Do market-wide circuit breakers calm the markets or panic them?*

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Abstract

Market-wide circuit breakers (MWCBs), which halt trading for 15 minutes across all U.S. stock exchanges, were triggered four times in March 2020. We provide some of the first evidence on the effectiveness of MWCBs using a difference-in-differences approach with tick history data. Although MWCBs increase stocks' realized volatility and quoted spread immediately after markets reopen, they boost stocks' trading volume and especially shore up purchases of the stocks that have been hit hard. When we extract the time stamps of stock trading surrounding trading halts, we find significant differences in market opening and reopening time between different stock exchanges. In sum, our results suggest that the MWCBs help to stabilize the markets despite aggravating the trading environment initially.

Keywords: Circuit breakers; Volatility; Liquidity; COVID-19.

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"Market-wide circuit breakers enforce a trading pause so that investors have time to absorb information, better understand what's happening in the market, and make decisions accordingly. The halt in trading this morning means that the market-wide circuit breakers functioned exactly as designed."

— Stacey Cunningham, President of NYSE, March 10, 2020

1 Introduction

The novel coronavirus disease (COVID-19) has prompted unprecedented swings in stock markets worldwide. In the U.S., market volatilities in March 2020 rivaled or surpassed those last seen in October 1987 and December 2008 (Baker et al., 2020). Many security exchanges around the globe have certain stabilizing mechanisms in place to temporarily halt trading under extreme market conditions. One of the most prominent mechanisms is the market-wide circuit breakers (MWCBs) in the U.S., which were introduced in the wake of Black Monday in 1987. MWCBs were advocated by the Brady Commission, who argued that these mechanisms "cushion the impact of market movements, which would otherwise damage market infrastructures" (Presidential Task Force on Market Mechanisms, 1988, pp. 66).

Despite the well-stated goals and wide adoption of MWCBs in many countries, it is not clear from a theoretical perspective that circuit breakers can accomplish their mission. Early studies find that circuit breakers interrupt the natural movement of prices, prevent mutually beneficial trades (Grossman, 1990), and delay price discovery (Fama, 1989). Furthermore, circuit breakers may have the perverse effect of increasing volatility by forcing agents to sub-optimally advance their trades (Subrahmanyam, 1995) and causing volatility contagion (Liu and Zeng, 2020). Even worse, the mere presence of rule-based circuit breakers makes it more likely for stock prices to reach the pre-determined threshold levels, a so-called "magnet effect" (Subrahmanyam, 1994; Chen et al., 2023). In contrast, Kyle (1988) argues that trading halts help reduce volatility, resolve order imbalance by allowing market participants to process information and revise positions. Also, in the presence of limited participation and information asymmetry, circuit breakers can help restore market order by reducing transactional risk (Greenwald and Stein, 1991).

As with the theoretical literature, the empirical literature on the merits of MWCBs is inconclusive, partly because they have been triggered only once prior to March 2020. MWCBs, which halt trading across all markets in the U.S., can be triggered at three thresholds that measure a decrease against the previous day's closing price of the S&P 500 index – 7% (level 1), 13% (level 2), and 20% (level 3). The precipitous drops in the S&P 500 index triggered level 1 MWCBs (a 15-minute trading halt) during the opening hour on March 9, 12, and 16, and later in the day on March 18 (Figure 1). In this paper, we make a first attempt to evaluate the efficacy of MWCBs amid COVID-19.

We use tick history data for all S&P 500 constituent stocks from Refinitiv DataScope. We calculate the minute-by-minute return, realized volatility, jump volatility, quoted spread, effective spread, and trading volume, among others, for individual stocks surrounding each of the trading halt. The challenge is to measure what would have happened in the absence of MWCBs. We construct two sets of counterfactuals based on different occasions, each of which captures significant market losses. Our baseline setting exploits the fact that the same level of MWCBs can only be triggered once per day when the S&P 500 index drops below its corresponding threshold for the very first time. Therefore, we use four occasions where the S&P 500 index fell below the 7% threshold for the second time on the same day as counterfactuals (Figure 1). In the empirical estimation, we control for stock fixed effects to remove any stock-invariant characteristics that can affect the outcomes. We perform a difference-in-differences (DD) estimation by comparing the before-and-after trading halt outcomes with the counterfactuals. Our analysis tracks the market dynamics from 3 minutes pre-halt to 15 minutes post-halt to allow for time-varying responses to MWCBs.

The effects of MWCBs on market outcomes are large and fluid — we find a significantly greater impact in the initial minutes than in subsequent minutes. The DD estimates reveal an immediate and intense increase in stocks' realized volatility. In the very first minute post-halt, volatility soars to a level that is higher than pre-halt by an annualized figure of 194%. Realized volatility stays elevated for over 10 minutes before subsiding to a level which is lower than pre-halt. Similar results are found for quoted spread, which stays widened for about 5 minutes after the market trading resumes. This evidence is consistent the finding that market makers are reluctant to post narrower spreads when facing liquidity crunch and uncertainty in bond markets amid COVID-19 (O'Hara and Zhou, 2021). Immediately following the trading halt, we find a significant increase in trading volume. Relative to pre-halt, trading volume is 116% higher in the very first minute post-halt and remains 40% higher for over 10 minutes. Furthermore, buyer-initiated trading volume and bid volume outgrow seller-initiated and ask volume during the first 5 minutes post-halt.

MWCBs can scare off investors. Alternatively, they can stabilize the market by providing a cooling-off period so that investors can process information and participate in the market (SEC, 1998). We investigate whether the trading halts can prevent panic sell-offs of stocks that were hit hard. We find a significantly negative relation between the 5-minute post-halt trading volume and the intra-day stock returns prior to the trading halt. In addition, those stocks which were hit hard prior to trading halts enjoy greater buyer-initiated trading volume and bid volume, and there is no evidence of panic sell-offs. Taken together, our results suggest that while circuit breakers panic the markets for a short period of time, especially by aggravating market volatility and quoted spread, they do help boosting trading and bidding volume which could prevent the markets from collapsing.

Although the first set of counterfactuals represents occasions of significant market decline, an important caveat is that investors understand the same level of MWCBs would not be triggered again on the same day. Our second counterfactual occasion preceded (rather than followed) the MWCBs on March 18. Shortly after 11AM on the morning of March 18, the S&P 500 index dropped within 20 points from the 7% threshold but rebounded before noon without triggering the circuit breakers. In particular, We use 11:14 AM, when the S&P 500 index dropped by 6%, as the cutoff time (Figure 1) to construct the second set of counterfactuals. Critical to our identification, this 6% drop is not on the direct path that eventually tripped the circuit breaker, as S&P 500 index rebounded before noon, then plummeted to reach the 7% threshold. Furthermore, having observed that the circuit breakers being triggered three times in the last two weeks, investors might feel the imminent pressure of MWCBs. In addition, since the MWCBs were triggered in early afternoon on March 18, focusing on March 18 alone can also alleviate the concerns that our baseline results are driven by the well-established intra-day pattern that stock volatility and volume are generally higher in the early morning (see, e.g., Admati and Pfleiderer, 1988; Anderson and Bolleslev, 1997). While this counterfactual is by no means perfect, most of our previous conclusions continue to hold when we examine the circuit breaker effect on March 18.

We then focus on the path of market outcomes leading up to the trading halt on March 18 to test the magnet effect hypothesis. During the 15-minute window before trading halt, we find that stock prices, stock volatility, and trading volume do not display any clear patterns in the 15-minute window prior to the trading halt. In sum, the empirical support for the magnet effect hypothesis is limited.

The U.S. is one of a handful countries with both MWCBs and individual stock trading halts in place (Chen et al., 2023). The individual trading halts are primarily mandated by the limit up-limit down (LULD) mechanisms. A recent study by Hautsch and Horvath (2019) shows that the LULD-induced trading pauses can cause extra volatility. Among the four days with market-wide trading halts, we only find a very small number of stocks that experienced additional trading pauses due to LULD. This evidence assures us that our results are not driven by individual stock trading halts.

We last examine the operation of MWCBs. MWCBs were triggered shortly after the market opened on March 9 and 12, and were triggered literally at the opening bell on March 16. The market opening (and reopening) mechanisms differ substantially between the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotation (NASDAQ). In particular, the NYSE offers the designated market makers (DMMs, formerly known as "specialists") some discretion to delay market opening and reopening (after trading halt) for a given security to ensure orderly trading. NASDAQ incorporates opening cross and halt cross (a call auction) into its continuous multi-dealer quote system to facilitate price formation Pagano et al. (2013).

We extract the time stamps for stocks' adjacent trades separated by each trading halt. The transaction time analysis reveals substantial differences in price dissemination between the two stock exchanges. During the first three early morning trading sessions, only 42% of the NYSE-listed S&P 500 index constituent stocks reported an opening trade before MWCBs were triggered, while the corresponding figure for NASDAQ was 93%. On average in our sample, it took NYSE stocks 150 seconds to report a trade after trading halt, whereas all NASDAQ stocks resumed trading immediately after the market reopened.[1] The speed and accuracy of price dissemination in financial markets are critical for price discovery. From this perspective, our findings highlight the differences between stock exchanges in the functioning of MWCBs.

Our paper contributes to the empirical literature on the effects of MWCBs. Based on evidence from the Tel-Aviv Stock Exchange during the 1987 market crash, Lauterbach and Ben-Zion (1993) conclude that trading halts help smooth the price adjustment and reduce order imbalances. Goldstein and Kavajecz (2004) examine the behavior of market participants around October 27, 1997, the only time that MWCBs have been triggered in the U.S. before 2020. They present evidence that traders attempt to advance transactions in anticipation of the trading halt. Our results are also related to the studies that investigate whether some forms of firm-specific trading halts and price limits affect price volatility and market efficiencies. Some of these papers study market behavior before and after trading halts (Corwin and Lipson, 2000; Christie et al., 2002; Brugler et al., 2018; Lin and Swan, 2019); some compare market behavior surrounding trading halts with other extreme times (Lee et al., 1994; Hautsch and Horvath, 2019) or exploit regulatory settings that do not trigger a trading halt (Brogaard and Roshak, 2016). Apart from the obvious fact that we focus on the most recent occurrence of MWCBs amid COVID-19, our choice of counterfactuals can mitigate the effects of most confounding factors.

As such, our paper is part of a literature attempting to understand how COVID-19 impacts financial markets. Alfaro et al. (2020) identify the relationship between unanticipated changes in predicted coronavirus infections and aggregate equity market returns. Ramelli and Wagner (2020) chronicle the stock market reaction to different stages of the COVID-19 outbreak. Contessi and De Pace (2020) investigate the transmission of COVID-19 shocks in a sample of 18 major stock markets. Baker et al. (2020) highlight the effects of policy responses in contributing to stock market volatility in the U.S. O'Hara and Zhou (2021) point out a new role of the Federal Reserve as the market maker of last resort in corporate bond markets. Cox and Woods (2023) find that COVID-19 has a significant impact on order routing, pre-trade transparency, and automated trading. Our study examines the performance of a critical component of the financial market architecture originally designed to address challenges posed by extreme events like COVID-19. Our findings lend empirical support to regulators' claims that MWCBs can "provide coordinated means to address potentially destabilizing market volatility".[2]

The remainder of the paper is organized as follows. Section 2 introduces the institutional background of MWCBs during the COVID-19 pandemic. Section 3 outlines data and the empirical methodology. Section 4 presents the baseline results, with more detailed analyses in Section 5. Section 6 examines the operations of MWCBs. Finally, Section 7 concludes.

2 Institutional Background

2.1 The Market-wide Circuit Breakers

Circuit breakers are market-wide trading halts designed to "to offer investors and the markets an opportunity to assess information and positions when the markets experienced a severe, rapid decline".[3] All U.S. futures and options exchanges also adopt concurrent trading halts to ensure cross-market coordination. The MWCBs were mandated by the U.S. Securities and Exchange Commission (SEC) in 1988 to prevent a market crash such as the Black Monday of 1987, when the Dow Jones Industrial Average (DJIA) plunged 22.6%. Since then, MWCBs have undergone a number of modifications. Table 1 summarizes these changes. Triggering thresholds of MWCBs were initially tied to changes in absolute points of DJIA. Trading would be halted for one hour and two hours when DJIA fell by 250 and 400 points, respectively. As the value of DJIA increased over time, the triggering thresholds of MWCBs were raised to 350 and 550 points since January 1997, with the length of trading halt reduced to 30 minutes and one hour, respectively.

Before March 2020, the only time that MWCBs were triggered occurred on October 27, 1997, known as the "mini-crash". At 2:36 PM that day, the DJIA fell by 350 points and triggered the circuit breakers, which halted trading for 30 minutes. Trading resumed at 3:06 PM, but the DJIA continued to drop, hitting the 550 points threshold at 3:30 PM, and eventually led to an early market closure. The SEC investigated this event and concluded that the triggering was "needless at best", and the early market closure did not appear to be necessary (SEC, 1998). As a result, the triggering thresholds of MWCBs were changed to be based on a moving benchmark, and the length of the trading halt would vary depending on the triggering time (middle panel of Table 1). This rule still used DJIA as the market index but recalculated it every quarter, based on the average closing value of DJIA in the month prior to the beginning of a new quarter.[4]

The most recent changes to trading halt rules occurred in the aftermath of the "flash crash" on May 6, 2010,[5] when a sudden 9% drop in DJIA within a few minutes was still not large enough to trigger MWCBs. Since February 2013, the broader market measure of S&P 500 index replaced DJIA as the reference to measure market decline, and the triggering thresholds were again revised. In particular, the threshold levels were measured against the closing value of the previous day's price (bottom panel of Table 1). Moreover, the rule of the triggering time periods was simplified to differ only before and after 3:25 PM. In the current form, the MWCBs are triggered at three threshold levels: 7% (level 1), 13% (level 2), both of which will halt market-wide trading for a minimum of 15 minutes when the decline occurs for the first time between 9:30 AM and 3:25 PM; and 20% (level 3), which will close the markets for the remainder of the day. During the trading halts, investors can cancel resting orders, and stock exchanges continue to accept orders but do not match orders.

2.2 COVID-19 and the MWCBs

COVID-19 roiled the U.S. stock markets since late February 2020. On March 9, as Italy announced a nation-wide lockdown policy, the growing fear of a COVID-19 induced global recession coupled with plunging oil prices caused stock prices to decline, triggering MWCBs at 9:34:13 AM. On March 11, the World Health Organization declared COVID-19 a global pandemic. Later on the same day, the U.S. president announced a travel ban on European countries. MWCBs were triggered at 9:35:44 AM the following day. Many central banks in the world announced drastic monetary policy measures that week. For instance, the Federal Reserve announced an emergency rate cut of 100 basis-point on March 15, along with a massive quantitative easing program. These emergency policy actions were interpreted as extremely negative economic outlook by the market. Consequently, MWCBs were triggered at 9:30:02 AM, two seconds after the market opened, on March 16. The fourth and last instance that triggered MWCBs occurred at 12:56:17 PM on March 18. In general, all four trading halts operated orderly, as we find little trading activities during the trading halts, and the market resumed trading precisely 15 minutes after MWCBs were triggered.

3 Data and Methods

3.1 Data and Variables

We use tick history data for all 505 constituent stocks of the S&P 500 index from DataScope Select.[6] We extract all trade and quote records, and first calculate minute-by-minute measures of (1) log-return; (2) average trade price; and (3) total trade volume. Some additional market outcomes are described below.

Measures of local volatility with the 1-minute bin are calculated using 1-second synchronized trade price. Two observations motivate us to use the 1-minute bin and the 1-second synchronized price: First, all the stocks are among the largest and most liquid stocks in the market and therefore we have lots of trading within a second. Second, the first three trading halts were triggered within five minutes of the official market opening and we cannot use the five-minute bin. To mitigate the impact of market micro-structure noise, we use the average trade price within each second as the synchronized price for any stock. Denote the 1-second synchronized price for stock i as $p_{i,\tau}$, for $i = 1, \ldots, 505$, $\tau = 0, 1, 2, \ldots, 60$. The 1-second log-return is computed as $r_{i,\tau} = \log(p_{i,\tau}/p_{i,\tau-1})$, $\tau = 1, 2, \ldots, 60$. The realized variance for the t^{th} minute is calculated as

$$RV_{i,t} = \sum_{\tau=1}^{60} r_{i,\tau}^2.$$

As $RV_{i,t}$ includes variations from both the continuous Brownian movements of the price process as well as discrete jumps, we disentangle these two components using the bipower variation proposed by Barndorff-Nielsen and Shephard (2004):

$$BV_{i,t} = \frac{\pi}{2} \sum_{\tau=2}^{60} |r_{i,\tau}| \cdot |r_{i,\tau-1}|,$$

where $BV_{i,t}$ is a jump-robust measure of local volatility and only includes variations from the continuous Brownian component. The contribution of jumps to the overall realized variance, jump variation, is hence defined as the difference between these two

$$JV_{i,t} = \max\left(RV_{i,t} - BV_{i,t},\ 0\right),$$

and also truncates at 0, as $JV_{i,t}$ should be non-negative. We then take the square root of these measures of volatility, and express them in percentage point form (*i.e.* realized volatility $\sqrt{RV_t} \times 100$ and jump volatility $\sqrt{JV_t} \times 100$).

Following Fong et al. (2017), we consider two measures of transaction costs. The first is the quoted spread. We extract the national best bid and offer prices and calculate the quoted spread as the average of (ask price − bid price)/ask price for each minute, expressed in percentage points. The second measure is an effective spread measure, where the percentage effective spread for the k^{th} trade of stock i is calculated as:

$$\text{Effective Spread}_{i,k} = 2 * |\ln(Price_{i,k}) - \ln(M_{i,k})|.$$

where $M_{i,k}$ is the mid-quote price immediately prior to the time of the k^{th} trade.

In addition, we calculate a high-frequency analog of the Amihud illiquidity measure (Amihud, 2002) using the absolute value of the 1-minute return divided by the total trade value for the same minute, then rescaled by 10^4. A higher value of Amihud illiquidity corresponds to a lower liquidity of a given stock.

3.2 Identification Approach

Prior empirical attempts to assess the effectiveness of MWCBs have been hampered by the inherent difficulty in finding an appropriate counterfactual (Ackert et al., 2001). In this paper, we use two sets of counterfactuals to proxy for what would have happened in the absence of MWCBs.

First, in our baseline analysis, we take advantage of the fact that level 1 MWCBs can only be triggered the first time when the market index drops below 7%, and identify four occasions when the S&P 500 index dropped below 7% later on the same days as the counterfactuals. MWCBs were triggered four times, at 9:34:14 AM, March 9; 9:35:44 AM, March 12; 9:30:02 AM, March 16; and 12:56:17 PM, March 18. These are the four treatment events in our baseline analysis. The four counterfactual time points are: 1:42:31 PM, March 9; 11:08:19 AM, March 12; 11:42:42 AM, March 16; and 3:15:28 PM, March 18, as demonstrated in Figure 1. There are a few advantages to this approach. Firstly, these counterfactuals allow us to directly observe what would have followed when the index drops below 7% in the absence of MWCBs. Secondly, the four days were among the worst days in stock market history. By choosing counterfactuals from the same day, we minimize the differences in general market conditions and firm characteristics between the treatments and the counterfactuals. Nevertheless, we acknowledge that market participants can behave differently, knowing that level 1 MWCBs will not be triggered again on the same day.

The second counterfactual captures a significant drop of the S&P 500 index which occurred on March 18 well before the actual triggering of circuit breakers. During the market decline on the morning of March 18, the S&P 500 index dropped within 20 points from triggering the circuit breakers. In particular, we use 11:14 AM, when the S&P 500 index dropped 6%, as an alternative counterfactual time to conduct the analysis. Critical to our identification, this 6% drop is not on the direct path that eventually tripped the circuit breaker, as S&P 500 index rebounded before noon, then plummeted to reach the 7% threshold. The advantage of using this counterfactual occasion is that investors could feel the triggering of circuit breakers imminent, especially after watching the MWCBs being triggered three times in the previous 10 days.

3.3 Empirical Specification

We employ an "event-study" difference-in-differences specification and estimate the minute-by-minute treatment effects from 3 minutes pre-halt to 15 minutes post-halt.[7] By contrasting the market outcomes between the treatments and the counterfactuals, we estimate the treatment effects of the 15-minute trading halt induced by MWCBs. The baseline model is specified as

$$Y_{s,i,t} = \alpha + \beta_s Treat_s + \sum_{t \neq -1} \gamma_t After_t + \sum_{t \neq -1} \beta_t^{CB} Treat_s \times After_t + I_i + I_s + T + T^2 + \varepsilon_{s,i,t}, \quad (1)$$

where $i = 1, \ldots, 505$, and $t = -3, -2, 1, 2, \ldots, 15$. In Equation (1), $Y_{s,i,t}$ denotes a given market outcome such as realized volatility, quoted spread, etc., for stock i in the t^{th} minute around a circuit breaker event of s. $Treat_s$ is a dummy variable that equals one for periods surrounding when MWCBs were triggered, and zero for the counterfactuals. $After_t$ is a dummy variable corresponding to the t^{th} minute surrounding the MWCBs for treatments. Negative values of t correspond to minutes before the exact time for the treatment events and counterfactuals. $t = -1$ are excluded from the model as the benchmark. We include stock I_i and date I_s fixed effects and cluster the standard errors by stocks. We also control for time-of-the-day effect with T and T^2 to account for the presence of a U-shaped intra-day volatility pattern (see, e.g., Admati and Pfleiderer, 1988; Anderson and Bolleslev, 1997). The effects of MWCBs are captured by the coefficient estimates β_t^{CB}, $t = -3, -2, 1, \ldots, 15$, which compare changes in outcomes surrounding the circuit breakers with changes for same stocks surrounding the counterfactual occasions.

4 The Effects of MWCBs

4.1 Baseline Results

In this section, we investigate the effects of all four instances of triggering MWCBs using the first set of counterfactuals. The coefficient estimates of β_t^{CB} from the baseline regression are depicted in Figure 2. The regression results are reported in Appendix A. In the figure, the trading halt is marked by the red vertical line at minute zero. The height of each bar corresponds to the magnitude of point estimate of β_t^{CB} for each minute, and the color shadings from dark to light indicate the statistical significance of the estimates at 1%, 5%, and 10% levels, with transparent bars indicating statistically insignificant estimates.

The validity of DD estimates rests on the assumption of parallel pre-existing trends between the treatments and the counterfactuals. One way to test this assumption is to check the coefficients β_{-3}^{CB} and β_{-2}^{CB}, which capture the differences between treatment and counterfactual groups 3-minute and 2-minute before the trading halt. During the pre-halt period, although the treatment group exhibits higher volatility, quoted/effective spread yet lower prices, the differences between the treatments and the counterfactuals are diminishing as time approaches the trading halt. Despite a violation of parallel trends assumption, such bias works against us finding a reversal in trend post-halt, which manifests in the plots shown in Figure 2. For other outcomes such as return and volume, there are no clear trends in the last 3 minutes pre-halt between the two groups. It suffices to say that MWCBs completely alter the trajectory of these outcomes after trading halts.

We find the effects of circuit breaker to be immediate and intense for almost all outcomes after trading resumes. Panel (a) of Figure 2 shows that relative to last minute pre-halt, stock prices drop by 0.7% in the first minute after market reopens; prices continue to drop before recovering to gain about 0.4% from the 10^{th} minute post-halt. Panel (b) reveals no consistent patterns in stock returns in the 15-minute post-halt period. Comparing changes across adjacent minutes separated by trading halt, we find that realized volatility and jump volatility post large spikes immediately after the trading halt, as shown in Panels (c) and (d). Despite a gradual decline pre-halt, realized volatility increases by 0.62 percentage point in the first minute post-halt, which translates to an annualized figure of 194%. Volatility stays elevated for more than 10 minutes before starting to decline; it eventually drops below the pre-halt level from the 13^{th} minute post-halt. We find very similar results for jump volatility in Panel (d).

The results on quoted spread and effective spread are depicted in Panels (e) and (f). Quoted spread widens by over 0.22 percentage point in the first minute post-halt and stays widened for 5 minutes. This evidence is consistent with the observation by Buiter and Sibert (2007) that market makers may lack the knowledge and the deep pockets to credibly post bid and ask prices during crisis period. However, from the 7^{th} minute post-halt, quoted spread falls rapidly and shrinks to a level well below the pre-halt spread. The effective spread soars by over 0.52 percentage point more than the pre-halt level, but such an increase turns out to be transitory, as it plunges to below the pre-halt level in a few minutes. The evidence that volatility and quoted spreads are heightened during the first few minutes after market reopens suggests that circuit breakers panic the markets initially. It takes volatility longer to return to its pre-halt level than the spread.

To gauge the market liquidity condition, we turn our attention to the results on Amihud illiquidity in Panel (g). The light-colored bars suggest that stock liquidity does not vary in a statistically significant fashion from pre- to post-halt. The contrast for trading volume before and after trading halt is most striking, as shown in Panel (h). The dependent variable $Y_{s,i,t}$ is the natural logarithm of trading volume in the t^{th} minute, hence the estimates β_t^{CB} represent percent changes. Our results indicate that investors rush to trade immediately after the market reopens. Relative to the last minute pre-halt, trading volume is 116% higher in the first minute, and remains about 40% higher for over 10 minutes post-halt. The dramatic increase in trade volume immediately following the trading halt is consistent with the discretionary liquidity trader arguments in Admati and Pfleiderer (1988). They show that trading volume is higher during certain periods because of the increased strategic liquidity-trading demand and the induced informed-trading volume as in Kyle (1985).

Our results reveal a positive volatility-volume relation in the first 10 minutes post-halt, which is consistent with the mixture-of-distribution hypothesis (MDH) in Clark (1973).[8] Using high-frequency intra-day trading data, Bollerslev et al. (2018) present evidence that the positive volume-volatility relation can be best explained by the differences-of-opinion models (see, e.g. Harrison and Kreps, 1978; Harris and Raviv, 1993; Kandel and Pearson, 1995; Scheinkman and Xiong, 2003; Banerjee and Kremer, 2010, among others.). The differences in opinions among investors are acute during the COVID-19 pandemics. Based on a survey of market investors during February and March 2020, Giglio et al. (2020) find that disagreement among investors about economic and stock market outlooks increased substantially following the stock market crash. In this sense, MWCBs provide different types of investors with an opportunity to process the information and participate in the market.

4.2 Dissecting Trading Volume

Volume alone conceals many important aspects of trading. We proceed to dissect the directional trade flows in great details in this section. Each transaction is classified as either buyer-initiated or seller-initiated according to the Lee and Ready (1991) algorithm. As in Chordia et al. (2002), we define a measure of order imbalance as the difference between the buyer-initiated volume and the seller-initiated volume. We also use several other related measures. Following Blume et al. (1989), we calculate difference between the bid and ask volumes at their respective national best bid and offer (NBBO) prices. Boehmer et al. (2021) provide an innovative method for tracking the retail investor activity with market orders. We follow their method to distinguish between retail investors' buy and sell volumes to shed light on how retail investors react to circuit breakers. The estimated circuit breaker effects β_t^{CB} on these outcomes are plotted in Figure 3.

The results in Panels (a) and (b) in Figure 3 reveal that both buyer-initiated volume and seller-initiated volume exhibit sustained increase over the 15-minute period post-halt relative to their pre-halt levels. Most notably, the buyer-initiated volume sprints to a significant 150% surge in the first minute after trading halt, and 80% for the seller-initiated volume. Similar results can be observed for the bid and ask volumes at the NBBO prices, as evidenced in Panels (c) and (d). When subtracting the seller-initiated volume from the buyer-initiated volume to measure order imbalance in Panel (e), we find that the buyer-initiated volume outgains the seller-initiated volume in most of the 15-minute window post-halt. The same exercise of subtracting the ask volume from the bid volume in Panel (f) shows that the bid volume outgains the ask volume in the initial three minutes post-halt. The last two panels of Figure 3 present evidence on how retail investors react to circuit breaker. Both retail buy and sell (using market orders) experience sustained increases subsequent to the trading halt. Rather than scaring off retail investors, circuit breakers prompt them to trade .

In sum, although the realized volatility and quoted spread deteriorate initially after trading halt, they improve within a short period of time. Meanwhile, investors shore up their trading especially their purchases immediately after the market reopens. From this perspective, MWCBs are effective in encouraging investors to bring their demands to market and preventing prices from free falling (Greenwald and Stein, 1991).

5 Further Analyses

5.1 Pre-halt Stock Return and Post-halt Trading Volume

The results above reveal that both buyer-initiated volumes and bid volume exhibit substantial increases immediately after the market reopens. One way that MWCBs can stabilize the market is to prevent or at least decelerate panic sell-offs for stocks that experience severe intra-day losses. To investigate this possibility, we regress various aspects of trading volume in the first 5 minutes post-halt on the stock's pre-halt return since previous day's close price, controlling for stock fixed effects. The results are shown in Table 2. We find a statistically significant inverse relationship between the pre-halt return and the post-halt volume in the whole sample as shown in Panel A, which suggests that the greater the fall in stock price pre-halt, the higher the trading volume across all spectrum post-halt. Comparing coefficients in Panel A, we find that the buyer-initiated volume (column 2) and the bid volume (column 4) exhibit larger responses to pre-halt stock returns than the seller-initiated volume (column 3) and the ask volume (column 5), implying that investors make more purchases than sells for harder-hit stocks after trading resumes.

We further decompose the sample in halves based on whether the pre-halt return is below (Panel B) or above (Panel C) the sample median return. The results show that the negative relation between trading volume and pre-halt returns is mostly driven by the stocks that post worse returns before circuit breakers. In Panel B, the relation between the trade, buyer-initiated, and bid volumes and pre-halt return are all statistically significant and negative. In contrast, in Panel C, the relation between most aspects of volume are pre-halt return is statistically indistinguishable from zero. Therefore, instead of selling off, the investors shore up the purchases of the stocks that were hit hard after trading halt. The overall evidence suggest that trading halts provide an opportunity for investors to purchase more than dump stocks. From this perspective, MWCBs stabilize the markets by preventing a downward spiral.

5.2 The Magnet Effect

The magnet effect, arguably a major unintended consequence of MWCBs (see, e.g. Subrahmanyam, 1994; Chen et al., 2023), implies that the very presence of circuit breakers can accelerate the movements of prices toward the thresholds as stock prices get closer to the thresholds. Subrahmanyam (1995) suggests that circuit breakers can increase ex-ante price volatility and induce investors to advance their trades suboptimally. In contrast, Subrahmanyam (1997) and Brogaard and Roshak (2016) posit a hypothesis that informed traders strategically hold back their trading to avoid trading halt and a circuit breaker can decrease volatility. In this section, we put the magnet effect hypothesis to data.

Our earlier results in Figures 2 suggest that stock prices fall at a slower rate while realized volatility decreases relative to counterfactuals during the 3-minute period leading up to the trading halt, which is inconsistent with the magnet effect hypothesis. Considering that the first few minutes after the market opens on March 9, 12, and 16 might not be the ideal window to test the magnet effect, we conduct a separate analysis based solely on March 18 data. Moreover, we select a counterfactual which preceded, but did not lead to, the actual breach of MWCBs on March 18. During the market decline on the morning of March 18, the S&P 500 index dropped within 20 points from the 7% threshold, but rebounded before noon without triggering the circuit breakers. Specifically, we use 11:14 AM, when the S&P 500 index dropped 6%, to construct a new set of counterfactuals. The advantage of using this counterfactual time is that investors could feel the possibility of circuit breakers triggering imminent, especially after watching the MWCBs being triggered three times in the previous 10 days.

Figures 4 and 5 present the estimates using the second set of counterfactuals for the March 18 treatment group. As in Figures 2 and 3, we plot the point estimates in different minutes as bars but extend the pre-halt window to 15 minutes. Panel (a) reveals no clear price patterns during the 15-minute pre-halt period. For instance, treatments' prices experience a noticeable rebound from minute -6 to -4 relative to counterfactuals. Similarly, we find no evidence of an accelerating decline in stock return in Panel (b). In fact, treatments' prices outgain counterfactuals' prices during most of the pre-halt window. Furthermore, realized volatility, jump volatility, quoted spread, effective spread and volume display little systematic changes during the period leading up to the triggering of circuit breakers. In sum, we do not find consistent empirical support for the magnet effect hypothesis in the data.

The analysis from the second counterfactual complements our baseline results. Due to the early occurrences of the first three trading halts, the effects of MWCBs can be confounded by the market opening effects. Although we control for the minute-of-the-day variable and its square term in our regressions and our conclusions are unchanged if we drop March 16 (when the circuit breaker was tripped at 09:03:02, which leaves us with no observations during pre-halt period for the treatment group) from our analysis, we perform the regressions using data on March 18 alone. The MWCBs were tripped in the early afternoon on March 18, which would not have the aforementioned issue. Besides, we can include a longer pre-halt window to better compare the pre-halt outcome trajectories with the post-halt trajectories.

Most of our earlier findings continue to hold, although a few differences do emerge. For instance, in Figure 4, the realized volatility and jump volatility retreat considerably after the initial jump, but they surge to substantially higher levels 5 minutes after trading halt. The average level of realized volatility from the 6^{th} to the 15^{th} minute is roughly on par with the average volatility during the 15 minutes before the trading halt. Quoted spread and effective spread both drop sharply after the treading halt. Results on various aspects of trading volume shown in Figure 5 remain similar to those in Figure 3. These results reinforce our conclusion that MWCBs panic the market for a short period of time before calming them down in due course.

5.3 Limit Up-Limit Down

In response to the flash crash in May 2010 when the Dow Jones index experienced a precipitous drop which was still not large enough to trigger the MWCBs, the SEC rolled out a new "limit up-limit down" (LULD) rule in 2012 to curb extraordinary market volatility. The LULD rule is intended to prevent stock trades from occurring outside of a set of pre-specified price bands. The bands are determined by a percentage level above and below the average reference price of the security over the immediately preceding 5-minute period. To accommodate more fundamental price movements, there will be a 5-minute trading pause if trading is unable to occur within the specified price band.

A recent study by Hautsch and Horvath (2019) find that individual stock trading pauses can even cause extra volatility. One might worry that our results are confounded by individual trading pauses due to the LULD mechanisms. To address this concern, we extract all trading pauses triggered by LULD on the four days of MWCBs. As we can see from Table 3, only 4 stocks tripped the LULD-induced trading pauses within the 5-minute period leading up to MWCBs. Even on March 18 when the MWCBs were triggered in the middle of the days, only 1 stock tripped the trading pause due to LULD within a 10-minute window. Therefore, our results are not contaminated by the trading pauses caused by the LULD mechanisms.

A related question arises as to whether MWCBs are entirely necessary given the presence of individual stock's trading halts. In unreported results, we find that individual-stock trading pauses lead to greater decreases in volatility and spread yet smaller increases in volume than market-wide trading halts. However, the results are based on a limited sample of stocks that experienced additional trading pauses these four days. More research is needed along this line of query.

5.4 Cross-sectional Heterogeneity

We next examine the cross-sectional heterogeneity in the effects of MWCBs. There is strong evidence that the trading halt effects vary across stocks of different sizes. Although all firms in the S&P 500 are among the largest in the U.S., there is significant variation in sizes. We sort firms according to their market capitalization at the end of 2019 into four groups: small (less than $10 billion), medium (between $10 billion and $50 billion), large (between $50 billion and $100 billion), and huge (over $100 billion). It is worth pointing out that some differences, such as the high frequency trading participation in stocks of different sizes can be important (Brogaard et al., 2014). We estimate Model (1) for each size group separately, and stack the point estimates in Figure 6. The results reveal that the post-halt outcomes vary across different firm sizes. We find that smaller firms experience greater and more persistent increases in volatility and quoted spread, yet less increase in trading volume than larger firms after the trading halt. Therefore, smaller firms are more negatively affected by the MWCBs than larger firms.

5.5 Other robustness tests

Our previous measures are based on 1-minute bins. Our results are very similar when we construct these measures based on 3-minute bins. In the above analysis, our treatment sample has few observations from March 16 but our control sample has quite a few observations from that day due to the very early occurrence of trading halt that day. When we drop the observations on March 16 from our analysis, our results are virtually unchanged. These results are available upon request.

6 The Operation of MWCBs

The above findings suggest that the responses to MWCBs are very intense in the first few minutes post-halt. However, not all stocks resumed trading immediately after the market reopened. In fact, many stocks did not even officially start trading before the MWCBs were triggered. This is particularly true for NYSE-listed stocks because the NYSE's centralized "manual" opening and reopening process can generate significant delays.

On the NYSE, a call auction opens the market. During this opening mechanism, designated market makers (DMMs) can determine an opening price by balancing electronically submitted trading interests and interests represented on the floor of the exchange. Similarly, those DMMs are responsible for facilitating the reopening auctions after trading halt and have some discretion over when to reopen stock trading in order to maintain a fair and orderly reopening process. For instance, if the order imbalance is sufficiently large, the DMMs may delay the opening to collect more orders.[9] In comparison, NASDAQ has only incorporated a call auction element (opening cross for market opening and halt cross after trading halt) into its continuous multi-dealer market. In this section, we describe the differences between stock exchanges in relation to the operation of MWCBs.

Of all 505 stocks in our sample, 135 are primarily listed on NASDAQ and 370 on NYSE.[10] We conduct a time analysis of stock trading by examining the exact timestamps of trades surrounding MWCBs. The first two panels of Table 4 summarize the time lapses between the last reported trade pre-halt (if any) and the triggering time for the MWCBs. The results reveal stark differences between the NYSE-listed stocks (Panel A) and the NASDAQ-listed stocks (Panel B). Out of all 370 NYSE stocks, only 202 stocks reported a trade before MWCBs were triggered 254 seconds after normal trading began on March 9 and therefore the rest 168 stocks have to start trading after 09:50:44; the number grew to 248 on March 12 as MWCBs were triggered 344 seconds after 9:30 AM. In comparison, for the first five trading days in March 2020, on average it takes these 370 NYSE-stocks 53 seconds after 9:30 AM to report the first trade, and the longest time is 269 seconds. In contrast, all 135 NASDAQ stocks reported a trade before the triggering of MWCBs on March 9 and March 12. Even on March 16, when MWCBs were triggered at 9:30:02 AM, 105 out 135 NASDAQ stocks reported a trade, whereas merely 12 NYSE stocks posted an opening trade. Unfortunately, our results also show that some trading activities did occur during the 15-minute trading halt, mostly on March 16 for the NASDAQ stocks. For instance, -7 in Panel B means that some stock transactions even occurred 7 seconds after the MWCBs were triggered, when all trading is supposed to be halted. Considering that the triggering of MWCBs happened immediately after the opening bell, some technical glitches or communication issues might have taken place.

For those stocks that did complete a trade before the trading halt, the average time lapse between the last trade pre-halt and the start time of the trading halt is significantly longer for the NYSE stocks, which suggests that their trading is more sporadic in the opening minutes than the NASDAQ stocks. Regarding the time lapse between the end of the trading halt and the first trade post-halt in Panels C and D of Table 4, we find that on average it takes the NYSE-listed stocks 150 seconds to post the first trade after trading resumes, while the corresponding time for the NASDAQ-listed stocks is less than one second. At a basic level, the delayed opening and reopening of NYSE stocks might have prevented two willing parties from realizing a trade. Furthermore, the S&P 500 index has to rely on a constituent stock's previous trading day's close price until the stock opens trading. Therefore, market index can be a bit stale with some component stocks not providing real-time prices during this turbulent period.[11] Interestingly, NASDAQ openly questions the role of played by NYSE's DMMs during the COVID-19 crisis.[12]

7 Conclusions

The COVID-19 pandemic provides an unfortunate yet valuable opportunity to study many important aspects of the financial market infrastructure. In this paper, we use four occurrences of the triggering of MWCBs within a span of 10 days in March 2020 to evaluate their effectiveness. Previous studies on MWCBs are mostly from a theoretical perspective and the findings on the effect of MWCBs are inconclusive. This paper contributes to this ongoing debate by providing some of the first empirical evidence on the efficacy of MWCBs amid the COVID-19 pandemic.

Using trade and quote data for all S&P 500 index constituent stocks and a difference-in-differences approach, we show that although MWCBs panic the markets in the first few minutes after the market reopens by inducing heightened volatility and wider spreads, they also boost trading volume, especially for the stocks that were hit hard. We use two different sets of counterfactuals and find largely consistent results. Furthermore, we do not find strong empirical support for the magnet effect hypothesis, a major unintended consequences of circuit breakers. Overall, the weight of evidence indicates that MWCBs can help to stabilize the markets although they aggravate the trading environment initially.

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Notes

1. To illustrate this point, on March 9, Yum! Brands' (YUM.NYSE) first trade was its market opening trade at 9:51:33 AM, which took place more than two minutes after the end of the 15-minute trading halt imposed by the MWCBs.

2. https://www.govinfo.gov/content/pkg/FR-1998-04-15/pdf/98-10027.pdf

3. See the footnote above.

4. https://www.sec.gov/rules/sro/bats/2012/34-67090.pdf

5. See, e.g., Menkveld and Zhou (2019) for a detailed description of this incident.

6. There are 505 stocks because several companies have dual-class shares included in the S&P 500 index.

7. The conclusions remain unchanged when we extend the post-halt window to 30 or 60 minutes or when we include pre-market trading. These results are available upon request.

8. The MDH proposes that the distribution of price changes is subordinated to a normal distribution, whose speed of evolution is governed by a latent information arrival process. The intensity of information flow can be, in turn, measured by the distribution of trading volume. This hypothesis hence implies a positive and contemporaneous relationship between volatility and trading volume.

9. https://www.nyse.com/publicdocs/nyse/NYSE_MWCB_FAQ.pdf

10. CBOE Global markets, the parent company of the Chicago Board Options Exchange, is listed on BATS Global Markets. In this study, we treat this company as NYSE-listed because we extract trading data from an unlisted trading privileges (UTP) through NYSE.

11. Despite the popular claim that DMMs' roles are diminishing in the electronic trading era, recent studies find that DMMs are still important. For instance, Bessembinder et al. (2015) argue that DMMs could prevent market failure and increase social welfare especially when uncertainties regarding fundamental value and information asymmetry are large. Clark-Joseph et al. (2017) show that DMMs play an economically significant role in liquidity provision, during two separate trading halts due to technological glitches.

12. https://www.nasdaq.com/articles/are-designated-market-makers-really-better-in-stressed-markets-2020-04-16

Table 1: The evolution of MWCBs

Effective from	Thresholds	Index	Trading halt rule	Trigger time of the day
	Black Monday, Oct 19, 1987			
Oct 1988	250 points	DJIA	Halt for 1 hour	
	400 points		Halt for 2 hours	
Jan 1997	350 points	DJIA	Halt for 30 minutes	
	550 points		Halt for 1 hour	
	Mini-crash, Oct 27, 1997			
Apr 1998	10%	DJIA	Halt for 1 hour	9:30 AM – 2:00 PM
			Halt for 30 minutes	2:00 PM – 2:30 PM
			No halt	2:30 PM – 4:00 PM
	20%		Halt for 2 hours	9:30 AM – 1:00 PM
			Halt for 1 hour	1:00 PM – 2:00 PM
			Close market for the day	2:00 PM – 4:00 PM
	30%		Close market for the day	
	Flash crash, May 6, 2010			
Apr 2013	7%	S&P500	Halt for 15 minutes	9:30 AM – 3:25 PM
			No halt	3:25 PM – 4:00 PM
	13%		Halt for 15 minutes	9:30 AM – 3:25 PM
			No halt	3:25 PM – 4:00 PM
	20%		Close market for the day	

Note: This table summarizes the main rules of MWCBs and major changes to the rules prompted by three events: Black Monday of 1987 (top panel), mini-crash of 1997 (middle panel), and flash crash of 2010 (bottom panel).

Table 2: Regressing 5-minute post-halt volume on pre-halt return

	(1) Trade	(2) Buyer-initiated	(3) Seller-initiated	(4) Bid	(5) Ask
			Panel A: Whole sample		
Pre-halt return	−1.933***	−2.024***	−1.838**	−2.789***	−2.137**
	(0.503)	(0.588)	(0.843)	(1.053)	(0.833)
Stock FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Observations	1,261	1,261	1,261	1,261	1,261
R^2	0.930	0.851	0.863	0.884	0.899
			Panel B: Pre-halt return below sample median		
Pre-halt return	−2.163**	−1.947**	−2.456	−3.555**	−1.700
	(0.850)	(0.935)	(1.722)	(1.628)	(1.588)
Stock FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Observations	638	638	638	638	638
R^2	0.960	0.914	0.893	0.917	0.933
			Panel C: Pre-halt return above sample median		
Pre-halt return	1.705	−0.165	3.805	5.565*	1.924
	(2.217)	(2.911)	(3.874)	(3.175)	(3.981)
Stock FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Observations	623	623	623	623	623
R^2	0.943	0.884	0.902	0.916	0.917

Note: This table presents the results from regressing various measures of 5-minute post-halt volumes on pre-halt stock returns on the four days of MWCBs. The sample includes all S&P 500 index constituent stocks, which posted at least one trade before trading halt (in order to calculate pre-halt returns) and at least one trade in the first five minutes after market reopens (in order to calculate post-halt volume). The dependent variables include the total volume, buyer-initiated volume, seller-initiated volume, bid volume and ask volume (all in logarithm) in the first five minutes post-halt. The pre-halt return is calculated by subtracting the logarithm of prior trading day's close price from the logarithm of the last price before trading halt. We further break down the sample into halves based on whether the pre-halt return is below (Panel B) or above sample median (Panel C). We control for stock and date fixed effects and report the standard errors clustered by stock in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Number of individual stock trading halts due to limit up-limit down (LULD)

Date	5 minutes pre-MWCBs	5 minutes post-MWCBs	Rest of the day
March 9	3	6	37
March 12	0	7	32
March 16	0	11	31
March 18	1	1	50

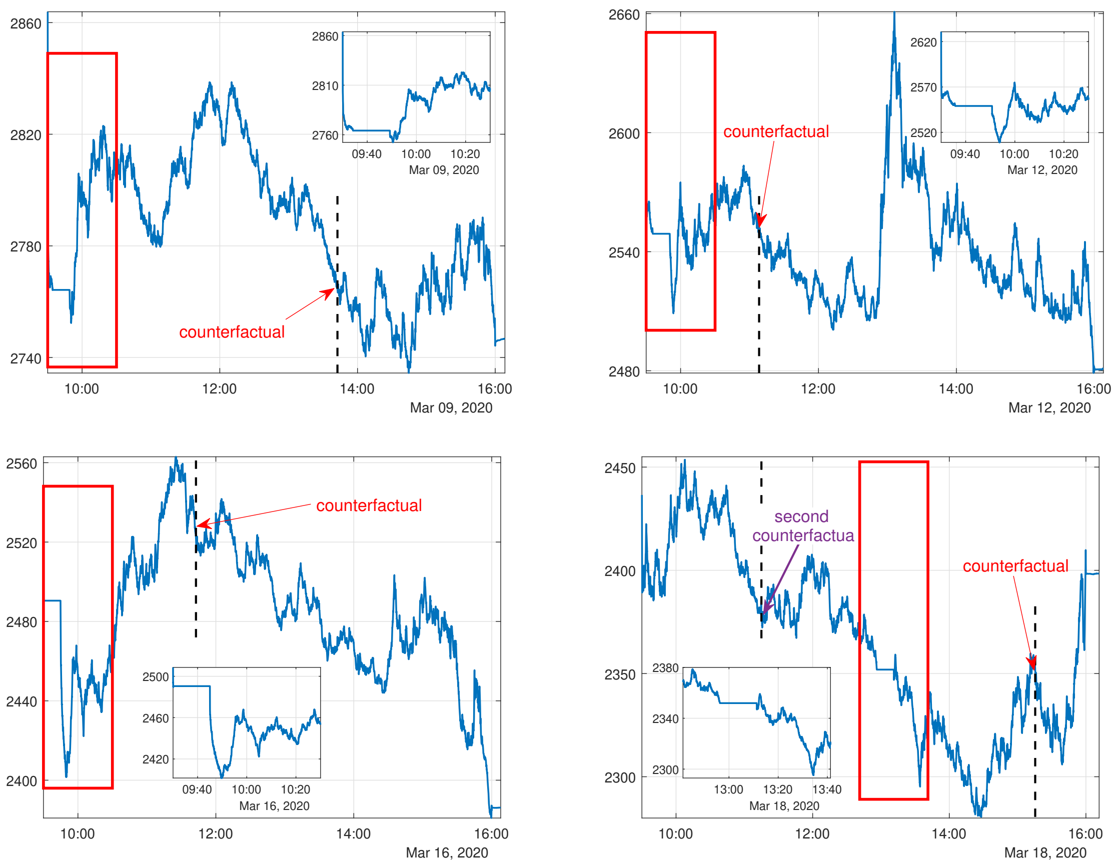
Note: This table lists the number of individual stock trading pauses caused by the LULD rule for 505 S&P 500 index constituent stocks on days of MWCBs. We break down the number of halts into three periods: a 5-minute window before the market-wide trading halt, a 5-minute window after after trading halt, and the rest of the day.

Table 4: Delays in market opening and reopening

Pre-halt time lapse between last trade and MWCBs (seconds)						
		Panel A: NYSE stocks				
Date	N	Mean	Std.Dev	Min	Median	Max
March 9	202	20.371	39.544	0	5	253
March 12	248	16.863	35.442	0	6	344
March 16	12	0.667	0.492	0	1	1
March 18	370	29.062	90.458	−1	14	1258
Total	832	22.906	66.495	−1	8	1258
		Panel B: NASDAQ stocks				
Date	N	Mean	Std.Dev	Min	Median	Max
March 9	135	8.244	19.269	0	2	151
March 12	135	4.807	6.907	0	2	35
March 16	105	−2.886	2.719	−7	−3	1
March 18	135	7.096	10.860	−1	2	63
Total	510	4.739	12.633	−7	1	151
Post-halt time lapse between MWCBs and first trade (seconds)						
		Panel C: NYSE stocks				
Date	N	Mean	Std.Dev	Min	Median	Max
March 9	370	190.438	219.533	0	117.5	1134
March 12	370	195.222	222.141	0	119	1146
March 16	370	159.616	196.081	0	94	1094
March 18	370	55.614	80.056	0	28	470
Total	1480	150.222	196.723	0	78	1146
		Panel D: NASDAQ stocks				
Date	N	Mean	Std.Dev	Min	Median	Max
March 9	135	0.778	6.471	0	0	62
March 12	135	0.356	4.045	0	0	47
March 16	105	0.170	0.377	0	0	1
March 18	135	0.111	0.315	0	0	1
Total	510	0.354	3.822	0	0	62

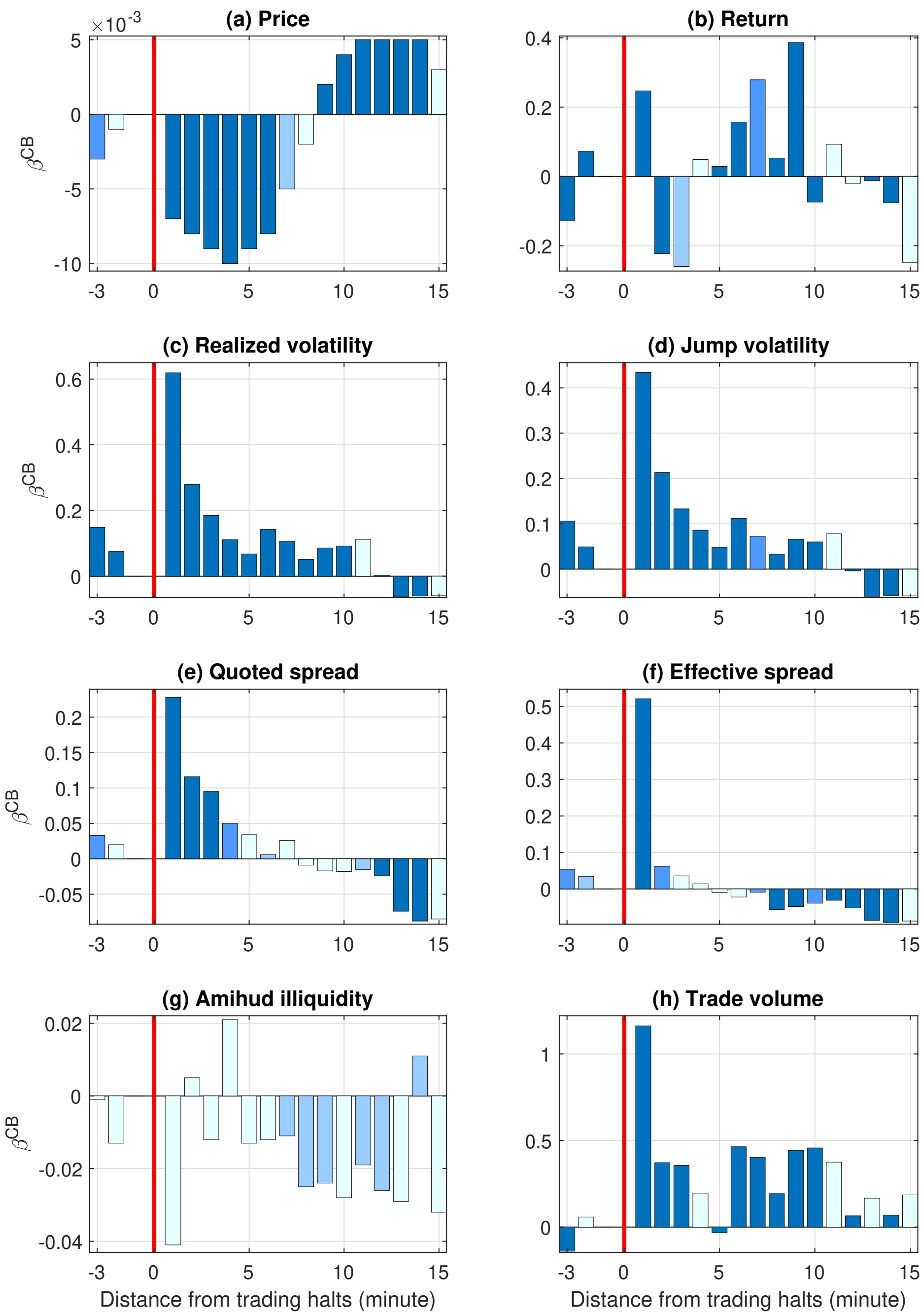
Note: This table presents descriptive statistics for the time lapse (in seconds) related to trading halts for 370 NYSE stocks and 135 NASDAQ stocks on four days when the MWCBs were triggered. The top half of the table describes the time lapse between the last trade (if any) after market opens (9:30 AM) and the beginning of trading halt. The bottom half of the table describes the time lapse between the end of trading halt and the first trade after market reopens.

Figure 1: S&P 500 index on days with trading halt



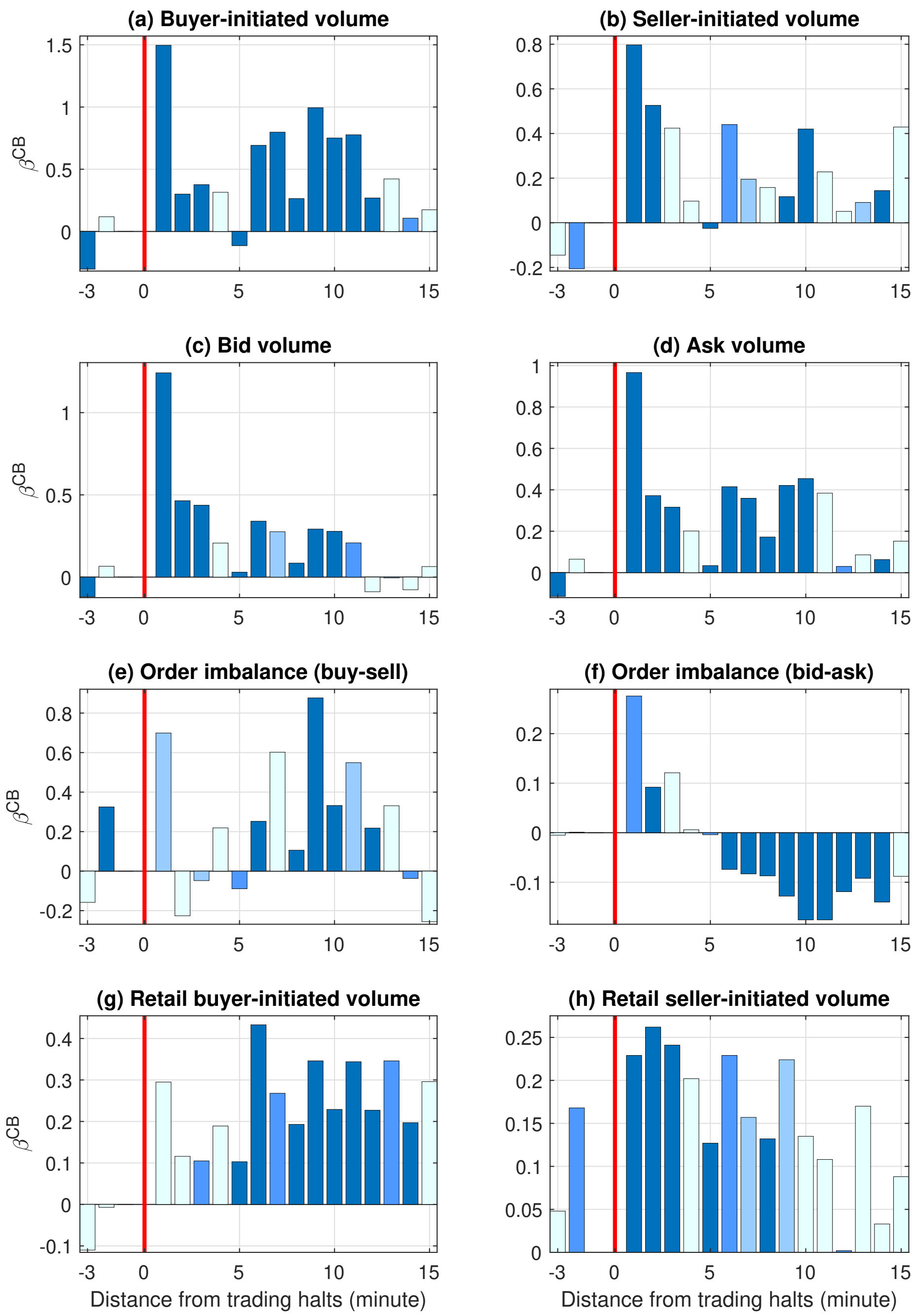
Note: The four panels plot the S&P 500 index from 9:30 AM to 4PM on the four days when the MWCBs were triggered. The stationary part of the line, with a zoomed out version inside each panel, corresponds to the 15-minute market-wide trading halt. The black dashed line corresponds to the time stamp to construct the first set of counterfactuals. On March 18 (the bottom right panel), the second counterfactual time, is also depicted.

Figure 2: Coefficient estimates β_t^{CB} using all four MWCBs



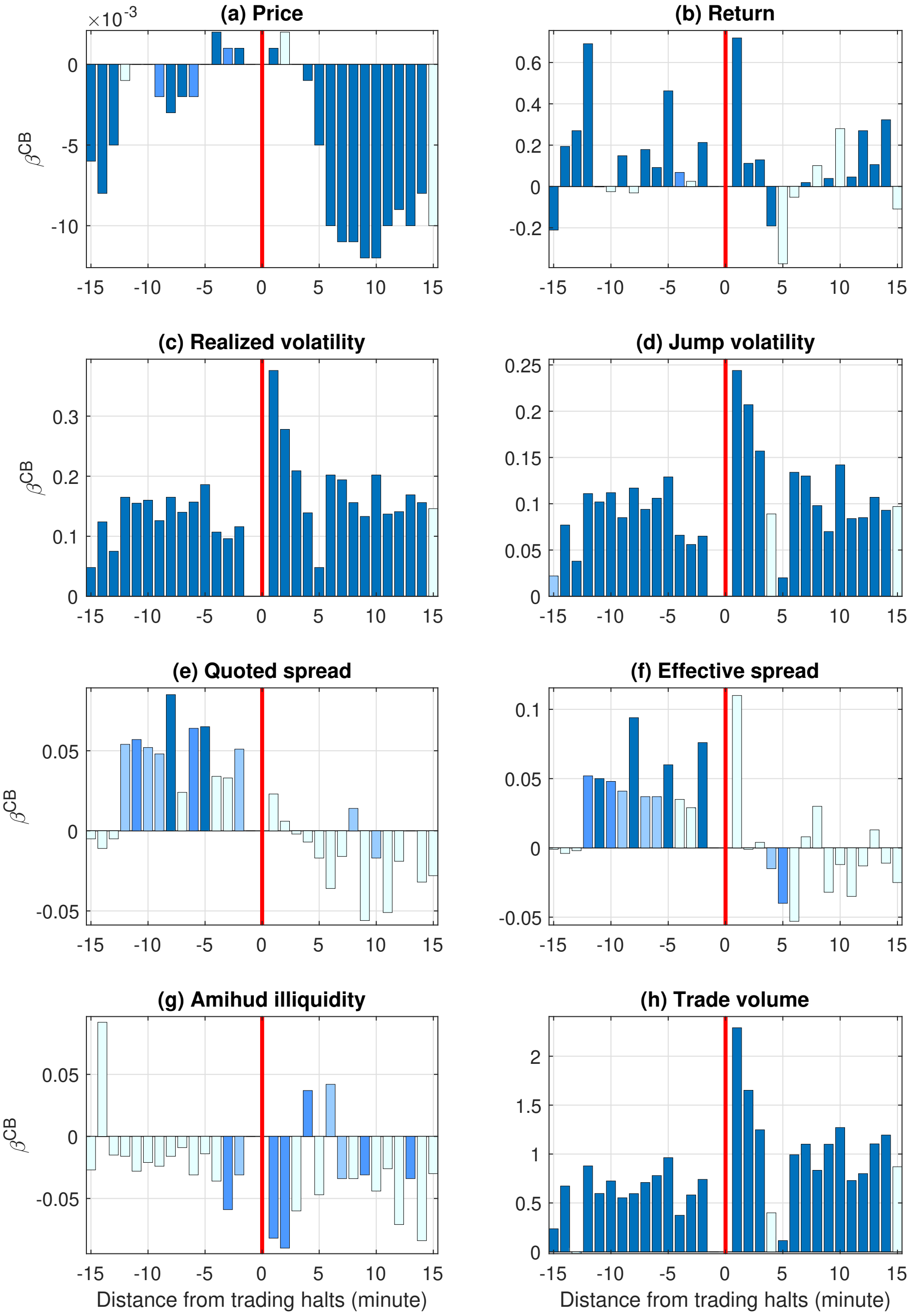
Note: This figure plots the regression coefficients β_t^{CB} for each minute t from estimating Equation (1). The sample includes all S&P 500 constituent stocks on the four days when the MWCBs were triggered. The horizontal axis represents each minute from 3 minutes pre-halt ($t = -3$) to 15 minutes post-halt ($t = 15$). The red vertical line at $t = 0$ denotes the time of the trading halt. The height of the bar corresponds to the magnitude of the coefficient estimate. The color of the bar denotes the statistical significance of the estimates. ▬ indicates statistically significant estimates at 1% level, ▬ at 5% level, ▬ at 10% level, ▭ insignificant estimates.

Figure 3: Coefficient estimates β_t^{CB} using all four MWCBs



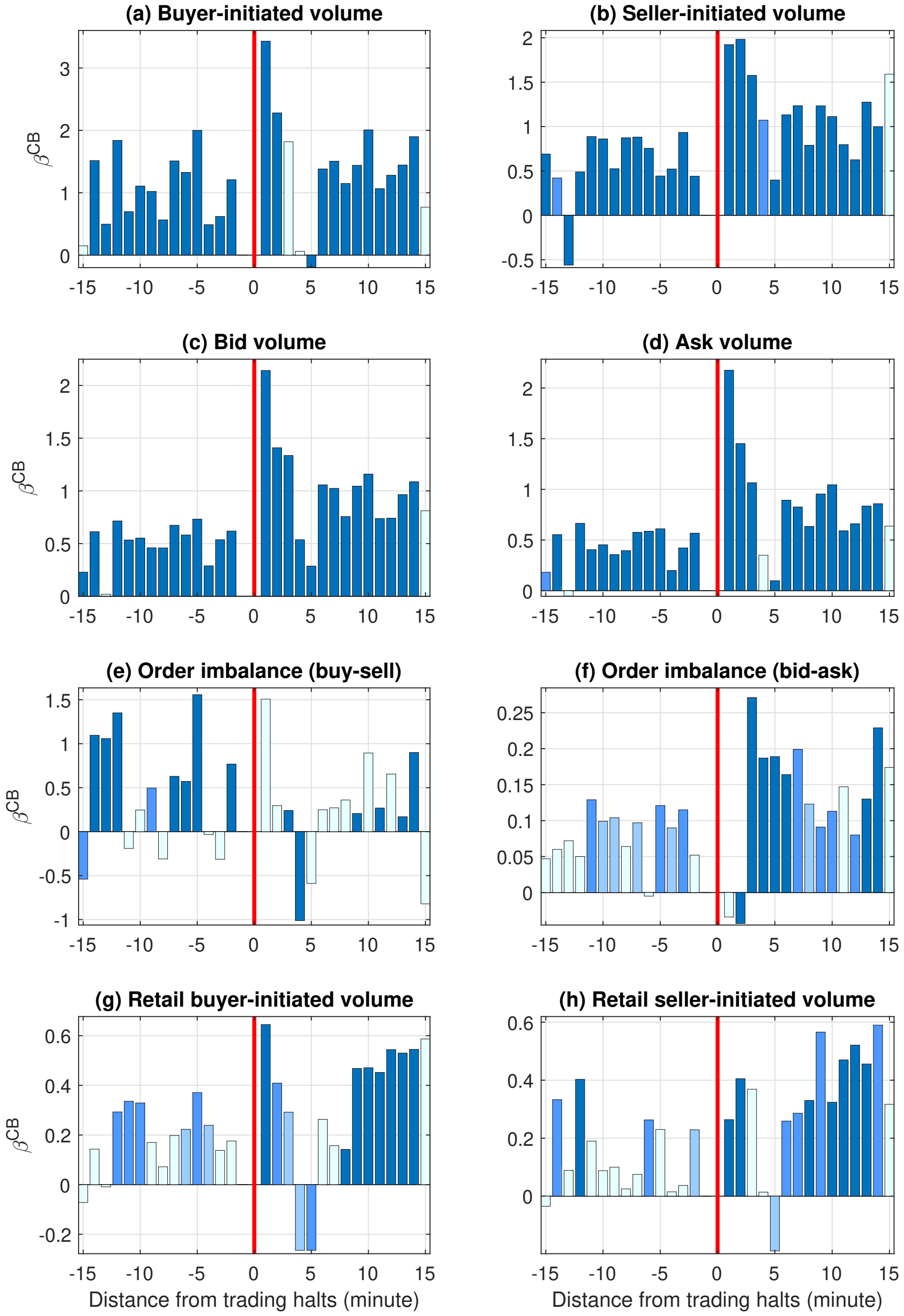
Note: This figure plots the regression coefficients β_t^{CB} for each minute t from estimating Equation (1). The sample includes all S&P 500 constituent stocks on the four days when the MWCBs were triggered. The horizontal axis represents each minute from 3 minutes pre-halt ($t = -3$) to 15 minutes post-halt ($t = 15$). The red vertical line at $t = 0$ denotes the time of the trading halt. The height of the bar corresponds to the magnitude of the coefficient estimate. The color of the bar denotes the statistical significance of the estimates. indicates statistically significant estimates at 1% level, at 5% level, at 10% level, insignificant estimates.

Figure 4: Coefficient estimates β_t^{CB} using 11:14 AM on March 18 as counterfactual



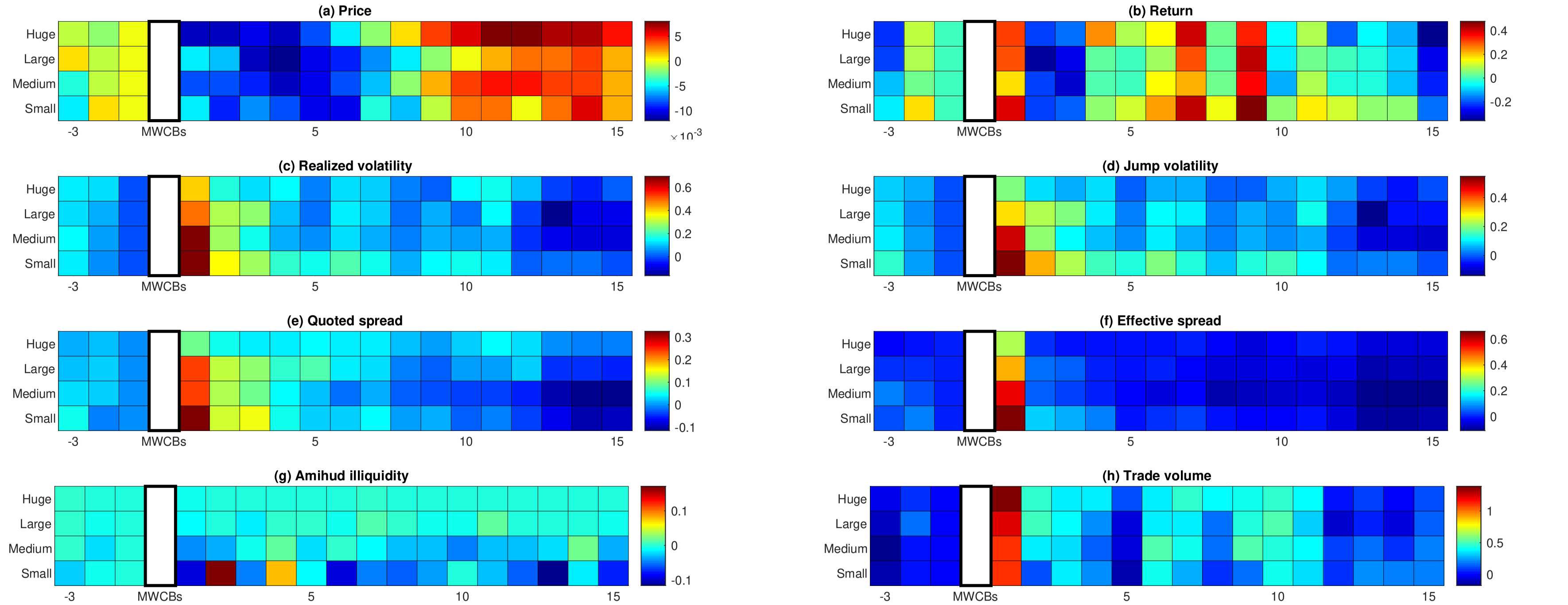
Note: This figure plots the regression coefficients β_t^{CB} for each minute t from estimating Equation (1) using the treatment and counterfactual on March 18 only. The counterfactual is constructed using 11:14 AM as the cutoff point when the S&P 500 index dropped below 6% before rebounding by noon without triggering the circuit breakers. The horizontal axis represents each minute from 15 minutes pre-halt ($t = -15$) to 15 minutes post-halt ($t = 15$). The red vertical line at $t = 0$ denotes the time of the trading halt. The height of the bar corresponds to the magnitude of the coefficient estimate. The color of the bar denotes the statistical significance of the estimates. ▭ represents statistically significant estimates at 1% level, ▭ at 5% level, ▭ at 10% level, ▭ insignificant estimates.

Figure 5: Coefficient estimates β_t^{CB} using 11:14 AM on March 18 as counterfactual



Note: This figure plots the regression coefficients β_t^{CB} for each minute t from estimating Equation (1) using treatments and counterfactuals on March 18 only. The counterfactuals are constructed using 11:14 AM when the S&P 500 index dropped below 6% before rebounding by noon without triggering the circuit breakers. The horizontal axis represents each minute from 15 minutes pre-halt ($t = -15$) to 15 minutes post-halt ($t = 15$). The height of the bar corresponds to the magnitude of the coefficient estimate. The color of the bar denotes the statistical significance of the estimates. represents statistically significant estimates at 1% level, at 5% level, at 10% level, insignificant estimates.

Figure 6: Comparison of estimated coefficients across size groups



Note: This figure plots the regression coefficients β_t^{CB} for each minute t from estimating Equation (1), for stocks of different sizes. We sort firms according to their market capitalization at the end of 2019 into four groups: small (less than \$10 billion), medium (between \$10 billion and \$50 billion), large (between \$50 billion and \$100 billion), and huge (over \$100 billion). The horizontal axis represents each minute from 3 minutes pre-halt ($t = -3$) to 15 minutes post-halt ($t = 15$). The blank bar at $t = 0$ denotes the time of the trading halt. The color of the bar indicates the magnitude of the coefficient estimates for each outcome and the color labels are depicted outside of the results box.

Appendix A Regression results

The below two tables report the baseline regression results from estimating Equation (1). The sample includes all S&P 500 constituent stocks on the four days when the MWCBs were triggered. *Treat* is a dummy variable that equals one for periods surrounding when MWCBs were triggered, and zero for the counterfactuals. $After_t$ is a dummy variable corresponding to the t^{th} minute surrounding the MWCBs for treatments. Negative values of t correspond to minutes before the exact time for the treatment events and counterfactuals. $t = -1$ are excluded from the model as the benchmark. We include stock and date fixed effects and cluster the standard errors by stocks. Controls include After_{-3}, After_{-2}, After_{1}, $\ldots$, After_{15}, t and t^2. *** indicates statistical significance at 1% level, ** at 5% level, * at 1% level. Standard error that are clustered by stock are reported in the parentheses.

Table A.1: Effects of MWCBs: Baseline results

	(1) Price	(2) Return	(3) Volatility	(4) Jump Volatility	(5) Quoted Spread	(6) Effective Spread	(7) Amihud Illiquid-ity	(8) Volume
Treat	−0.025***	0.028	0.196***	0.169***	0.183***	0.151***	0.030**	0.021
	(0.002)	(0.020)	(0.016)	(0.013)	(0.014)	(0.015)	(0.014)	(0.045)
Treat*$After_1$	−0.007***	0.247***	0.619***	0.434***	0.228***	0.521***	−0.041***	1.162***
	(0.001)	(0.046)	(0.033)	(0.025)	(0.019)	(0.043)	(0.014)	(0.047)
Treat*$After_2$	−0.008***	−0.223***	0.279***	0.213***	0.116***	0.062***	0.005	0.372***
	(0.001)	(0.033)	(0.020)	(0.017)	(0.017)	(0.016)	(0.030)	(0.049)
Treat*$After_3$	−0.009***	−0.260***	0.185***	0.133***	0.095***	0.036**	−0.012	0.356***
	(0.001)	(0.029)	(0.019)	(0.016)	(0.016)	(0.016)	(0.017)	(0.052)
Treat*$After_4$	−0.010***	0.049*	0.111***	0.086***	0.050***	0.014	0.021	0.196***
	(0.001)	(0.027)	(0.016)	(0.014)	(0.014)	(0.014)	(0.023)	(0.048)
Treat*$After_5$	−0.009***	0.029	0.068***	0.048***	0.034**	−0.010	−0.013	−0.032
	(0.001)	(0.025)	(0.019)	(0.015)	(0.013)	(0.014)	(0.015)	(0.049)
Treat*$After_6$	−0.008***	0.157***	0.143***	0.112***	0.006	−0.022	−0.012	0.464***
	(0.001)	(0.024)	(0.016)	(0.014)	(0.014)	(0.016)	(0.023)	(0.047)
Treat*$After_7$	−0.005***	0.279***	0.106***	0.072***	0.026*	−0.009	−0.011	0.403***
	(0.001)	(0.025)	(0.016)	(0.014)	(0.015)	(0.014)	(0.014)	(0.046)
Treat*$After_8$	−0.002*	0.053**	0.051***	0.033**	−0.009	−0.056**	−0.025*	0.193***
	(0.001)	(0.021)	(0.015)	(0.013)	(0.014)	(0.023)	(0.013)	(0.045)
Treat*$After_9$	0.002	0.386***	0.086***	0.066***	−0.017	−0.048***	−0.024*	0.442***
	(0.001)	(0.023)	(0.015)	(0.013)	(0.014)	(0.015)	(0.013)	(0.046)
Treat*$After_{10}$	0.004***	−0.074***	0.092***	0.060***	−0.018	−0.039***	−0.028*	0.457***
	(0.001)	(0.022)	(0.023)	(0.020)	(0.013)	(0.014)	(0.015)	(0.047)
Treat*$After_{11}$	0.005***	0.093***	0.112***	0.078***	−0.015	−0.031**	−0.019	0.375***
	(0.001)	(0.023)	(0.016)	(0.014)	(0.013)	(0.014)	(0.015)	(0.047)
Treat*$After_{12}$	0.005***	−0.020	0.003	−0.004	−0.024*	−0.052***	−0.026*	0.065
	(0.001)	(0.019)	(0.015)	(0.012)	(0.013)	(0.014)	(0.014)	(0.045)
Treat*$After_{13}$	0.005***	−0.012	−0.062***	−0.060***	−0.074***	−0.086***	−0.029*	0.167***
	(0.001)	(0.019)	(0.017)	(0.016)	(0.013)	(0.013)	(0.015)	(0.048)
Treat*$After_{14}$	0.005***	−0.076***	−0.060***	−0.058***	−0.088***	−0.092***	0.011	0.069
	(0.001)	(0.021)	(0.015)	(0.013)	(0.012)	(0.014)	(0.029)	(0.044)
Treat*$After_{15}$	0.003***	−0.248***	−0.059***	−0.059***	−0.085***	−0.088***	−0.032*	0.186***
	(0.001)	(0.019)	(0.013)	(0.012)	(0.013)	(0.013)	(0.017)	(0.046)
Treat*$After_{-3}$	−0.003**	−0.127***	0.149***	0.106***	0.033**	0.054**	−0.001	−0.139***
	(0.001)	(0.025)	(0.018)	(0.015)	(0.015)	(0.024)	(0.017)	(0.048)
Treat*$After_{-2}$	−0.001	0.073***	0.075***	0.049***	0.020	0.034*	−0.013	0.058
	(0.001)	(0.023)	(0.013)	(0.011)	(0.014)	(0.019)	(0.014)	(0.049)
FEs and Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,689	65,689	63,901	62,951	63,361	65,689	65,689	65,689
R^2	0.992	0.060	0.337	0.317	0.423	0.234	0.030	0.694

Table A.2: Effects of MWCBs: Volume

	(1) Buyer initiated	(2) Seller initiated	(3) Bid	(4) Ask	(5) Order imbalance (buy-sell)	(6) Order imbalance (bid-ask)	(7) Retail buy	(8) Retail sell
Treat	−0.176**	0.048	0.233***	0.087*	−0.224**	0.146***	−0.266***	−0.049
	(0.087)	(0.082)	(0.046)	(0.044)	(0.104)	(0.032)	(0.081)	(0.080)
Treat*After$_1$	1.496***	0.797***	1.242***	0.966***	0.699***	0.276***	0.295***	0.229***
	(0.102)	(0.086)	(0.054)	(0.045)	(0.122)	(0.044)	(0.086)	(0.081)
Treat*After$_2$	0.300***	0.526***	0.464***	0.372***	-0.226*	0.092**	0.116	0.262***
	(0.091)	(0.089)	(0.049)	(0.043)	(0.115)	(0.040)	(0.079)	(0.078)
Treat*After$_3$	0.376***	0.424***	0.437***	0.316***	-0.048	0.121***	0.105	0.241***
	(0.096)	(0.087)	(0.051)	(0.045)	(0.116)	(0.034)	(0.078)	(0.086)
Treat*After$_4$	0.315***	0.097	0.207***	0.201***	0.219*	0.006	0.189**	0.202***
	(0.094)	(0.090)	(0.046)	(0.042)	(0.119)	(0.032)	(0.074)	(0.076)
Treat*After$_5$	−0.114	−0.025	0.030	0.034	−0.089	−0.004	0.103	0.127
	(0.097)	(0.084)	(0.045)	(0.043)	(0.117)	(0.032)	(0.076)	(0.079)
Treat*After$_6$	0.692***	0.440***	0.340***	0.415***	0.252**	−0.074**	0.433***	0.229***
	(0.088)	(0.083)	(0.044)	(0.040)	(0.108)	(0.032)	(0.080)	(0.082)
Treat*After$_7$	0.798***	0.195**	0.276***	0.359***	0.602***	−0.083***	0.268***	0.157**
	(0.086)	(0.083)	(0.043)	(0.040)	(0.108)	(0.031)	(0.077)	(0.077)
Treat*After$_8$	0.264***	0.158*	0.085*	0.172***	0.106	−0.087***	0.193**	0.132*
	(0.085)	(0.085)	(0.046)	(0.042)	(0.110)	(0.031)	(0.077)	(0.079)
Treat*After$_9$	0.994***	0.117	0.292***	0.421***	0.877***	−0.128***	0.346***	0.224***
	(0.090)	(0.082)	(0.044)	(0.041)	(0.113)	(0.031)	(0.082)	(0.084)
Treat*After$_{10}$	0.751***	0.420***	0.278***	0.454***	0.332***	−0.176***	0.229***	0.135*
	(0.096)	(0.083)	(0.047)	(0.043)	(0.112)	(0.031)	(0.076)	(0.081)
Treat*After$_{11}$	0.777***	0.228***	0.208***	0.384***	0.549***	−0.176***	0.344***	0.108
	(0.090)	(0.082)	(0.045)	(0.041)	(0.109)	(0.032)	(0.077)	(0.081)
Treat*After$_{12}$	0.269***	0.051	−0.089**	0.030	0.218*	−0.119***	0.227***	0.002
	(0.088)	(0.081)	(0.044)	(0.039)	(0.111)	(0.031)	(0.077)	(0.080)
Treat*After$_{13}$	0.422***	0.091	−0.005	0.086**	0.331***	−0.092***	0.346***	0.170**
	(0.093)	(0.081)	(0.044)	(0.040)	(0.114)	(0.029)	(0.077)	(0.085)
Treat*After$_{14}$	0.107	0.144*	−0.077*	0.063	−0.037	−0.140***	0.197**	0.033
	(0.084)	(0.079)	(0.041)	(0.040)	(0.104)	(0.029)	(0.079)	(0.084)
Treat*After$_{15}$	0.174**	0.429***	0.064	0.152***	−0.256**	−0.088***	0.296***	0.088
	(0.086)	(0.082)	(0.041)	(0.041)	(0.109)	(0.031)	(0.073)	(0.079)
Treat*After$_{-3}$	−0.303***	−0.145	−0.119***	−0.115***	−0.158	−0.005	−0.110	0.048
	(0.098)	(0.089)	(0.046)	(0.040)	(0.127)	(0.032)	(0.077)	(0.078)
Treat*After$_{-2}$	0.118	−0.206**	0.066	0.065	0.325***	0.001	−0.007	0.168**
	(0.096)	(0.091)	(0.044)	(0.042)	(0.118)	(0.028)	(0.077)	(0.073)
FEs and Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,689	65,689	65,689	65,689	65,689	65,689	65,689	65,689
R^2	0.530	0.535	0.767	0.781	0.035	0.064	0.702	0.677