2020, and the non-volatile period is the rest of the year 2020, excluding the volatile period. The information is taken from the LULD Plan (https://www.luldplan.com/).

Daily Average	Feb 24 - May 1, 2020	2020 Excluding Feb 24 - May 1
LULD Pause	187.0	20.5
Limit State	978.7	200.5
% of Pause over Limit State	18.11%	10.22%

3 Data and empirical setting

3.1 Sample data

To investigate the effect of circuit breakers during the March 2020 volatile market condition, we use TAQ data from the NYSE. The TAQ data include the intraday quote, trade, and message data with millisecond-level timestamps. The quote data include the National Best Bid Offer (NBBO) and the depth at NBBO; the trade data include the transaction price and volume; and the message data include flags for trading halts (including MWCB, LULD, and other regulatory halts) together with other admin messages (such as short selling restrictions). In addition, we get the intraday price of the S&P500 index and VIX index from Cboe Global Markets. We also get firm characteristics from CRSP and Compustat. Finally, we get the membership list of the S&P500 index, Russell 1000 index, and Russell 2000 index from the respective indexing agency's website.

With the aforementioned dataset, we select a sample of 34 stocks[9] around the cut-off of the S&P500 index, ranked by market capitalization. Half of the stocks are in the S&P500 index, while the remaining half is just out of the S&P500 index. The two groups of stocks would have similar firm characteristics, whereas they might be subject to different institutional attention, such as ETFs and index funds. Such differences allow us to investigate the differential effects of index tracking during trading halts.

[9] We are currently expanding the sample stocks.

To prevent firm fundamental characteristics from affecting the comparison between the S&P500 stocks and the non-S&P500 stocks, we use the propensity score matching (Rosenbaum and Rubin (1983)). The matching process selects the 34 stocks, which are 17 pairs of one-to-one matched stocks based on measures during the first week of March.[10]

Table 4 shows the summary statistics of the sample stocks[11] in the first week of March 2020. Although not the largest stocks in the market, the sample stocks have large market capitalization and high trading volume—the mean market capitalization is about $10 billion, and the mean daily trading volume is about two million shares. Moreover, the table results confirm that there are no significant differences between the two groups of stocks.

Table 4. Summary Statistics

This table provide the summary statistics of our sample stocks. The measures are taken during the first week of March 2020 and include the average closing price, daily return, daily volatility as measured by realized variance, traded share volume, and market capitalization. The table also reports the summary statistics for stock in the S&P500 index and not in the S&P500 index, matched by propensity scores (Rosenbaum and Rubin (1983)) based on the above measures. In addition, the table shows the mean difference and the p-values of the corresponding T-tests. The data are gathered from CRSP and TAQ.

Measure	All	S&P500	Non-S&P500	Difference	p-value
Price ($)	108.4499	109.2317	107.6681	1.5636	0.9619
Return	-0.0084	-0.0082	-0.0085	0.0003	0.9190
Volatility	0.0292	0.0287	0.0296	-0.0009	0.7129
Volume (Shares)	2,022,153.2118	1,785,488.5647	2,258,817.8588	-473,329.2941	0.5496
Market Cap ('000$)	10,388,413.9936	10,522,443.5629	10,254,384.4243	268,059.1386	0.6730

3.2 Empirical setting and variable construction

To investigate the intraday market conditions during the March 2020 volatility surge, we follow Easley et al. (2012) and implement a volume clock instead of a chronological clock. The volume clock setup has several advantages over a chronological clock setup. First, the volume clock highlights the period of volatile market condition. A large amount of trading during a short period of time would spread over several observations and provide a richer set of information. Moreover, traditional market microstructure measures based on low-frequency settings, such as Kyle, Roll, and Amihud measures, perform well in a high-frequency setting (Easley et al. (2021)). Lastly, since the first three MWCB took place a few minutes after the market opened or even before the market opened, the chronological clock setting would not provide much information during the "before" window in a before/after analysis. In comparison, a volume clock measure could rely on the previous days and overnight information.

When implementing the volume clock setting, for each stock in our sample, we divide and group the trading and quote data during March 2020 into volume bulks. Each volume bulk has the same dollar volume traded, set as 1/50 the average daily dollar volume during the first week of March 2020. Hence, we have about 50 observations on an average day and more than 50 observations on a volatile trading day.

For each volume bulk, we set the time bar (τ) as one minute, get the beginning and ending time stamps, and record the administrative messages. Following Easley et al. (2012) and Easley et al. (2021), we compute multiple stock-volume bulk measures. For each transaction, we also implement the Lee and Ready (1991) algorithm to determine whether it is a buy-initiated trade or a sell-initiated trade. In

[10] We describe the propensity score matching procedure in the appendix.

[11] The sample stocks include well-known companies, such as Fair Isaac Corporation (FICO) and Dell Technologies Inc. (DELL).

the following formulas, D_τ is the signed direction of the trade, obtained by the Lee and Ready (1991) algorithm.

- Return is computed as the logarithmic difference between consecutive mid-point prices

$$r_\tau = ln(P_\tau^{mid}) - ln(P_{\tau-1}^{mid}) \tag{2}$$

- Return volatility is computed as the sum of squared returns

$$RV = \sum_\tau r_\tau^2 \tag{3}$$

- Quoted spread is the difference between the National Best Ask and National Best Bid, divided by the mid-point quoted price.

$$QS_\tau = \frac{P_\tau^{ask} - P_\tau^{bid}}{P_\tau^{mid}} \times 100 \tag{4}$$

- Effective spread is computed as

$$ES_\tau = 2 \times D_\tau \times \frac{P_\tau^{trade} - P_\tau^{bid}}{P_\tau^{mid}} \times 100 \tag{5}$$

- Realized spread is given by

$$RS_\tau = 2 \times D_\tau \times \frac{P_\tau^{trade} - P_{\tau+t}^{bid}}{P_\tau^{mid}} \times 100 \tag{6}$$

  Where $P_{\tau+t}^{mid}$ is the mid-point price t minutes after the trade took place. We take t as five minutes in this specification.

- The Goyenko et al. (2009) spread measure captures the permanent price change over a t-minute window, and it is computed as

$$GHT_\tau = 2 \times D_\tau \times [ln(P_{\tau+t}^{mid}) - ln(P_\tau^{mid})] \times 100 \tag{7}$$

  Where $P_{\tau+t}^{mid}$ is the mid-point price t minutes after the trade took place. We take t as five minutes in this specification.

- Order imbalance is the difference between the quoted size at National Best Ask and the quoted size at National Best Bid. A positive order imbalance suggests selling pressure.

$$IO_\tau = Size_\tau^{ask} - Size_\tau^{bid} \tag{8}$$

- The Roll measure (Roll (1984)) is computed as

$$R_\tau = 2\sqrt{|cov(\mathbf{\Delta P}_\tau, \mathbf{\Delta P}_{\tau-1})|} \tag{9}$$
$$\mathbf{\Delta P}_\tau = [\Delta P_{\tau-W}, \Delta P_{\tau-W+1}, ..., \Delta P_\tau]$$

  Where $\Delta P_{\tau-W}$ is the change in the last traded price between bars $\tau - 1$ and τ, and W is the look-back window size, which we set as 50. Then Roll impact is the Roll measure divided by the dollar value traded.

$$Roll_\tau = \frac{R_\tau}{P_\tau V_\tau} \times 1,000,000 = \frac{2\sqrt{|cov(\mathbf{\Delta P}_\tau, \mathbf{\Delta P}_{\tau-1})|}}{P_\tau V_\tau} \times 1,000,000 \tag{10}$$

- Kyle's lambda (Kyle (1985)) is given by

$$\lambda_\tau = \frac{P_\tau - P_{\tau-W}}{\sum_{i=\tau-W}^{\tau} b_i W_i} \times 100 \tag{11}$$

Where $b_i = sign(P_i - P_{i-1})$, and W is the 50 observation look-back window.

- The Amihud illiquidity measure (Amihud (2002)) is calculated as

$$Amihud_\tau = \frac{1}{W} \sum_{i=\tau-W+1}^{\tau} \frac{|r_\tau|}{P_i V_i} \times 1,000,000 \tag{12}$$

Where r_i, P_i, and V_i are the return, price, and volume traded at bar i, and W is 50 (look-back window size).

- The volume-synchronized probability of informed trading (VPIN) (Easley et al. (2012, 2016)) is

$$VPIN_\tau = \frac{1}{W} \sum_{i=\tau-W+1}^{\tau} \frac{|V_i^S - V_i^B|}{V_i} \tag{13}$$
$$V_i^B = V_i Z(\frac{\Delta P_i}{\sigma_{\Delta P_i}}), \quad V_i^S = V_i - V_i^B$$

Where W is the look-back window size, which equals 50. Additional details can be found in Easley et al. (2016).

3.3 Methodology

To investigate the market condition around trading halts, we employ various regression models. First, we run the following before and after regression.

$$Y_{i,t} = \beta PostCB_{i,t} + \Gamma' Controls + \alpha_i + \varepsilon_{i,t} \tag{14}$$

Each observation is the n volume bulks before and after the trading halt t for stock i. $Y_{i,t}$ is the stock trading conditions outlined in the previous section. $PostCB_{i,t}$ is a dummy variable that equals one for observations after the trading halt, and zero otherwise. Its estimated coefficient β captures the before and after changes in the dependent variables during trading halts. The control variables include the average stock closing price during the first week of March 2020, the log market capitalization during the first week of March 2020, the average trading volume during the first week of March 2020, the average return volatility (realized variance) during the first week of March, the contemporaneous intraday return on the S&P500 index, the contemporaneous change in VIX index, the contemporaneous squared change in VIX index. We also include stock fixed effects α_i to control for unobserved stock-specific characteristics.[12] The standard errors are computed using OLS.

In addition, we also employ the difference-in-differences regressions to contrast the differential effects on S&P500 stocks and non-S&P500 stocks using our matched sample.

$$Y_{i,t} = \beta_1 PostCB_{i,t} + \beta_2 S\&P500_i \times PostCB_{i,t} + \Gamma' Controls + \alpha_i + \varepsilon_{i,t} \tag{15}$$

$S\&P500_i$ is a dummy variable that equals one for stocks that constitute the S&P500 index and zero otherwise. The remaining variables are defined the same way as in the before/after model. β_2 in this regression captures the difference-in-differences effects of trading halts and S&P500 membership. It could potentially shed light on the index funds/ETFs trading around the circuit breakers.

[12] We do not include time fixed effects, as they are colinear with the before/after dummy variable.

Furthermore, we interact the $PostCB_{i,t}$ dummy, which includes both MWCB and LULD breaks, with a MWCB dummy variable.

$$Y_{i,t} = \beta_1 PostCB_{i,t} + \beta_2 MWCB_{i,t} + \beta_3 MWCB_{i,t} \times PostCB_{i,t} + \Gamma' Controls + \alpha_i + \varepsilon_{i,t} \tag{16}$$

The interaction term captures the differential effects between market-wide circuit breakers and single-stock circuit breakers.

4 Empirical results

4.1 Before and after market-wide circuit breakers

To establish the changes in trading conditions around MWCBs, we run the before and after regression using the twelve variables specified in the previous section as the dependent variables. Table 5 reports the estimated coefficients of the before and after regressions, which rely on a five-volume-bulk before and after window (in total, ten volume bulks). The event windows last, on average, 13 minutes, excluding the 15-minute trading halt. The regression estimation results are qualitatively unchanged using five to ten volume bulks as the event window. Thus, we only report and discuss the results with five volume bulks in this paper.

Column (1) and column (2) report the results for the analysis on stock return and stock volatility. The estimated before-after coefficient is positive and statistically significant at a 5% significant level. The positive coefficient shows that the average stock price return is higher after the market-wide trading halts than before such halts, suggesting that the MWCB could alleviate and stabilize the sharp decline in stock prices under volatile market conditions. The corresponding coefficient for realized variance is insignificant, suggesting equally active trading before and after the trigger of MWCBs.

We report the estimated results of various quoted price-based measures in columns (3) to (6). The estimated coefficient on the quoted bid-ask spread is 0.071 and statistically significant, showing that the bid-ask spreads are, on average, 7.1bps wider after the MWCBs. Such a result suggests that the liquidity providers might perceive the trading halts as increased uncertainty and set wider spreads to compensate for the risk. Despite the widening in the quoted spreads, the results on trading costs and price impact (i.e., effective spread, realized spread, and the GHT measure) suggest an improvement (or no deterioration) in the market quality after the trading halts. The effective spread captures the difference between traded prices and quoted mid-point prices and proxies for the trading costs. The estimated coefficient (column (4)) is -0.328 and statistically significant, and it suggests that the trading costs are, on average, 32.8bps lower after the trading resumes than before the trading halt. The before-after coefficient of the realized spread, which captures the immediate price impact, is statistically insignificant, as shown in column (5). Finally, the before-after effect regarding the GHT measure, which captures the price impact over five volume bulks, is also negative and statistically significant. The result suggests that trades generate 42.0bps less impact on quoted mid-points after the MWCBs. Overall, the spread-based measures suggest that market-wide trading halts reduce the cost of trading and price impact, despite widening NBBO spreads.

Furthermore, we report the results on order imbalances in column (7). According to the definition outlined in the previous section, a positive order imbalance signals selling pressure, and a negative number signals buying pressure. The estimated coefficient on $PostMWCB$ is negative and statically significant. It indicates that the MWCBs alleviate the selling pressure the market experienced right before the market-wide trading halts.

In addition, we run the before and after analysis for various market microstructure measures. Column (8) reports the results for the Roll impact, which uses the autocovariance of price sequences to predict effective bid-ask spread. Consistent with the results on the effective spread (column (4)), the estimated

Table 5. Before and After MWCB

This table reports the before and after regression result for the market-wide circuit breakers. The dependent variables are computed according to the description in Section 3.2, and the event window is 5 volume bulks before and after the MWCBs. $PostMWCB$ is a dummy variable that equals one for observations after the trading halt, and zero otherwise. The control variables include the average stock closing price during the first week of March 2020, the log market capitalization during the first week of March 2020, the average trading volume during the first week of March 2020, the average return volatility (realized variance) during the first week of March, the contemporaneous intraday return on the S&P500 index, the contemporaneous change in VIX index, the contemporaneous squared change in VIX index. We also include stock fixed effects. The OLS standard errors are reported in parenthesis.

	Return	RV	QS	ES	RS	GHT	Order Imbalance	Roll Impact	Kyle	Amihud	VPIN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Post MWCB	0.011**	0.000	0.071**	-0.328***	0.008	-0.420**	-281979.104***	-0.474***	0.066	0.001	0.052***
	(0.005)	(0.001)	(0.032)	(0.088)	(0.179)	(0.210)	(67242.174)	(0.114)	(0.437)	(0.001)	(0.016)
Price	0.000	-0.000	0.001***	0.000	-0.001	0.001	-821.083*	0.001	-0.001	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(418.624)	(0.001)	(0.003)	(0.000)	(0.000)
log Market Cap	-0.000	-0.000	0.063***	0.018	0.160	-0.152	40097.544	0.259***	0.082	0.001***	0.013
	(0.003)	(0.000)	(0.018)	(0.049)	(0.100)	(0.117)	(37405.382)	(0.064)	(0.243)	(0.000)	(0.009)
log Volume	0.000	0.000	-0.070***	0.007	-0.196*	0.206	-54675.178	-0.284***	-0.068	-0.001***	0.002
	(0.003)	(0.000)	(0.019)	(0.053)	(0.108)	(0.126)	(40426.002)	(0.069)	(0.263)	(0.000)	(0.010)
Std	-0.001**	0.000*	0.006*	0.001	-0.001	0.001	15439.067**	0.021*	-0.012	0.000**	-0.005***
	(0.001)	(0.000)	(0.003)	(0.009)	(0.017)	(0.020)	(6560.375)	(0.011)	(0.043)	(0.000)	(0.002)
SPX ret	-0.076***	0.009***	0.367**	0.285	-1.845**	2.457**	55619.007	1.151**	0.917	0.010***	-0.081
	(0.026)	(0.003)	(0.154)	(0.424)	(0.868)	(1.015)	(325720.826)	(0.554)	(2.115)	(0.003)	(0.077)
ΔVIX	-0.001***	0.000***	0.003***	0.001	-0.010***	0.014***	5694.401***	0.010***	-0.006	0.000***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.003)	(1037.888)	(0.002)	(0.007)	(0.000)	(0.000)
$(\Delta\text{VIX})^2$	0.003	-0.000	-0.011	-0.084**	-0.020	-0.067	-30598.773	-0.074	0.067	-0.000	0.000
	(0.002)	(0.000)	(0.013)	(0.036)	(0.074)	(0.086)	(27717.678)	(0.047)	(0.180)	(0.000)	(0.007)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	230	230	230	230	230	230	230	230	230	230	230
R^2	0.332	0.258	0.626	0.223	0.217	0.224	0.341	0.454	0.033	0.428	0.229

Note: *p<0.1; **p<0.05; ***p<0.01

Post MWCB coefficient for the Roll impact measure is negative and statistically significant. Such a result echoes that the trading costs, measured by effective spread, are lower after the market-wide trading halts. Further results show no significant changes regarding Kyle's lambda and the Amihud illiquidity measure before and after the MWCBs. We interpret the insignificance as the lack of market quality deterioration after the market-wide trading halts. Lastly, the VPIN measure has a positive and significant before-after coefficient, suggesting that trading after the MWCBs becomes more informative. The increase in informed trading also justifies the widened bid-ask spreads, as the market makers face higher adverse selection cost and demand wider spreads as compensation for risk.

Overall, the results presented in Table 5 indicate that MWCBs could stabilize the market condition during periods of extreme volatility. We see improvement in stock returns, trading costs, order imbalance, and price informativeness. The above results support the efficacy of the MWCBs during market turmoil.

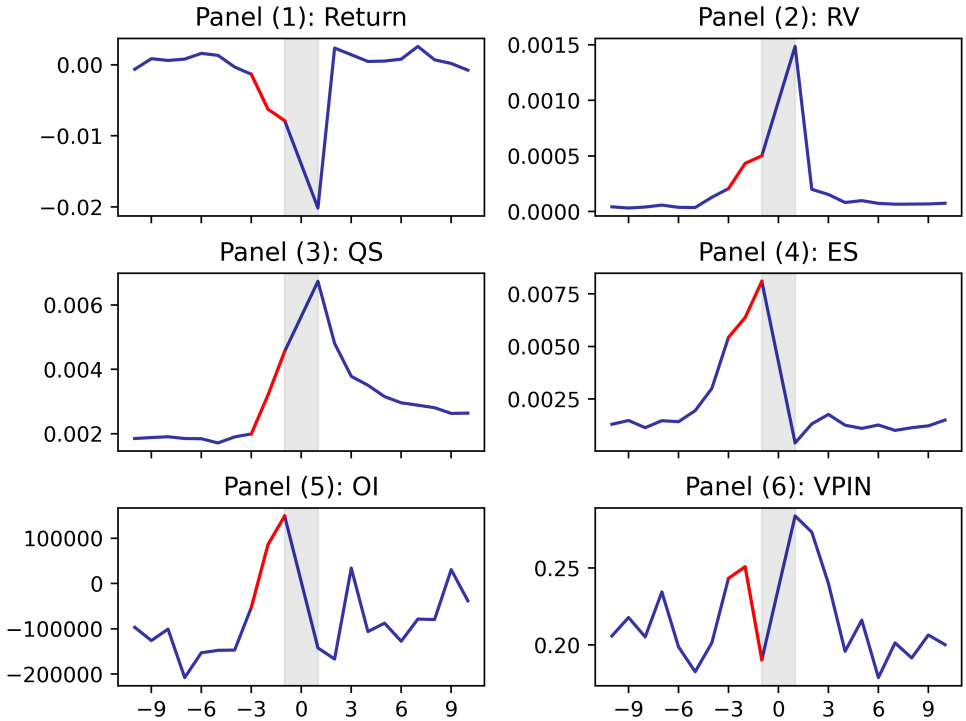
4.2 Holding back hypothesis

While the before and after analysis captures the changes in market condition around the market-wide trading halts, investigating the trend can shed light on the trading behavior of market participants. For instance, an improving time trend or slower deterioration of the market quality measures right before the MWCBs might support the holding-back hypothesis, suggesting that market participants tend to hold back from aggressive trading to avoid getting into positions that they cannot lay off in case of trading halts or to even avoid the trading halts. Contrary, a deterioration at a faster pace as the market index approaches the trading halt trigger might indicate magnet effects—traders tend to trade intensively and exacerbate the trigger of trading halts.

Figure 1 plots the time dynamic of six market quality measures around the MWCBs. For each

Figure 1. Measures time trend

The plots illustrate the time dynamic of six market quality measures around the MWCBs: return, return volatility (RV), quoted spread (QS), effective spread (ES), order imbalances (OI) and the probability of informed trading measure (VPIN).



measure, we plot the ten volume bulks before and after the market-wide trading halts, marked by the shaded area (trading halts commence at volume bulk=-1 and finish at volume bulk=+1). The red portion of the time trend highlights the observation right before the trigger of MWCBs. Each observation is the average across our sample firms and across all four MWCBs in the U.S. during March 2020.

Regarding return volatility, a similar pre-trading halt pattern is observed in Panel (2), which plots the dynamic of average realized variance around MWCBs. The stock return volatility starts to increase at volume bulk=-5 and at a faster pace until volume bulk=-3. Although continues to increase, the volatility's speed of adjustment reduces right before the MWCBs, as the red portion of the curve becomes concave. Such a pattern also supports the holding back hypothesis, as traders hold back from aggressive trading and reduce the acceleration of market volatility.

Panel (3) and panel (4) plot the time dynamics of quoted spread and effective spread, respectively. These spread-based measures do not demonstrate the "slowing down" pattern shown in return and volatility. Instead, the quoted spread increases at a constant rate, and the effective spread increases at a higher speed leading to the MWCBs. The non-decelerating dynamics suggest reluctant liquidity provision leading up to the MWCBs. The lack of liquidity supply widens the bid-ask spread and increases the price impact of liquidity demanding orders.

The dynamic of order imbalance is shown in panel (5). Starting from volume bulk=-7, buying pressure (negative order imbalance) turned into selling pressure (positive order imbalance), signaling the sell-off before trading halts. Moreover, we observe the switch in convexity pattern described above—the selling pressure is piling up at a slower pace right before the trigger of the market-wide trading halts. Lastly, panel (6) plots the evolution of the VPIN measure, which increases at a faster pace from volume bulk=-5, slows down at volume bulk=-3, and starts to decrease at volume bulk=-2. These dynamics serve as evidence that traders hold back on their aggressive (selling) trading right before the MWCBs with the intention to avoid market-wide trading halts.

In addition, the patterns plotted in Figure 1 also confirm our before and after regression results—market quality improves after the market-wide trading halts. Overall, the visual evidence does not support the magnet effect, which suggests that market participants rush to exit their position ahead of the MWCBs and exacerbate the market-wide trading halt. We find that the MWCBs improve market conditions without causing panic trading during extreme volatility and serve as an effective safeguarding mechanism employed by the exchanges.

4.3 S&P500 Index stocks

Our sample consists of 17 pairs of matched stocks, based on their market capitalization ranking at the beginning of March 2020, half at the bottom of the S&P500 index and half just out of the market index. Comparing the two groups of stock would shed light on whether index funds or index membership have differential impacts during the MWCBs.

Table 6 reports the estimation results after including an interaction term with an S&P500 dummy variable, which equals one for the stocks in the S&P500 index. In general, we do not observe significant differential effects on the S&P500 stocks on top of the sample average effects, except for the Roll Impact measure. Column (8) in the table suggests that the stocks in the market index experience an increase in the covariance-based effective spread, compared with the average stock in the sample.

Table 6. Index Membership

This table reports the before and after analysis with the interaction with a S&P500 index membership dummy for the market-wide circuit breakers. The dependent variables are computed according to the description in Section 3.2, and the event window is 5 volume bulks before and after the MWCBs. $PostMWCB$ is a dummy variable that equals one for observations after the trading halt, and zero otherwise. $S\&P500$ is a dummy variable that equals one for stock in the market index, and zero otherwise The control variables include the average stock closing price during the first week of March 2020, the log market capitalization during the first week of March 2020, the average trading volume during the first week of March 2020, the average return volatility (realized variance) during the first week of March, the contemporaneous intraday return on the S&P500 index, the contemporaneous change in VIX index, and the contemporaneous squared change in VIX index. We also include stock fixed effects. The OLS standard errors are reported in parenthesis.

	Return	RV	QS	ES	RS	GHT	Order Imbalance	Roll Impact	Kyle	Amihud	VPIN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Post MWCB	0.009	-0.000	0.044	-0.335***	-0.157	-0.247	-270878.673***	-0.697***	-0.464	0.000	0.032
	(0.007)	(0.001)	(0.041)	(0.112)	(0.228)	(0.267)	(85980.648)	(0.144)	(0.555)	(0.001)	(0.020)
Post MWCB×S&P500	0.003	0.001	0.052	0.014	0.326	-0.341	-21873.779	0.439**	1.045	0.001	0.040
	(0.008)	(0.001)	(0.050)	(0.137)	(0.279)	(0.327)	(105170.384)	(0.176)	(0.679)	(0.001)	(0.025)
Price	0.000	-0.000	0.001***	0.000	-0.000	0.001	-828.679*	0.001	-0.001	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(421.257)	(0.001)	(0.003)	(0.000)	(0.000)
log Market Cap	-0.000	-0.000	0.061***	0.017	0.146	-0.136	41081.463	0.239***	0.035	0.001***	0.012
	(0.003)	(0.000)	(0.018)	(0.049)	(0.100)	(0.117)	(37796.156)	(0.063)	(0.244)	(0.000)	(0.009)
log Volume	0.000	0.000	-0.068***	0.007	-0.180*	0.190	-55740.115	-0.262***	-0.017	-0.001***	0.004
	(0.003)	(0.000)	(0.019)	(0.053)	(0.109)	(0.127)	(40849.275)	(0.068)	(0.264)	(0.000)	(0.010)
Std	-0.001**	0.000*	0.006*	0.001	-0.000	0.000	15381.135**	0.022**	-0.009	0.000**	-0.005***
	(0.001)	(0.000)	(0.003)	(0.009)	(0.017)	(0.020)	(6582.677)	(0.011)	(0.042)	(0.000)	(0.002)
SPX ret	-0.076***	0.009***	0.367**	0.285	-1.850**	2.463**	55969.513	1.144**	0.900	0.010***	-0.082
	(0.026)	(0.003)	(0.154)	(0.425)	(0.867)	(1.015)	(326539.759)	(0.547)	(2.108)	(0.003)	(0.077)
ΔVIX	-0.001***	0.000***	0.003***	0.001	-0.010***	0.014***	5689.926***	0.010***	-0.006	0.000***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.003)	(1040.706)	(0.002)	(0.007)	(0.000)	(0.000)
$(\Delta VIX)^2$	0.003	-0.000	-0.012	-0.085**	-0.026	-0.061	-30233.951	-0.081*	0.050	-0.000	-0.001
	(0.002)	(0.000)	(0.013)	(0.036)	(0.074)	(0.087)	(27842.305)	(0.047)	(0.180)	(0.000)	(0.007)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	230	230	230	230	230	230	230	230	230	230	230
R^2	0.332	0.260	0.628	0.223	0.222	0.228	0.341	0.471	0.045	0.430	0.239

Note: *p<0.1; **p<0.05; ***p<0.01

Overall, comparing stocks in the S&P500 index with those just out of the market index, we find no significant differential impacts. The results suggest that market index membership or index fund trading do not affect the market quality when the market halts trading.

4.4 Market-wide circuit breakers and Limit Up/Limit Down

Besides the four MWCBs triggers during March 2020, we also record frequent occurrences of single-stock circuit breakers, also known as Limit Up/Limit Down (LULD), in the U.S. The extremely volatile market environment provides us with a laboratory to compare the MWCBs with the LULD. With this aim, we investigate the differential effects of the two types of trading halt safeguards by expanding our sample to include both MWCB halts and LULD halts and running the following regression.

$$Y_{i,t} = \beta_1 PostCB_{i,t} + \beta_2 MWCB_{i,t} + \beta_3 MWCB_{i,t} \times PostCB_{i,t} + \Gamma' Controls + \alpha_i + \varepsilon_{i,t} \tag{17}$$

Each observation is a stock-trading halt, including both MWCB halts and LULD halts. We exclude the observations with overlapping halts, for example, when an MWCB starts before the stock resumes trading after triggering a LULD halt, to have a clearer separation of the two mechanisms. $PostCB$ is a dummy variable that equals one for observations after the trading halts, and $MWCB$ is a dummy variable that indicates the market-wide trading halts. Thus, the coefficient on $PostCB \times MWCB$, β_3, captures the differential effect of MWCB on top of both types of trading halts.

Table 7. MWCB and LULD

This table reports the before and after analysis with the interaction with a MWCB dummy for all circuit breakers (MWCBs and LULD). The dependent variables are computed according to the description in Section 3.2, and the event window is 5 volume bulks before and after the MWCBs. $PostCB$ is a dummy variable that equals one for observations after the trading halt, and zero otherwise. $MWCB$ is a dummy variable that equals one for market-wide trading halts, and zero for LULD trading halts. The control variables include the average stock closing price during the first week of March 2020, the log market capitalization during the first week of March 2020, the average trading volume during the first week of March 2020, the average return volatility (realized variance) during the first week of March, the contemporaneous intraday return on the S&P500 index, the contemporaneous change in VIX index, the contemporaneous squared change in VIX index. We also include stock fixed effects. The OLS standard errors are reported in parenthesis.

	Return	RV	QS	ES	RS	GHT	Order Imbalance	Roll Impact	Kyle	Amihud	VPIN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Post CB	0.027**	-0.001	-0.159**	-0.243	1.629***	-1.782***	-224395.954	0.149	0.000	0.002	0.076**
	(0.014)	(0.001)	(0.066)	(0.202)	(0.560)	(0.557)	(138865.550)	(0.245)	(0.791)	(0.002)	(0.036)
MWCB	-0.047***	-0.000	-0.371***	-0.187	1.970***	-2.091***	112340.352	0.045	-0.462	-0.002	-0.104**
	(0.015)	(0.001)	(0.074)	(0.228)	(0.591)	(0.588)	(156271.785)	(0.246)	(0.835)	(0.002)	(0.040)
Post CB×MWCB	-0.016	0.001	0.236***	-0.081	-1.559**	1.299**	-40272.334	-0.576**	0.051	-0.001	-0.035
	(0.016)	(0.001)	(0.075)	(0.232)	(0.632)	(0.629)	(159060.563)	(0.275)	(0.893)	(0.002)	(0.041)
Price	0.000	-0.000	0.001***	0.000	-0.001	0.001	-799.672*	0.001*	-0.001	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(469.898)	(0.001)	(0.002)	(0.000)	(0.000)
log Market Cap	0.003	-0.000	0.083***	0.024	0.067	-0.049	34871.342	0.259***	0.103	0.001***	0.019
	(0.004)	(0.000)	(0.021)	(0.065)	(0.165)	(0.164)	(44792.904)	(0.065)	(0.233)	(0.000)	(0.011)
log Volume	0.000	0.000	-0.067***	0.012	-0.225	0.235	-56037.816	-0.287***	-0.063	-0.001**	0.002
	(0.005)	(0.000)	(0.022)	(0.067)	(0.170)	(0.169)	(46229.339)	(0.067)	(0.240)	(0.001)	(0.012)
Std	-0.001	0.000	0.006	0.001	-0.006	0.006	14719.514*	0.020*	-0.012	0.000	-0.005**
	(0.001)	(0.000)	(0.004)	(0.011)	(0.028)	(0.027)	(7505.700)	(0.011)	(0.039)	(0.000)	(0.002)
SPX ret	-0.025	0.006***	0.262*	-0.181	-1.740	2.768**	135817.642	0.841*	0.667	0.007**	-0.147**
	(0.028)	(0.002)	(0.136)	(0.418)	(1.206)	(1.201)	(286741.971)	(0.501)	(1.705)	(0.003)	(0.073)
ΔVIX	-0.001***	0.000***	0.003***	0.001	-0.012***	0.015***	5283.798***	0.009***	-0.006	0.000***	-0.000
	(0.000)	(0.000)	(0.001)	(0.002)	(0.004)	(0.004)	(1105.841)	(0.002)	(0.006)	(0.000)	(0.000)
$(\Delta VIX)^2$	0.002	-0.000	-0.008	-0.084*	0.015	-0.106	-20577.059	-0.054	0.072	-0.000	-0.004
	(0.003)	(0.000)	(0.015)	(0.046)	(0.115)	(0.114)	(31305.646)	(0.045)	(0.162)	(0.000)	(0.008)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	277	277	277	277	268	268	277	260	268	277	277
R^2	0.209	0.229	0.596	0.195	0.278	0.370	0.250	0.458	0.031	0.361	0.236

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7 reports the estimated results of the MWCB and LULD comparison regression model. Column (1) and column (2) show that there are no significant differences between MWCB and LULD regarding their effects on stock return and volatility. After each trading halt, stock return increases 2.7% on average,

and there are no significant changes in volatility. Such a pattern is consistent with the finding of the before-after analysis for MWCBs.

Interestingly, we find statistically different impacts on spread-based measures when comparing the MWCBs with the LULDs in columns (3)-(6). Column (3) shows that, on average, the quoted bid-ask spread decreases by 15.9bps after a stock experiences a trading halt. Such a decrease is statistically significant. The coefficient on the interaction term is 23.6bps, statistically significant, and greater than 15.9bps. It suggests that MWCBs' effects on quoted spread are different from those of LULD halts—the quoted spread decreases after single-stock halts, while it increases after market-wide trading halts. Such a discrepancy indicates that liquidity providers perceive higher risks or are more reluctant to supply liquidity after MWCBs than after LULDs. Column (4) shows no significant changes in effective spreads before and after trading halts, and there are no significant differences between the two types of trading halts. Columns (5) reports the results on realized spread, which measures the immediate price impact following a trade execution. On average, the realized spread increases by 162.9bps, and it is statistically significant. The coefficient on $PostCB \times MWCB$ is -1.559 and statistically significant, which suggests that the impact of MWCB is smaller. As these two coefficients are similar in magnitude with opposite signs, the results go in line with the results of the MWCB before and after analysis, which shows no significant results. Column (6) reports the estimation results for the GHT price impact, which indicate that the longer-term price impact reduces significantly by 178.2bps after trading halts. The MWCBs halts have a significantly lower impact, as the interaction term is in the opposite sign of the $PostCB$ coefficient and statistically significant.

Lastly, columns (7)-(11) present the estimation results for order imbalance and the market microstructure measures. The results show no significant differences between MWCBs and the average of all trading halts regarding their impacts on order imbalance, Kyle's lambda, the Amihud measure, and the VPIN. The result of the Roll Impact measure suggests that triggering MWCBs lowers the covariance-based effective spread.

Altogether, the analysis comparing MWCBs with LULD suggests the lack of differential effects between the two mechanisms regarding return characteristics and the market microstructure measures. The impacts on the spread-based measures are different between the two types of trading halts. Compared with LULD halts, the MWCBs have greater impacts on deterring liquidity suppliers and smaller effects on price impacts.

5 Conclusions

Making use of the extremely volatile market conditions during March 2020, which led to four market-wide trading halts and record-high episodes of single-stock circuit breakers in the U.S., we study the efficacy of these market-wide circuit breakers trading halt mechanisms employed by the exchanges during extremely volatile market environment. Using a sample of 17 pairs of matched stocks around the S&P500 index cutoff, we investigate how market quality measures, including stock returns, volatility, spread-based measures, order imbalance, and market microstructure measures, evolve around market-wide trading halts. Comparing these measures before and after the MWCBs, we find that, in general, the market condition improves significantly after the trading halt. More specifically, we find significantly higher stock return, lower price impact, lower selling pressure, and improved price informativeness after trading resumes from MWCBs. At the same time, we find that the quoted bid-ask spread widens after the MWCBs, suggesting that liquidity suppliers increase the bid-ask spreads facing the increased uncertainty after the market halts trading.

Furthermore, we investigate the time trend of the market quality measures leading up to the market-wide trading curbs. We find that the speed of deterioration decreases at the market getting closer to the trading halts, as evidenced by the change of convexity in the time trend right before the trigger of

the MWCBs. The reduced acceleration hints that market participants refrain from aggressive trading, hoping to prevent the market-wide trading halts. This phenomenon is consistent with the holding back hypothesis and alleviates the concern that investors rush to execute trades and worsens market conditions (the magnet effect).

Additionally, we complement the analysis by comparing the effects on S&P500 firms with non-S&P500. We document no significant differences in the effects of the MWCBs between the stocks at the bottom of the S&P500 index and those just outside the market index. This result suggests that index membership or index funds do not have additional impacts on market quality during MWCBs. Moreover, we also compare the effects of the market-wide trading halt and the single-stock trading halts. We find that the liquidity suppliers tend to become more reluctant to provide liquidity after MWCBs than after LULD halts. Otherwise, there are no significant differences between these two types of trading halts.

Overall, these results have important policy implications, as they indicate that the circuit breakers triggered during March 2020 contributed to alleviating the pressure in the financial market. We find that the circuit breakers in the U.S. are designed adequately and serve as an effective safeguarding mechanism employed by the exchanges.

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Appendix A: Propensity score matching

To prevent firm fundamental characteristics from affecting the comparison between the S&P500 stocks and the non-S&P500 stocks, we use the propensity score matching (Rosenbaum and Rubin (1983)). More specifically, we run the following logistic regression for the 450-550 ranked stocks based on their market capitalization at the end of 2019 and then compute the estimated propensity scores $\hat{p}_i$ for each stock i.

$$Z_i = c + \beta_1 Price_i^{1w} + \beta_2 Return_i^{1w} + \beta_3 ln(Market\,Cap_i^{1w}) + \beta_4 Volatility_i^{1w} + \varepsilon_i \tag{18}$$

$$Z_i = ln\frac{p_i}{1-p_i}$$

For stock i, Z_i is a dummy variable that equals 1 for stocks in the S&P500 index as of the first week of March 2020 and 0 otherwise. The independent variables are the average stock price, daily return, logarithmic market capitalization, and return volatility during the first week of March. We then use the nearest neighbor matching to get the 17 pairs of one-to-one matched stocks.