# CIRCUIT BREAKERS AND MARKET QUALITY

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# Circuit breakers and market quality

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**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*). Also, when compared with single-stock halts, market-wide trading halts are associated with a more significant reduction in selling pressure and panic trading. In a subsample analysis, we document that index membership and index fund trading do not have additional impacts on market quality during trading halts. 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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# 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, some theoretical studies have raised concerns about the effectiveness and benefits of circuit breakers, arguing, for example, that circuit breakers could make it more likely prices would reach the triggering threshold (the so-called *magnet effect*). On the other hand, the triggering of market-wide circuit breakers has been so rare that empirical tests of 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.

This paper aims to study the effectiveness of the U.S. market-wide circuit breakers by examining the market conditions around the trading halts in March 2020. In particular, we study their impact on market quality (e.g., liquidity conditions and price informativeness), trading behavior (e.g., the magnet and holding back effect), the differential effect between market-wide and single-instrument circuit breakers, and the effect of index membership. We use the intraday trades and quotes (TAQ) data provided by the NYSE and use all stocks in the S&P500 index as our sample. Relying on our sample data[2], 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. In addition, we complement the analysis by comparing the effects on S&P500 firms with non-S&P500 firms, which consist 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.

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. On average, stock return increases by 6.5 percentage points (p-value < 0.1) after trading resumes from the MWCBs. Moreover, we find a significant reduction in trading costs and improved liquidity. We document that, on average, the quoted bid-ask spreads narrow by 37.5 bps (p-value < 0.01), the effective spreads of executed trades reduce by 16.5 bps (p-value < 0.1), and the price impact (measured by the Goyenko et al. (2009) measure, Kyle's lambda (Kyle (1985)), and Roll impact (Roll (1984))) reduces significantly. We also find resolved selling pressure (measured by order imbalance at the top of the order book) and improved price informativeness (measured by the volume-synchronized probability of informed trading (VPIN) as in Easley et al. (2012, 2016)). Such improvements suggest that market-wide circuit breakers could improve market quality during extreme volatility. Our findings align with the Kyle (1988) theory model, which states that circuit breakers can decrease volatility and resolve order imbalances. Furthermore, our results support the Greenwald and Stein (1991) model, which predicts that circuit breakers can reduce transactional costs

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[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]A previous version of this paper was circulated, where we used the 17 pairs of matched stocks around the market index as the main sample for all analyses. The findings are qualitatively unchanged after expanding the sample to all stocks in the S&P500 index.

and bring buyers' demand to the market.

Empirically, while there exist comprehensive studies on the single-security circuit breakers,[3] market-wide circuit breakers have not been thoroughly investigated due to their infrequent occurrences. Concurrently, Li and Yao (2020) also study the MWCBs in the U.S. and find that the MWCBs help to stabilize the markets despite aggravating the trading environment initially. They rely on the subsequent drop in the market index following the initial one, which triggered that trading halt, as the counterfactual observations to establish causal effects.[4]

Second, we investigate the holding back hypothesis and the magnet effect hypothesis. The holding back hypothesis states that 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 the triggering point. Consistent with the holding back hypothesis, we provide graphic evidence that the deterioration of stock return, selling pressure, and uninformed trading slows down or even improve right before the trigger of the MWCBs. For instance, we find that the trend of stock return, while declining and heading towards the trading halt, increases right before the trading halt. Such a change in the direction 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 positions that they cannot lay off in anticipation of the MWCBs or 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 align with the intuition that the presence of holding back or of magnet effect depend on the market structure and the design and calibration of circuit breakers. For example, markets with more institutional traders might tend to hold back, while markets with higher retail participation might tend to show magnet effects. Also, 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.

In addition, we compare the effects of the market-wide trading halts and the single-stock trading halts (Limit Up/Limit Down or LULDs). Compared with LULDs, we find that MWCBs are associated with a more significant reduction in selling pressure and uninformed panic trading. Otherwise, there are no significant differences between these two types of trading halts regarding the stocks' fundamental characteristics, such as return, volatility, and spreads. Lastly, we complement the analysis by studying the differential effects of MWCBs on S&P500 stocks and non-S&P500 stocks by using a matched sample of 17 pairs of stocks around the market index cutoff. Adding the interaction terms with an index membership dummy variable, 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 fund trading do not have a differential impact around MWCBs.

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

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[3]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 (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.

[4]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.

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.

# 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 (MWCBs) 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.[5] 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 the 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[6] 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 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.[7]

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.

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[5]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.

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

[7]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.

## 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 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 an 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&P500 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.

$$Price\,Band = Reference\,Price \pm Reference\,Price \times Percentage\,Parameter \qquad (1)$$

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 2. 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, or 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

**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 | | |

minutes, and the halt can be extended for another five minutes.[8]

Based on the LULD 2020 Annual Report[9], Table 3 compares the LULD Pause during the 2020 volatile period with the non-volatile period[10] and reports the daily average number of the Limit States and LULD Pauses. On average, during the non-volatile period, there were around 200 Limit States, and roughly 10% of the Limit States resulted in a LULD pause. Such figures increased notably during the volatile market period. There were almost 1,000 occurrences of the 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 daily average 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

To investigate the effect of circuit breakers during the March 2020 volatile market, we use the 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 the 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 prices of the S&P500 index and VIX index from Cboe Global Markets. Finally, we get the membership list of the S&P500 index from the indexing agency's website.

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[8]For more information about the Limit Up/Limit Down Plan, see https://www.luldplan.com.

[9]The LULD 2020 Annual Report is available at https://www.luldplan.com/studies.

[10]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).

## 3.1   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 conditions. 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's Lambda, Roll Impact, and Amihud illiquidity measures, perform well in a high-frequency setting (Easley et al. (2021)). Lastly, since the first three MWCBs 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 ($\tau$) 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 or a sell-initiated trade. In the following formulas, $D_\tau$ 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

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

- Realized spread is given by

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

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 $\tau$, 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

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

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

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

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).

## 3.2 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 $\beta$ captures the before and after changes in the dependent variables during trading halts. The control variables include the contemporaneous intraday return on the S&P500 index, change in the VIX index, and squared change in

the VIX index. We also include stock fixed effects $\alpha_i$ to control for stock-specific characteristics.[11] The standard errors are computed using OLS.

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

$$Y_{i,t} = \beta_1 PostCB_{i,t} + \beta_2 MWCB_{i,t} + \beta_3 MWCB_{i,t} \times PostCB_{i,t} + \Gamma'Controls + \alpha_i + \varepsilon_{i,t} \qquad (15)$$

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 eleven variables specified in the previous section as the dependent variables. Table 4 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 median event window is 15 minutes, excluding the 15-minute trading halt. We exclude observations with an event window longer than one day, which may suggest the stock experiences trading halts other than the MWCBs. 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) reports the result of the analysis of stock return. The estimated before-after coefficient is positive and statistically significant at a 10% significant level. On average, stock returns increase by 6.5 percentage points after continuous trading resumes from the MWCBs. This positive coefficient shows that the average stock price return is higher after the market-wide trading halts than before, suggesting that the MWCB could alleviate and stabilize the sharp decline in stock prices under volatile market conditions. The corresponding coefficient for realized variance (in Column (2)) is statistically insignificant, suggesting equally active trading before and after the MWCBs.

We report the estimated results of various spread-based measures in Columns (3) to (6), which capture different aspects of transaction costs and liquidity. The estimated coefficient on the quoted bid-ask spread is -0.375 and statistically significant (p-value < 0.01), showing that the bid-ask spreads are, on average, 37.5 bps narrower after the MWCBs. Such a result suggests that the liquidity providers might perceive a less uncertain market condition and are willing to charge a narrower bid-ask spread for liquidity provision. In line with the narrowing 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 -0.165 and statistically significant at a 10% significance level, suggesting that the trading costs are, on average, 16.2bps 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 negative but 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 (p-value < 0.05). The result suggests that trades generate 95.3bps 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.

Furthermore, we report the results of 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

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

## Table 4. 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 3.1, and the event window is five volume bulks before and after the MWCBs. The sample stocks include all stocks in the S&P500 index. $PostMWCB$ is a dummy variable that equals one for observations after the trading halt and zero otherwise. The control variables include the contemporaneous intraday return on the S&P500 index, the contemporaneous change in the VIX index, and the contemporaneous squared change in the 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 | 0.065* | -0.058 | -0.375*** | -0.165* | -1.776 | -0.953*** | -1013432.479*** | -0.188*** | -0.448** | 0.002 | 0.089*** |
| | (0.036) | (0.081) | (0.034) | (0.087) | (1.248) | (0.369) | (154959.808) | (0.022) | (0.205) | (0.002) | (0.005) |
| SPX ret | -7.367* | 16.566* | 17.433*** | 4.087 | 10.685 | 49.375 | 9706828.875 | 8.955*** | 16.715 | 0.411** | -0.455 |
| | (3.861) | (8.698) | (3.605) | (9.321) | (133.997) | (39.587) | (16642438.057) | (2.378) | (22.124) | (0.181) | (0.506) |
| $\Delta VIX$ | -0.002** | 0.001 | 0.005*** | -0.001 | 0.016 | 0.017*** | 27422.693*** | 0.005*** | 0.001 | 0.000 | -0.001*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.021) | (0.006) | (2586.732) | (0.000) | (0.003) | (0.000) | (0.000) |
| $(\Delta VIX)^2$ | 0.013 | -0.010 | -0.087*** | -0.030 | -0.211 | -0.242 | -116768.308* | -0.041*** | -0.340*** | -0.000 | 0.004** |
| | (0.015) | (0.034) | (0.014) | (0.037) | (0.525) | (0.155) | (65173.025) | (0.009) | (0.086) | (0.001) | (0.002) |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,798 | 2,798 | 2,798 | 2,798 | 2,798 | 2,798 | 2,798 | 2,798 | 2,774 | 2,774 | 2,774 |
| $R^2$ | 0.212 | 0.228 | 0.247 | 0.177 | 0.126 | 0.194 | 0.206 | 0.452 | 0.153 | 0.250 | 0.314 |

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

signals buying pressure. The estimated coefficient on $PostMWCB$ is negative and statically significant (p-value < 0.01). It indicates that the MWCBs could alleviate the selling pressure during the declining market.

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 and GHT (Columns (4) and (6)), the estimated $PostMWCB$ coefficient for the Roll impact measure is negative and statistically significant (p-value < 0.01). Similarly, we find a significant decrease (p-value < 0.05) in Kyle's Lambda. Such results echo that the trading costs are lower after the market-wide trading halts. Further results show no significant changes regarding the Amihud illiquidity measure before and after the MWCBs. Lastly, the VPIN measure has a positive and significant (p-value < 0.01) before-after coefficient, suggesting that trading after the MWCBs becomes more informative.

Overall, the results presented in Table 4 indicate that MWCBs could stabilize the market condition during periods of extreme volatility. We see improved stock returns, trading costs, order imbalance, and price informativeness. These findings align with the Kyle (1988) theory model, which states that circuit breakers can decrease volatility and resolve order imbalances, and support the Greenwald and Stein (1991) model, which predicts that circuit breakers can reduce transactional costs and bring buyers' demand to the market.

## 4.2   Holding back hypothesis

While the before and after analysis captures the changes in market conditions 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. Measures time trend

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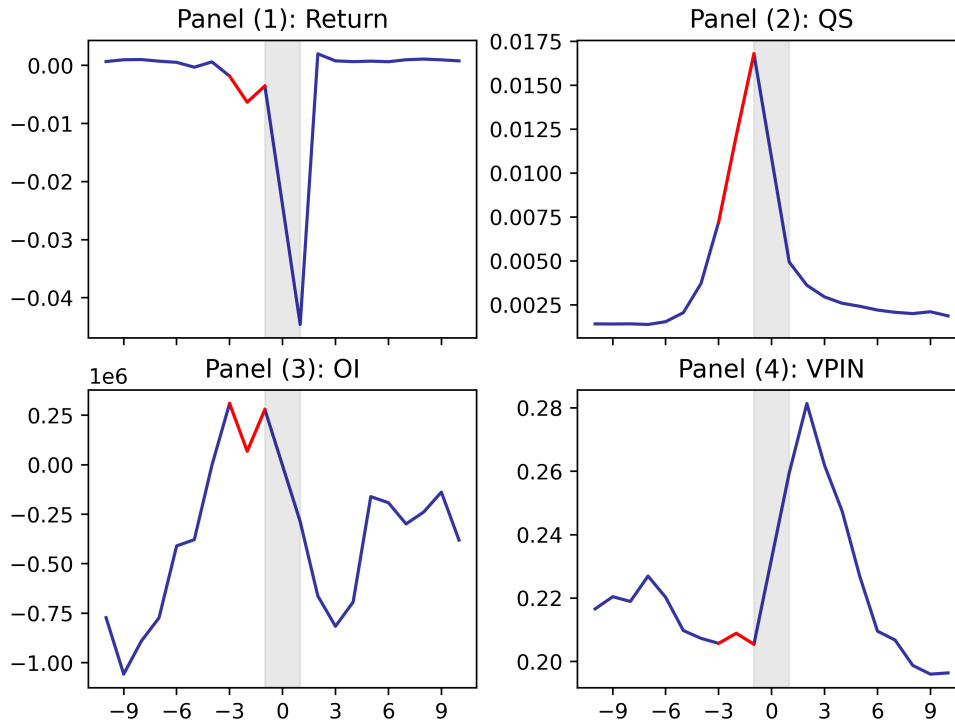


Figure 1 plots the time dynamic of four market quality measures around the MWCBs. For each measure, we plot the ten volume bulks before and after the market-wide trading halts, marked by the shaded area (trading halts commence at volume bulk -1 and finish at volume bulk +1). The red portion of the time 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.

In Panel (1), focusing on the trend leading up to the trading halt, we observe that the average stock return starts to decrease around volume bulk -9 and -8, although slowly. Then, it declines drastically, starting at volume bulk -3. The rapid and increasing rate drop in return continues until volume bulk -1, where the direction of travel reverts. Instead of further decline, stock returns increase at the last observation right before the trigger of the MWCBs. Such a pattern supports the holding back hypothesis, as traders hold back from aggressive trading and reduce the acceleration of the market decline.

Panel (2) plots the time dynamic of the average quoted spread around the MWCBs. Starting from volume bulk -5, the quoted spread increases at a steady yet not accelerating pace, leading to the trigger of the market-wide trading halt. Moreover, the dynamic of order imbalance is shown in Panel (3). Starting from volume bulk -9, buying pressure (negative order imbalance) turned into selling pressure (positive order imbalance), signaling the sell-off before trading halts. Right before the trigger of the MWCB, we observe a drop in the selling pressure at volume bulk -3, the same pattern observed in the return dynamic. Lastly, we observe a similar pattern for the VPIN measure (Panel (4))—the probability of informed trading, as opposed to uninformed panic trading, increases right before the market-wide trading halts. These dynamics serve as evidence that traders hold back on their aggressive (selling) trading right before the MWCBs 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 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). The extremely volatile market environment provides us with a laboratory to compare the MWCBs with the LULDs. 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.

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

Each observation is a stock-trading halt, including both MWCB 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 $PostCB \times MWCB$, $\beta_3$, captures the differential effect of MWCB on top of both types of trading halts.

### Table 5. 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 3.1, 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 contemporaneous intraday return on the S&P500 index, the contemporaneous change in the VIX index, and the contemporaneous squared change in the 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 | -0.010 | -0.009 | -0.221*** | 0.018 | 0.750 | -0.914 | 815539.742* | -0.039 | -0.048 | -0.001 | -0.063*** |
| | (0.085) | (0.190) | (0.082) | (0.213) | (3.296) | (0.987) | (420613.212) | (0.061) | (0.561) | (0.005) | (0.014) |
| MWCB | -0.176** | 0.180 | -0.002 | -0.220 | 2.363 | -0.224 | 1441255.187*** | 0.086 | 0.211 | -0.001 | -0.170*** |
| | (0.088) | (0.198) | (0.084) | (0.218) | (3.178) | (0.952) | (405507.213) | (0.058) | (0.536) | (0.004) | (0.013) |
| Post CB×MWCB | 0.074 | -0.050 | -0.142 | -0.185 | -2.485 | -0.054 | -1802696.141*** | -0.143** | -0.392 | 0.003 | 0.152*** |
| | (0.091) | (0.204) | (0.088) | (0.228) | (3.502) | (1.049) | (446901.838) | (0.065) | (0.594) | (0.005) | (0.015) |
| SPX ret | -7.030** | 15.925** | 15.753*** | 4.410 | 9.241 | 51.114 | 8041354.664 | 8.337*** | 15.967 | 0.387** | -0.306 |
| | (3.483) | (7.822) | (3.336) | (8.618) | (121.669) | (36.446) | (15525378.193) | (2.188) | (20.190) | (0.165) | (0.495) |
| $\Delta VIX$ | -0.001*** | 0.001 | 0.005*** | -0.001 | 0.015 | 0.017*** | 26601.318*** | 0.005*** | 0.000 | 0.000 | -0.001*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.019) | (0.006) | (2472.483) | (0.000) | (0.003) | (0.000) | (0.000) |
| $(\Delta VIX)^2$ | 0.013 | -0.011 | -0.085*** | -0.031 | -0.199 | -0.243* | -112873.492* | -0.040*** | -0.331*** | -0.000 | 0.004* |
| | (0.014) | (0.032) | (0.014) | (0.035) | (0.492) | (0.148) | (62833.467) | (0.009) | (0.081) | (0.001) | (0.002) |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,103 | 3,103 | 3,092 | 3,092 | 3,044 | 3,044 | 3,044 | 3,024 | 3,000 | 3,000 | 3,000 |
| $R^2$ | 0.195 | 0.216 | 0.244 | 0.165 | 0.127 | 0.178 | 0.198 | 0.454 | 0.153 | 0.248 | 0.317 |

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

Table 5 reports the estimated results of the MWCB and LULD comparison regression model. Overall, the estimated results in Columns (1)-(6) show no significant difference between the market-wide trading halts and the single-stock trading halts regarding the stock return, volatility, and the four bid-ask spread based measures.

Interestingly, in general, MWCBs are associated with higher selling pressure than LULDs, as confirmed by the positive and significant (p-value < 0.01) coefficient of $MWCB$ for the order imbalance measure

(Column (7)). Moreover, MWCBs are more effective in resolving selling pressures, as the estimated coefficient for $PostCB \times MWCB$ for order imbalance is negative and statically significant (p-value < 0.01).

Lastly, Columns (8)-(11) present the estimation results for the market microstructure measures. The results show that, compared with LULDs, MWCBs are associated with a larger decrease in price impact as measured by Roll Impact (Column (8)) and a larger increase in the probability of informed trading (Column (11)). There are no statistically significant differences regarding Kyle's Lambda and the Amihud illiquidity measure.

Altogether, the analysis comparing MWCBs with LULDs suggests the lack of differential effects between the two mechanisms regarding return characteristics and the spread-based transaction cost measures. The impacts on order imbalance, Roll Impact, and VPIN suggest that MWCBs might be more efficient in resolving selling pressure and deterring uninformed panic trades.

## 4.4  S&P500 Index membership

To shed light on whether stocks in the market index and not in the market index experience similar impacts around the MWCBs, we conduct a subsample analysis by comparing stocks at the bottom of the S&P500 and stocks just outside the market index. With our dataset, we select a sample of 34 stocks 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, but 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.

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.[12]

Table 6 shows the summary statistics of the sample stocks[13] 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 7 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.

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 does not affect the market quality when the market halts trading.

## 5  Conclusions

Using 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 an extremely

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

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

## Table 6. Subsample summary statistics

This table provides the summary statistics of our 17 pairs of matched sample stocks around the cutoff of the S&P500 index. 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 |

## Table 7. Index membership

This table reports the before and after analysis with the interaction with an S&P500 index membership dummy for the market-wide circuit breakers. The dependent variables are computed according to the description in Section 3.1, 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 contemporaneous intraday return on the S&P500 index, the contemporaneous change in the VIX index, and the contemporaneous squared change in the 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) |
| 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

volatile market environment. Using a sample of about 500 stocks in the S&P500 index, 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, reduced trading costs, lower price impact, lower selling pressure, and improved price informativeness after trading resumes from MWCBs.

Furthermore, we investigate the time trend of the market quality measures leading up to the market-wide trading curbs. We find that the deterioration in multiple measures stops and reverts as the market gets closer to the trading halts. These changes in the direction of the time dynamic hint that market participants refrain from aggressive trading, hoping to prevent market-wide trading halts. This phenomenon is consistent with the holding back hypothesis and alleviates the concern that investors rush to execute trades and worsen market conditions (the magnet effect).

Additionally, we compare the effects of the market-wide trading halt and the single-stock trading halts. Compared with LULDs, we find that MWCBs are associated with a more significant reduction in selling pressure and uninformed and panic trading. Otherwise, there are no significant differences between these two types of trading halts regarding the stocks' fundamental characteristics, such as return, volatility, and spreads. Moreover, we also 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.

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 $i$.

$$Z_i = c + \beta_1 Price_i^{1w} + \beta_2 Return_i^{1w} + \beta_3 ln(Market\,Cap_i^{1w}) + \beta_4 Volatility_i^{1w} + \varepsilon_i \qquad (17)$$

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

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.