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Single stock circuit breakers on the London Stock Exchange: do they improve subsequent market quality?

James Brugler
Oliver Linton

The Institute for Fiscal Studies
Department of Economics, UCL

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Single stock circuit breakers on the London Stock Exchange: Do they improve subsequent market quality?

James Brugler[†] and Oliver Linton[‡]

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Abstract

This paper uses proprietary data to evaluate the efficacy of single-stock circuit breakers on the London Stock Exchange during July and August 2011. We exploit exogenous variation in the length of the uncrossing periods that follow a trading suspension to estimate the effect of auction length on market quality, measured by volume of trades, frequency of trading and the change in realized variance of returns. We also estimate the effect of a trading suspension in one FTSE-100 stock on the volume of trades, trading frequency and the change in realized variance of returns for other FTSE-100 stocks. We find that auction length has a significant detrimental effect on market quality for the suspended security when returns are negative but no discernible effect when returns are positive. We also find that trading suspensions help to ameliorate the spread of market microstructure noise and price inefficiency across securities during falling markets but the reverse is true during rising markets. Although trading suspensions may not improve the trading process within a particular security, they do play an important role preventing the spread of poor market quality across securities in falling markets and therefore can be effective tools for promoting market-wide stability.

Keywords: Circuit breakers, market microstructure, market quality

JEL Classification: G12, G14, G15, G18

[†]Faculty of Economics, University of Cambridge, Austin Robinson Building, Sidgwick Avenue, Cambridge CB3 9DD, United Kingdom. Email: jab244@cam.ac.uk.

[‡] Faculty of Economics, University of Cambridge, Austin Robinson Building, Sidgwick Avenue, Cambridge CB3 9DD, United Kingdom. Email: obl20@cam.ac.uk.

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1 Introduction

Many equity and futures exchanges around the world have mechanisms in place to temporarily suspend trading under certain market conditions, commonly referred to as circuit breakers. While the precise form that these mechanisms take can differ from one exchange to another, they are generally designed to achieve similar goals - to ameliorate unnecessary or transitory volatility in prices and to protect markets from periods of extreme illiquidity. In the aftermath of the "Flash Crash" in May, 2010, when major US equity indices lost 5-6% in a matter of minutes only to shortly recover much of these losses, US regulators were quick to point to the introduction of single-stock circuit breakers as well as a recalibration of market-wide circuit breakers as potential measures to mitigate the possibility or such an event reoccurring (U.S. SEC & CFTC, 2010).

However, despite the common aims underpinning the use of circuit breakers, it is not immediately apparent *a priori* how circuit breakers of different varieties will affect the trading process in different market environments. At the most basic level circuit breakers, by construction, prevent two otherwise willing counterparties from executing a transaction, possibly preventing the realization of a mutually beneficial trade. Indeed in a fully competitive trading environment with no information asymmetry, circuit breakers will lead to a departure from the first-best outcome in certain circumstances. However, in the presence of market power or information asymmetry, circuit breakers can help to improve market quality through a number of channels such as by reducing transitory price deviations driven by noise traders (Westerhoff, 2003) and reducing credit risk for levered investors (Chowdhry and Nanda, 1998; Brennan, 1986). Algorithmic trading at very low latencies potentially increases the likelihood of price instability over very short time horizons and circuit breakers may also play an important role in mitigating this risk (Linton, O'Hara and Zigrand, 2012).

Considering the many different ways that circuit breakers can affect the trading process and market quality, it is clear that empirical analysis has an important role to play in assessing the efficacy of these instruments. Making such causal inference is complicated mainly by the inherent difficulty in defining an appropriate counter-factual that accurately describes the state of the world if the price process was unchanged but a circuit breaker had not occurred. Despite this, empirical analysis using a variety of identification techniques have been conducted on a host of exchanges: USA, Japan, Taiwan, Korea, Malaysia, Turkey, Israel and Greece.

This paper examines the efficacy of circuit breakers on the London Stock Exchange (LSE) during July and August 2011, a particularly volatile period in global financial markets. We seek to answer two related empirical questions. Firstly, using variation in the length of the uncrossing period that follows all trading suspensions on the LSE, we determine the local effect of suspension length on the magnitude of market microstructure noise or price inefficiency in market prices (measured by the change in realized variance at high frequencies) as well as the volume and frequency of trading. The randomly assigned uncrossing period lasts from 0-30 seconds and provides an exogenous source of variation in the length of a suspension that allows us to make causal inference that would otherwise not be possible. Secondly, we estimate the effect of a suspension in one FTSE-100 stock on the change in realized variance and the levels of volume and frequency of trading for other stocks in the FTSE-100. That is, whether or not suspensions in a given security helps to limit contagion of poor market quality to other securities, or whether a suspension merely leads to a spillover of trading and volatility from the suspended security to other securities. This is achieved by comparing the trading process of all other FTSE-100 stocks in instances where a given stock triggers a circuit breaker with those where a circuit breaker is very nearly triggered but ultimately is not. Throughout our analysis we allow the effects to differ between events that occur at the upper and lower price limits.

We find that in the case of suspension length, longer auctions lead to a greater deterioration in market quality (greater price inefficiency for a given volume and number of trades) during lower limit events but find no significant effect for upper limit events. Regarding spillovers across securities, however, we find that suspensions at the lower limit lead to a statistically significant improvement in market quality for related securities following a suspension within a given sector (i.e. for those stocks with the same Bloomberg industry classification) but we do not observe a significant effect for stocks in other sectors. For events at the upper limits, we observe a significant increase in trade intensity and in the magnitude of market microstructure noise both for securities in the same sector as the event stock and outside that sector. Taken together, the evidence indicates that while circuit breakers may delay price discovery within a security potentially leading to efficiency losses and, for events at upper price limits, may do the same for other securities, they do help to prevent contagion of poor market quality across related securities when returns are negative. Due to observed empirical correlations between asset returns, market liquidity and cross-asset correlations, we believe that the spillover results for the lower limit events are of the most interest for policy makers concerned with promoting market-wide stability and therefore argue that single stock circuit breakers can play an important role in achieving this aim.

Relating our results to the existing theory, the delay of price discovery and increase in subsequent volatility is consistent with the predictions of Lehmann (1989) and Fama (1989), although we note that the effect is relatively short lived, and appears to manifest in the upper tail of the distribution of subsequent volatility following a trading halt. Furthermore, since auction length does not have a significant effect on the intensity of the trade arrival process, it is plausible that the deterioration in market quality is due to a lack of liquidity following longer auctions rather than delayed price discovery per se. We also find that the conditional volatility of high-frequency returns increases with proximity to the price limit, consistent with the presence of a "magnet effect" as predicted by Subrahmanyam (1994). Market microstructure theory to date has had less to say about spillovers across securities. One exception is Spiegel and Subrahmanyam (2000) who analyze the effect of trading halts around impending news announcements in one security on trading in related securities, concluding that trading halts should lead to a decrease in liquidity for other securities in the same industry. Our results suggest that this only the case when prices are rising although, importantly, we are considering trading halts that are not due to impending material announcements, and so the spillover mechanism being elucidated in Spiegel and Subrahmanyam (2000) is not directly applicable to our case. We also note that in the case of positive returns, we observe an increase in trade intensity so it is not clear that our results are being driven by a decrease in liquidity. Regarding the asymmetric spillover effects of suspensions in the cases of rising and falling markets, these results can potentially be understood using the framework of Brunnermeier and Pedersen (2009) who elucidate feedback effects between asset returns, market liquidity and funding liquidity. Specifically, one reason why we might observe an improvement in the market quality of other securities during a lower-limit suspension is that, via the well documented "leverage effect" in equity markets, such environments are associated with higher volatility. This can in turn lead to more onerous margin requirements for leveraged traders, as well as tighter funding conditions for market makers, and can potentially have the effect of tipping the market into an equilibrium characterized by poor liquidity and even greater volatility. By removing the most volatile stock from trading, even temporarily, we may help limit the onset of these feedback mechanisms and potentially prevent tipping from a good equilibrium to a bad equilibrium. This is by no means the only mechanism that could rationalize the asymmetric spillover effects we observe and developing models to better understand this could potentially be a fruitful angle for future theoretical research.

This paper contributes to the existing literature in a number of ways. Firstly, we provide the first empirical evidence that we know of regarding the effect of single-stock circuit breakers on market quality for other securities, which has direct relevance for market-wide stability.[1] We also exploit a hitherto unused source of exogenous variation in suspension length to make inference about the effect of suspension length on market quality. Furthermore, to the best of our knowledge, this is the first paper to examine circuit breakers on the LSE specifically - an exchange of relative global importance as well as one with meaningful differences in the nature of circuit breakers in place compared with those on exchanges that have previously been studied.[2] We also demonstrate that an identification strategy commonly used to estimate the effect of price limits and circuit breakers in the literature suffers from bias due to censoring of the outcome variables. Lastly, we present a theoretical analysis of first passage times to static price limits when prices follow geometric Brownian motion, in both the univariate and bivariate settings.

The paper proceeds as follows. In section 2 we discuss previous theoretical and empirical contributions to the circuit breaker literature. Section 3 describes the details of circuit breakers on the LSE including how the price limits are set by the exchange, as well as how the suspension progresses

[1] Jiang et al. (2009) & Tookes (2008) consider the across-stock spillover effect of news-related trading suspensions on the New York Stock Exchange, however there are material differences in the nature of such effects when the suspension is due to the price process of the securities rather than news announcements of a material nature.

[2] The LSE was the largest exchange in Europe by trading value in 2011, and the largest outside of the USA, Japan and China (World Federation of Exchanges, 2013)

and continuous trading resumes. We also consider the role of circuit breakers when prices follow geometric Brownian motion, and provide formulae for the first passage time for both the one-sided and two-sided barrier crossing problem, as well as the joint density of first passage times for multiple correlated securities in this section. Section 4 outlines our empirical methodology including definitions of market quality and our identification techniques. Section 5 describes the dataset in detail. Section 6 contains results for the regressions outlined in section 4 that assess the efficacy of circuit breakers on the LSE, as well as times-series regressions that describe how the mean and variance of the high-frequency returns process are affected by distance from price limits and variance ratio tests for high frequency returns. Section 7 summarizes these results and discusses directions for future research.

2 Related Literature

Theoretical contributions to the literature have highlighted a number of channels through which circuit breakers can either lead to an improvement or deterioration of the trading process and market quality. If markets are efficient, in the Fama (1970) sense that prices reflect all available information, then trading halts can result in a deviation from the first-best outcome. In such an environment, inefficiencies can manifest through prevention of mutually beneficial trades (Grossman, 1990), delayed price discovery (Fama, 1989), excess volatility and magnet effects whereby price limits become self-fulfilling (Subrahmanyam, 1994), volatility spillovers to subsequent trading days (Lehmann, 1989) and higher trading costs for uninformed or small investors (Subrahmanyam, 1997).

However, in a trading environment that deviates from full information and perfect competition, trading halts and price limits can theoretically lead to an improvement in welfare. Specifically, improvements can be wrought from mitigation of information asymmetry (Spiegel and Subrahmanyam, 2000), reduction in "transactional risk"[3] (Greenwald and Stein, 1991; Kodres and O'Brien, 1994), reduction of counter-party risk in derivatives markets and for leveraged investors (Chowdhry and Nanda, 1998; Brennan, 1986), limitations to the gains from market manipulation (Kim and Park, 2010) and the associated costs of monitoring market manipulation (Deb et al., 2010), and by reducing volatility and price deviations from fundamentals driven by noise traders (Westerhoff, 2003).

In practice, trading rules differ significantly from exchange to exchange and the variety of different instruments in place to mediate excessive price movements makes it difficult to generalize conclusions about their efficacy. At a basic level these instruments can be categorized into two groups: price limits, whereby continuous trading is not stopped but trades are not permitted at any price above or below a predefined level for a set period of time (typically the remainder of that day), and trading halts, whereby continuous trading is stopped for a set period of time. Trading

[3]Transactional risk refers to the risk of a market order being executed at an unfavorable price.

rules may also differ as to whether the instrument applies to a single security or to a wider set of securities. Examples of exchanges using price limits include the Istanbul Stock Exchange, Kuala Lumpur Stock Exchange, Taiwan Stock Exchange, and Tokyo Stock Exchange while variants of trading suspensions are in place on the New York Stock Exchange (NYSE), the Deutsche Bourse, Euronext-Paris, the Tel Aviv Stock Exchange, the Korea Exchange (previously known as the Korean Stock Exchange), and the London Stock Exchange. The Continuous Spanish Stock Market (aka the SIBE) implements a combination of price limits and discretionary trading suspensions. Table 1 contains a summary of the different variants of price limits and trading suspension rules in place on the ten largest exchanges by total value traded in 2013 according to World Federation of Exchanges (2013). Empirical analysis of circuit breakers has been conducted on exchanges that use both types of instruments however for the purposes of this discussion, we focus on work that analyzes trading suspensions specifically rather than price limits as these are most similar to the mechanisms in place on the LSE.[4]

Table 1: Circuit breakers and price limits in global equity exchanges

Market stabilization measures employed on the ten largest stock exchanges by total value traded in 2013 according to World Federation of Exchanges (2013). The second column indicates whether the exchange employs measures to stop all trading under certain circumstance (circuit breakers). The third column indicates whether the exchange uses price limits (trading is prevented outside certain bands but trading within the bands may still occur). The fourth column reports the total value traded on the exchange during 2013 in billions of US dollars. The fifth column indicates whether these measures are applied to individual securities, or to a market-wide index. *Sources:* Coleman et al. (2013), U.S. SEC (2013), Tokyo Stock Exchange (2010), Shanghai Stock Exchange (2010), Korea Exchange (2009) & Hong Kong Stock Exchange (2010).

Exchange	**CBs**	**Limits**	**Value ($bn)**	**Notes**
NYSE & NASDAQ	Yes	Yes	21,294.90	Market-wide CBs, stock specific limits
Shanghai & Shenzen SEs	No	Yes	6,943.04	Stock-specific price limits
Tokyo Stock Exchange	Yes	Yes	5,804.18	Market-wide CBs, stock specific limits
London Stock Exchange	Yes	No	2,075.18	Stock-specific circuit breakers
NYSE-Euronext (Europe)	Yes	No	1,532.47	Stock-specific circuit breakers
Toronto Stock Exchange	Yes	Yes	1,272.17	Coincides with US markets
Deutsche Bourse	Yes	No	1,233.90	Stock-specific circuit breakers
Hong Kong SE	No	No	1,215.01	-
Korea Exchange	Yes	Yes	1,201.44	Market-wide CBs, stock specific limits
Australian SE	No	No	821.31	-

Market-wide circuit breakers on US stock and futures exchanges were first introduced following

[4]For the interested reader, empirical analysis of the effect of price limits has been conducted for the Tokyo Stock Exchange (Kim and Rhee, 1997), Athens Stock Exchange (Phylaktis et al., 2002), Taiwan Stock Exchange (Huang et al., 2001; Cho et al., 2003), Kuala Lumpur Stock Exchange(Chan et al., 2005), and the Istanbul Stock Exchange (Bildik and Gülay, 2006).

the “Black Monday” stock-market crash in 1987 (Kim and Yang, 2004). Since then the format and parameters of circuit breakers on these exchanges have undergone a number of modifications, notably in 1998, when percent moves in the DJIA index replaced absolute points moves as the basis for a circuit breaker (Goldstein et al., 1998) and following the Flash Crash on May 6, 2010 (U.S. SEC & CFTC, 2010). Currently, US equity markets including the NYSE and NASDAQ use two kinds of trading suspensions; a market-wide circuit breaker when the S&P500 falls to a certain level below the previous day’s closing price, and a “limit-up-limit-down mechanism”, rolling price limits that apply to single stocks with price bands calculated over the previous five minutes trading (U.S. SEC, 2013). Prior to the Flash Crash, the NYSE also used “liquidity replenishment points” (LRPs), whereby trading in a stock is temporarily converted from the electronic market to a manual auction market after a sufficiently large price movement (NYSE Euronext, 2010). In interviews with market participants by regulators following the Flash Crash, the SEC and CFTC identified that many market participants were able to route orders to other exchanges during such an event, potentially limiting the effectiveness of the mechanism (U.S. SEC & CFTC, 2010). Furthermore, market participants mentioned that widespread triggering of LRPs across the market was a factor in forming expectations that market-wide liquidity was poor. The new limit-up limit-down mechanisms are designed to replace LRPs with the aim of ensuring trading rules are not unnecessarily complex although the NYSE believes that LRPs have “delivered concrete benefits to investors” through stabilizing prices and preventing erroneous trades (SEC, 2013).

Several studies have assessed the impact of the suspension mechanisms in place prior to 2010. Gerety and Mulherin (1992) exploit the observation that the lack of trading overnight can be considered a type of trading halt and show that a measure of expected overnight volatility is significant in regressions for the closing volume. The authors argue that this is evidence that some participants are unwilling to hold overnight risk and thus by extension some would be unwilling to hold risk during a trading suspension. Lee et al. (1994) compare the volatility and volume around discretionary suspensions with the average volatility and volume at the same time of day for the same day and stock, and also after matching stocks using absolute returns from the beginning to the end of the trading halt. Volatility and volume are found to be significantly higher after the suspensions compared with the control group. Corwin and Lipson (2000) compare liquidity, order book depth and volatility around news related and order-imbalance related trading suspensions on the NYSE during 1995-1996. They show that total order book depth falls and spreads rise ahead of halts of both kinds, but market and limit order submissions rise substantially towards the end of the suspension and remain high for around two hours subsequent to the resumption of trading.[5] Goldstein and Kavajecz (2004) examine trading in the lead-up to the the October 1997 market-wide suspension and find that while participants did not significantly change the number or volume of trades as the DJIA approached the limit price, the proximity of sell-limit orders to the best bid did

[5] Orders submitted during a halt are not executed until the end of the trading halt.

reduce and that there was a concentration of cancellations of buy orders ahead of the event. One of the few papers to consider how trading suspensions impact related securities rather than the security undergoing the suspension is Jiang et al. (2009) who look at the effect of news-specific trading halts on the NYSE on stocks with the same four-digit SIC code as the halted stock. They show that while spreads and the price impact of trades do increase in related securities, so do quoted depth, trade numbers and trade volumes. Another example that considers cross-security effects during trading halts is Tookes (2008) who presents a model that analyzes how information in one security may affect informed trading in other related securities. The implications of the model are tested by considering how informative are trades in related securities for a security undergoing a suspension due to an impending earnings announcement. She finds that such trades are informative for the suspended security. It is important to keep in mind that both Tookes (2008) and Jiang et al. (2009) are considering information-related trading suspensions rather than trading based circuit breakers, as are in place on the LSE.

Analysis of trading suspensions outside of the USA include Lauterbach and Ben-Zion (1993) who examine trading on the Tel Aviv Stock Exchange (TASE) around the October 1987 crash commonly known as "Black Monday", and Kim et al. (2008) who compare the impact of discretionary trading halts and price limits on the SIBE. Lauterbach and Ben-Zion (1993) compare the order imbalance and price movements between the 20th and 21st of October, 1987 of TASE stocks that were placed into a suspension after the opening auction and those that continued to trade. Their results suggest that trading halts moderated order imbalance and excessive price swings but did not have a longer-term impact on trading in these securities. Kim et al. (2008) compare market statistics for Spanish stocks that trade on the SIBE following both a discretionary halt, and after prices reach their predefined limits. Their results indicate that both the volume and speed of trading increase after both kinds of events but that liquidity only improves after a trading halt, although this analysis does not attempt to control for non-random selection into the two categories of events.

Given the inherent difficulty in conducting causal inference for the evaluation of the efficacy of circuit breakers (discussed above), as well as data limitations, experimental evidence can potentially allow for a more nuanced understanding of how market participants react to such trading rules. Ackert et al. (2001) takes such an approach and designs experiments that examine the trading process under different trading rules (no circuit breakers, short-term trading halts and long-term trading halts) and differing levels of information asymmetry. They find that circuit breakers do not have a meaningful effect on price deviations from fundamental values, which is driven entirely by information asymmetry, but the possibility of long-term trading halts leads participants to accelerate their trading. Further, short-term and long-term trading halts are found to be equally likely to occur. Ackert et al. (2005) perform a similar experimental but where participants are unsure if a subset of the investors has private information. In such a setting, it is plausible that circuit breakers could serve to temper the effects of some participants erroneously concluding that private information is present. However, they find that this is not the case and that prices deviate further from fundamentals following a trading suspension.

3 Circuit breakers on the London Stock Exchange

The LSE continuously monitors the state of the order book for securities throughout the trading day and compares potential execution prices against two types of reference prices referred to as dynamic and static reference prices. If the ex-ante price of a potential execution breaches any of the reference prices, the market will enter a temporary suspension referred to as an automatic execution suspension period (AESP), initially lasting five minutes followed by an uncrossing auction to resume continuous trading. During this AESP, participants may submit limit and market orders and the exchange continuously publishes the theoretical price and volume that the uncrossing auction would generate if it was run at that point in time, taking into account the orders placed by participants so far (London Stock Exchange, 2011). In this sense, the AESPs on the London Stock Exchange can be considered a switch from continuous trading to auction mode trading.

Throughout the day, the dynamic reference prices are set as certain deviations up or down from the price of the last automated trade in that security. The static reference prices are determined as a certain deviation up or down from the uncrossing price of the previous auction (typically the opening auction). The thresholds are determined at the LSE market sector level and take into account average liquidity of the securities in that sector. All FTSE-100 sectors in our sample had a dynamic threshold of 5% and a static threshold of 10% during the time period spanned by our data (1st July - 31st Aug 2011). For FTSE-250 sectors, all but one had a static threshold of 10%, with dynamic thresholds varying from 5-15%.

The suspension can be extended by a predefined period if the potential uncrossing price deviates by too wide a margin from the previous automated trade price (referred to as a price monitoring extension), or if the uncrossing algorithm would result in unfilled market orders at the resumption of trading (referred to as a market order extension). The end of suspensions are also subject to a random time period of between 0-30s before the resumption of continuous trading. The stated aim of this is to remove the incentive to enter erroneous orders that would unduly affect price formation towards the end of the auction (London Stock Exchange, 2000).

Within the subset of all LSE securities that comprise the FTSE-100 index, there were a total of 28 events over our sample period (see table 2), with eight due to a breach of a fixed price limit above the reference price, nineteen due to a breach of a lower limit and one due to a breach of the dynamic reference price. In all securities on the LSE that trade on average at least 100 times per day (approximately once every five minutes), there were a total of 708 trading suspensions. We estimate that around 25 of these were dynamic limit breaches although data limitations make it impossible to rule out the possibility that a dynamic and static limit breach occurred simultaneously.[6] Nevertheless, it is clear that a very significant majority of events are static limit breaches and our analysis is generally restricted to these kinds of events.

3.1 Static price limits with Brownian price processes

In this section we investigate how a static circuit breaker system such as that which is in place on the London Stock Exchange might operate under a standard frictionless model for stock prices. Suppose that the log price of a given stock $p_t = \log P_t$, where P_t denotes the price at time t, evolves according to

$$dp_t = \sigma dB_t, \; t \in [0,1], \tag{1}$$

where σ is the diffusion coefficient/daily volatility parameter and the day length is normalized to one. Suppose that a static threshold c is set as a percentage price change. This means that the circuit breaker would trigger whenever

$$|p_t - p_0| > c$$

for some $t \in [0,1]$, where p_0 is the opening price. We characterize the probability that this happens for some time during a trading day as a function of the volatility and the threshold parameter. Related to this is the distribution of the first passage time τ, where $\tau = \min\{t : |p_t - p_0| > c\}$. This is a standard barrier crossing problem for Brownian motion, except that the time horizon is finite. We have that

$$\Pr\left[\sup_{0\le t\le 1} |p_t - p_0| > c\right] = 1 - \frac{2}{\pi}\sum_{j=0}^{\infty} \frac{(-1)^j}{j+\frac{1}{2}} \exp\left(-\left(j+\frac{1}{2}\right)^2 \pi^2 a^2/2\right), \tag{2}$$

$$f_0(t|, a) = \sum_{j=-\infty}^{\infty} \frac{2a(1+4j)}{\sqrt{2\pi t^3}} \exp\left(-\left(4j+1\right)^2 a^2/2t\right), \tag{3}$$

where $a = c/\sigma$ (see Darling and Siegert (1953)). Equation (2) is the probability of a passage across the threshold during the trading day and equation (3) is the density function for the first passage time (actually, this density has support [0,∞), to obtain the density on [0,1] we should renormalize by the probability that \tau<1). From (2) it is clear that the probability of crossing the barrier decreases with c/σ.

The one-sided probability was considered by Bachelier (1901), and is much simpler to present. In particular, let $\tau_a = \min\{t : p_t > p_0 + c\} = \min\{t : B_t > a\}$. Then the density function for barrier

[6] For example, a trade-to-trade price move of 5% could trigger both a dynamic and static limit breach simultaneously if the absolute return from open was in excess of 5% prior to the sequence of trades that would trigger a dynamic breach.

crossing and the probability of a barrier crossing are given by

$$f_0(t|x,a) = -\frac{a}{t^{3/2}}\phi\left(\frac{a}{\sqrt{t}}\right) = \frac{a}{\sqrt{2\pi t^3}}\exp\left(-\frac{a^2}{2t}\right) \tag{4}$$

$$\Pr\left[\tau_a \le t\right] = 2\left[1 - \Phi\left(\frac{a}{\sqrt{t}}\right)\right]. \tag{5}$$

Substituting $a = c/\sigma$ and evaluating (5) at $t = 1$ gives the probability of observing a circuit breaker on a given day at the limit price c under the simple model of stock prices given in (1):

$$\Pr\left[\sup_{0\le t\le 1} p_t > p_0 + c\right] = 2\left[1 - \Phi\left(\frac{c}{\sigma}\right)\right] \tag{6}$$

and similarly for the downside crossing. Note that for $c/\sigma = 5$, the probability of a crossing is very low and the density rises monotonically towards the end of the day.[7] Figure 1 shows the first passage hazard function ${}^{f_0}/_{1-F_0}$ for $c/\sigma = 5$ and for $c/\sigma = 1$. In the latter case we witness the early peak in hazard function.

In practice we see higher density of hits early in the day and at the end of the day. This partly reflects the fact that on days where no trades occur during the opening auction, the static reference price is set to the previous closing price. If this occurs after a particular volatile overnight period, the first automated trade of the day can result in a static limit breach. Furthermore, intraday patterns in volatility whereby volatility is relatively higher early and late in the day would imply that dynamic limit breaches are more likely during these times, unconditional on the price path to that point in time.

However, it is also possible that we would observe mass in the density of static limit breaches from the opening auction price early in the trading day. To see this, suppose that (1) holds but that σ is stochastic and in fact is drawn from some density $\sigma \sim H(\sigma)$. In that case we may find days where c/σ is small (with early peak of hitting times) and other days with higher c/σ and a later peak of density. Unconditionally we could observe a U-shaped density. Figure 2 contains the annualized standard deviation of five minute log returns over all days in our sample for each FTSE-100 stocks (each stock and day combination contributing a single data point). These data indicate that there are many days where the volatility of returns is sufficiently large to result in a ratio of c/σ of the order that would generate early peaks in the crossing-time hazard function as observed in figure 1.

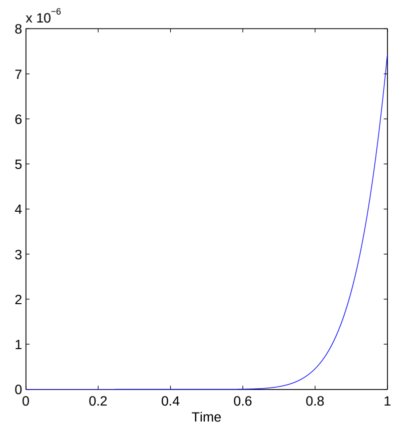
The above analysis is relevant for the understanding what happens for each individual stock. It is also of interest to understand the situation for a cross-section of stocks. The multivariate

[7] This ratio would correspond to an annualized volatility of around 32% for a 10% static price limit. For a ratio of 1 as per the second set of figures in figure 1, the ratio corresponds to an annualized volatility of 159%.

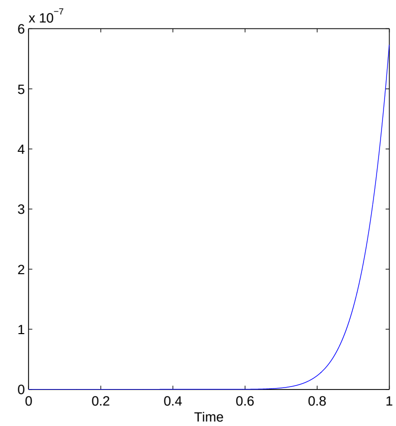
Figure 1: Hazard function and CDF for first passage time

Hazard functions and CDFs for the one-sided first passage time to a fixed barrier for stock prices that follow geometric Brownian motion when volatility is low and high. The first passage time to barrier c is defined as $\tau = \min\{t : |p_t - p_0| > c\}$ where p_t is the log stock price at time t. For GBM without drift, the PDF and CDF for τ are given by $f_0 = \frac{a}{\sqrt{2\pi t^3}} \exp\left(-\frac{a^2}{2t}\right)$ and $F_0 = 2\left[1 - \Phi\left(\frac{a}{\sqrt{t}}\right)\right]$ respectively where $a = c/\sigma$. The hazard function is defined as $f_0/1 - F_0$.

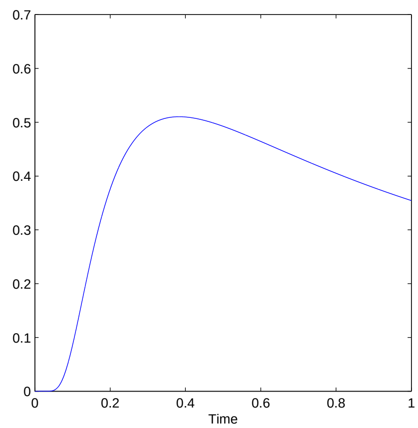
(a) Hazard function $c/\sigma = 5$



(b) CDF $c/\sigma = 5$



(c) Hazard function $c/\sigma = 1$



(d) CDF $c/\sigma = 1$

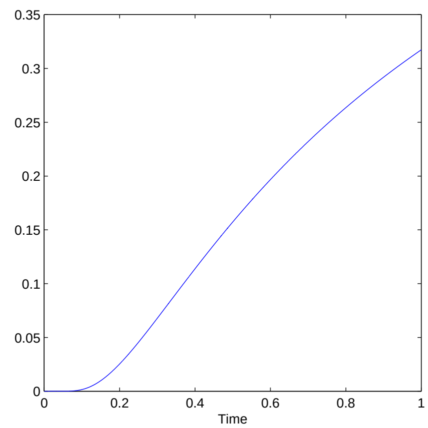
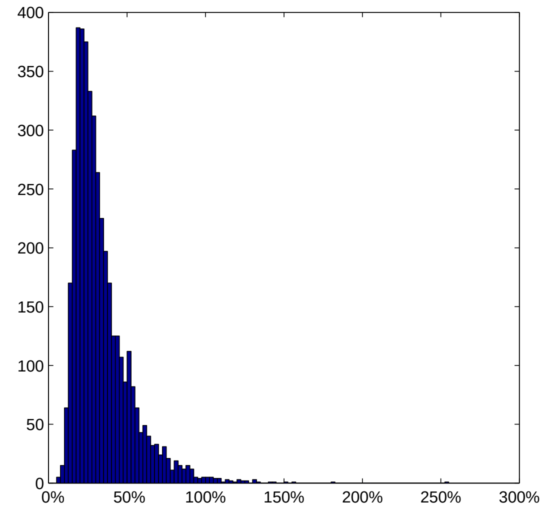


Figure 2: Annualized standard deviation of 5 min returns of all FTSE-100 stocks

Annualized standard deviations of 5 min returns for each FTSE-100 stock during each day in our sample. The annualized standard deviation for stock i on day t is calculated as $\sigma_{i,t}^{Ann} = \sqrt{252 \times 102}\sigma_{i,t}^{5min}$ and $\sigma_{i,t}^{5min}$ is the sample standard deviation of 5 minute log returns for stock i and day t. A daily volatility of 1% corresponds to an annualized value of 15.9%.



boundary crossing problem has also been studied. Metzler (2010) considers the situation where a vector of prices are observed that evolve according to the multivariate diffusion

$$dX_t = \Sigma^{1/2} dB_t$$

where Σ is the instantaneous covariance matrix, a function of σ_1, σ_2, ρ, and $X_0 = x$ is the initial condition, while B is a vector of independent standard Brownian motions. He calculates the density of the random variable $\tau_i = \inf\{t > 0 : X_{it} = 0\}$, the first passage time of X_i to zero from initial condition x_i (in our case, $X_{it} = p_{it} - p_{i0} + c$). Define:

$$a_i = x_i/\sigma_i$$

$$r_0 = \sqrt{\frac{a_1^2 + a_2^2 - 2\rho a_1 a_2}{1-\rho^2}}$$

$$\theta_0 = \begin{cases} \pi + \tan^{-1}\left(\frac{a_2\sqrt{1-\rho^2}}{a_1 - \rho a_2}\right) & a_1 < \rho a_2 \\ \frac{\pi}{2} & a_1 = \rho a_2 \\ \tan^{-1}\left(\frac{a_2\sqrt{1-\rho^2}}{a_1 - \rho a_2}\right) & a_1 > \rho a_2 \end{cases}$$

$$\alpha = \begin{cases} \pi + \tan^{-1}\left(-\frac{\sqrt{1-\rho^2}}{\rho}\right) & \rho > 0 \\ \frac{\pi}{2} & \rho = 0 \\ \tan^{-1}\left(-\frac{\sqrt{1-\rho^2}}{\rho}\right) & \rho < 0. \end{cases}$$

Then the joint density of τ_1, τ_2, denoted $f(s,t)$ is given as follows:

For $s < t$

$$f(s,t) = \frac{\pi \sin\alpha}{2\alpha^2\sqrt{s(t - s\cos^2\alpha)(t-s)}} \exp\left(-\frac{r_0^2}{2s}\frac{t - s\cos 2\alpha}{(t-s) + (t - s\cos 2\alpha)}\right) \\ \times \sum_{j=1}^{\infty} j \sin\left(\frac{j\pi(\alpha - \theta_0)}{\alpha}\right) I_{j\pi/2\alpha}\left(\frac{r_0^2}{2s}\frac{t-s}{(t-s) + (t - s\cos 2\alpha)}\right) \tag{7}$$

For $s > t$

$$f(s,t) = \frac{\pi \sin\alpha}{2\alpha^2\sqrt{t(s - t\cos^2\alpha)(s-t)}} \exp\left(-\frac{r_0^2}{2t}\frac{s - t\cos 2\alpha}{(s-t) + (s - t\cos 2\alpha)}\right) \\ \times \sum_{j=1}^{\infty} j \sin\left(\frac{j\pi\theta_0}{\alpha}\right) I_{j\pi/2\alpha}\left(\frac{r_0^2}{2t}\frac{s-t}{(s-t) + (s - t\cos 2\alpha)}\right). \tag{8}$$

Here, $I_x(.)$ is the Bessel function of the first kind.

Inspecting equations (7) and (8) we note that for positively correlated Brownian motions with zero drift, the joint density of first passage times for the components has a singularity at the point $s = t$. This implies that even under a rational, frictionless model of stock prices, circuit breakers are relatively likely to be triggered simultaneously when the underlying prices are positively correlated. Bearing in mind the fact that extreme values are asymptotically independent even for highly correlated Gaussian random variables (Longin and Solnik, 2001), the singularity in the joint density of the first passage times is surprising.

To summarize, the distribution of first passage times from stock prices that follow geometric Brownian motion model without drift provides a number of predictions about the probabilities of circuit breakers, both in the univariate and multivariate case. Firstly, the shapes of the hazard function and CDFs of the first passage time have different properties depending on the initial distance to the barrier and the underlying volatility. For close barriers or high volatility, the hazard function can attain a maximum value on the interior of the time domain, and the CDF can have a concave region. For relatively distant barriers or low volatility, these functions are convex increasing functions throughout the entire time domain. Comparing these predictions with our data, we note that the CDF of events across all LSE securities in our sample region has a concave region early in the day's trading (see figure 3). This is consistent with high volatility relative to distant to the barrier, although it is important to note that this is partially driven by opening auctions that do not generate a trade (as discussed above).

In the multivariate case, the model predicts that circuit breakers are relatively likely to be triggered simultaneously when the underlying price processes are positively correlated, even when the underlying process is Gaussian. Anecdotally, regulators noted that many market participants noticed the simultaneous triggering of NYSE LRPs across many securities and took this as a sign of market-wide instability following the Flash Crash in May 2010 (U.S. SEC & CFTC, 2010). The results above may provide additional perspective to these events, although the work on joint densities of first passage times is so far confined to bivariate geometric Brownian motion without drift, so it is not straightforward to generalize these results.

4 Empirical methodology for identifying causal effects of circuit breakers

Our empirical approach to analyzing the efficacy of circuit breakers seeks to answer two related questions. Firstly, we investigate how the variation in the length of a trading suspension affects subsequent market quality for a security that breaches a static price limit. Secondly, we investigate the effect of a trading suspension in a particular FTSE-100 stock following a static limit breach on subsequent market quality for other FTSE-100 stocks. In both cases we use identification strategies that are robust to the issue of censoring of the outcome variable (discussed in section 4.2.1 below). For the case of auction length, we exploit a natural experiment that exists due to the nature of trading rules on the LSE (outlined in detail section 4.1). For spillovers effects across securities, we use a quasi-regression discontinuity approach (outlined in detail in section 4.2). Importantly our regression strategy is not heavily model dependent and allows us to make causal inference regarding the effect of suspensions within and across securities (Angrist and Pischke, 2008).

We consider three related market statistics: the volume of trades, the number of trades, and the change in realized variance from before and after an "event", each measured over 5 and 30 minute for the case of auction length, and over 5 minutes for the spillovers. For events where an AESP occurs and hence continuous trading is suspended (which we refer to as "halts"), the interval preceding the event is defined as the 5 or 30 minute period prior to the suspension of automated trading and the interval following the event is defined as the 5 or 30 minute period immediately after the end of the suspension, and the resumption of automated trading. For "near halts", whereby a stock trades within 1% of the price limit that would lead to a suspension but ultimately does not cross this barrier, the interval preceding the event is defined as the 5 or 30 minute period prior to the point in time where the distance from the price of that stock to the price limit attains a minimum. The interval following the event is defined as the 5 or 30 minute period immediately after this. We focus on these relatively short term measures of market quality partly due to the short length of the circuit breakers themselves and also the desire to understand the impact of these trading suspensions on market quality shortly after the suspension ends. Furthermore, as many circuit breakers occur early or late in the trading day, increasing the total interval over which we measure these statistics over reduces the number of observations in our sample.

Volume and number trades are calculated as the total number of shares traded and total number of trades executed on the LSE electronic order book during the particular interval respectively.[8] The change in realized variance (ΔRV) is calculated as the difference in the sum of squared log returns in the interval following an event (halt or near-halt) and the sum of squared log returns in the interval preceding the event:

$$\Delta RV = RV^t_{T'' \to T'' + \bar{T}} - RV^t_{T' - \bar{T} \to T'} \tag{9}$$

where T' is the time of the event, T'' is the time immediately after the event, t is the frequency of observations (10 seconds for 5 minute intervals and 30 seconds for 30 minute intervals), $\bar{T}$ is the length of the event (5 or 30 minutes) divided by t, and, the realized variance from period T_1 to T_2 measured at frequency t is given by:

$$RV^t_{T_1 \to T_2} = \sum_{i=2}^{N} \left(\log P_{T_1 + i \times t} - \log P_{T_1 + (i-1) \times t} \right)^2 \tag{10}$$

where P_s is the price of the most recent trade at time s and N is the number of t intervals between T_1 and T_2.

In a frictionless model of stock prices, realized variance is a consistent estimator of the quadratic variation of the underlying price process as the measurement frequency increases asymptotically (Hansen and Lunde, 2006). However, when market microstructure effects are present, it is well known that realized variance is not a consistent estimator of the quadratic variation of the underlying price process (e.g. see Zhou (1996), Hansen and Lunde (2006) or Bandi and Russell (2008)). While recent work has highlighted that as an estimator of daily quadratic variance, appropriately sampled realized variance performs as well as other more sophisticated estimators Liu et al. (2012), in our case, we are sampling at relatively high frequencies so market microstructure effects are very likely to be present (Patton, 2011) and probably dominate the underlying volatility component. To demonstrate, we can decompose the RV of returns in the presence of market microstructure noise

[8]The LSE gives assigns the flag "automated Trade" or AT to these trades.

over a particular period as

$$
\begin{aligned}
RV &= \sum_{i=2}^{M} \left(p_t - p_{t-1} + \eta_t - \eta_{t-1}\right)^2 && (11)\\
RV &= \sum_{i=2}^{M} \left(r_t + \varepsilon_t\right)^2 && (12)\\
RV &= \sum_{i=2}^{M} r_t^2 + 2\sum_{i=2}^{M} r_t\varepsilon_t + \sum_{i=2}^{M} \varepsilon_t^2 && (13)
\end{aligned}
$$

where p_t is the log of the efficient price at time t, η_t denotes the market microstructure noise, r_t is the log return and $\varepsilon_t = \eta_t - \eta_{t-1}$. The third term of equation (13) ensures that even if the market microstructure noise is i.i.d, the RV is a biased estimator for the quadratic variation of efficient returns.[9]

However, for studying the effects of circuit breakers on market quality, it is precisely these market microstructure effects that we are most concerned about. Circuit breakers are only warranted in cases where market prices diverge from efficient prices, which is precisely when market microstructure effects (perhaps due to poor liquidity or high adverse selection costs for liquidity providers) are large in magnitude. As such, the fact that RV contains a term capturing the market microstructure noise is useful for our analysis, as this can be considered a transitory component of volatility (as opposed to the fundamental volatility of the efficient returns process), or a measure of price inefficiency. Under some assumptions about the processes governing the efficient returns and the market microstructure noise, the difference in RV from before and after an event (halt or near-halt) can be interpreted as a noisy measure of the change in magnitude of market microstructure noise or price inefficiency that is present in the market prices. For example, suppose that true prices follow standard Brownian motion with constant volatility, and the market microstructure frictions are independent of the true prices. We can write (with slight abuse of notation) the difference in RV during periods $1 \to M'$ and $M'' \to N$ with $M'' > M'$ as:

$$
\Delta RV = \left(\sum_{i=M''}^{N} r_t^2 - \sum_{i=1}^{M'} r_t^2\right) + 2\left(\sum_{i=M''}^{N} r_t\varepsilon_t - \sum_{i=1}^{M'} r_t\varepsilon_t\right) + \left(\sum_{i=M''}^{N} \varepsilon_t^2 - \sum_{i=1}^{M'} \varepsilon_t^2\right) \qquad (14)
$$

and $\mathbb{E}\left[\Delta RV\right]$ as

$$
\mathbb{E}\left[\Delta RV\right] = \mathbb{E}\left[\sum_{i=M''}^{N} \varepsilon_t^2\right] - \mathbb{E}\left[\sum_{i=1}^{M'} \varepsilon_t^2\right]. \qquad (15)
$$

We can think of ΔRV as capturing the change in the magnitude of market microstructure noise as

[9] In fact this term diverges to infinity almost surely as the measurement frequency increases asymptotically (Bandi and Russell, 2008).

well as additional terms related to the volatility of the returns process and the covariance of the returns with the market microstructure noise. That fundamental prices follow Brownian motion with constant volatility and the returns are independent of the market microstructure noise are sufficient (but not necessary) conditions for these terms to have expected value of zero, and hence the change in RV is a (noisy) measure of the change in the magnitude of market microstructure noise or transitory volatility between the two periods. In fact, so long as the returns process is weakly stationary and the covariance between the returns and the market microstructure noise is constant before and after an event (halt or near halt), ΔRV can be considered a noisy measure of the change in the magnitude of market microstructure noise in the realized prices.

4.1 Identifying the effect of suspension length on market quality

In the case of the effect of auction length on market quality, we exploit the randomized uncrossing time (detailed in section 3) that follows the end of a trading halt as a source of exogenous variation in the length of auctions. This uncrossing period lasts between 0 and 30s and so represents a natural experiment where the length of the suspension is varied by up to 10% of the base length of five minutes.

By regressing market quality on the randomized auction length and suitable control variables, we are able to make inference at the margin regarding whether longer suspensions lead to more orderly markets. If longer auctions improved market quality, perhaps by allowing more time for liquidity suppliers to analyze recent price movements and thus decrease their exposure to informed trading, or perhaps by allowing more time for other market makers to begin supplying liquidity when spreads become wide, then we would expect to see the realized variance to be smaller following longer auctions. On the other hand, if the main effect of the suspension was to prevent participants from making mutual beneficial trades, or a magnet effect, we would expect to see larger ΔRV following longer auctions. The expected effect on volume and number of trades is less clear, as more frequent or higher volume trading could be indicative of better or worse market quality in different situations. However, interpretation of these regressions alongside the results regarding returns volatility may be illuminating, as doing so provides information about whether increased or decreased volatility is occurring alongside increased or decreased volume, or trading frequency.

4.2 Identifying spillover effects across securities

For analyzing the spillover effect of a suspension in one security on the market quality of related securities, our identification strategy relies on finding near-halts in the FTSE-100 stocks, stocks that traded to within 1% of the static price limit but did not breach this limit, and comparing these events with actual suspensions. Crucially, the effect we are examining is not in the actual stock undergoing the event but for all other FTSE-100 stocks eliminating the issue of mechanical dependence of outcome variables of interest on the censored price process in the control group (see section 4.2.1 for a discussion of the salience of this issue). We form an unbalanced panel of all stocks (excluding the event stock) during all halts and near halts in the FTSE-100, and including both within-sector and out-of-sector stocks during each event and estimate the effect of a suspension both using the two-way random effects estimator and OLS with heteroscedasticity robust standard errors. These regressions estimate the effect of a suspension for other securities both within the same Bloomberg industry sector as the event stock, and securities outside this sector.

The potential channels through which the suspension of a security undergoing extreme price movements can affect other related securities are numerous. On the one hand, a volatile stock can influence the price process of other stocks by revealing sector-wide information, through corporate exposures between related entities (especially in the financial sector), via margin calls, through interactions between volatility and funding costs for market makers (e.g. Brunnermeier and Pedersen (2009)) or through short-term or high-frequency correlation traders. Some of these effects reflect new information about the fundamental value of the related securities, while others, such as margin calls and noise trading, do not. If the latter effects unduly dominate, or if the price movements in the initially volatile stock are transitory, removing the volatile security from continuous trading may help to break the transmission of volatility across related securities. However, it may also be the case that suspending the volatile security leaves some market participants with exposures they do not wish to have, and they attempt to hedge this exposure by trading in related securities. This mechanism could lead to a more severe transmission of volatility across a sector than if continuous trading never ceased. The results of our regressions help provide evidence about which set of effects dominate, and thus whether the LSE circuit breakers help to limit contagion across securities or not.

4.2.1 Issues with identification using near-limit events for within stock effects

Perhaps the key empirical challenge in the circuit breaker literature is defining an appropriate counterfactual that well describes what the state of the market would have been if a circuit breaker was not triggered. A common approach that has been followed in the past is to compare market statistics for a particular security after an event in that security with the market statistics for similar securities that very nearly triggered an event but ultimately did not (which we refer to as near-halts above). Examples of previous research that rely on this method or something similar include Kim and Rhee (1997), Huang et al. (2001), Chan et al. (2005) and Bildik and Gülay (2006).

However a potentially important issue with this approach is that of censoring of the outcome variable in the control group, namely the distribution of the prices. To illustrate, suppose we are considering a market with a daily return limit of $\pm 10\%$ whereby a breach of this level would lead to a suspension of trading. Suppose we assign securities to a control group if the maximum absolute daily return is above 9% but less than 10%. If we compare trading statistics in the period after a true limit event with those of a control stock in the period after the maximum absolute return is reached, the distribution of the latter statistics are conditional not just on the return reaching 1% of the barrier, but also that all subsequent returns during the period being analyzed do not breach the limit. That is to say, for some measure of market quality $q_{i,t}$ for some stock in group $i = \{c, e\}$ where c denotes the control group and e denotes the event group, we would be comparing $f\left(q_{e,t} \middle| |r_{e,t}| \geq \bar{r}\right)$ with $f\left(q_{c,t} \middle| |r_{e,t}| \geq \bar{r} - \varepsilon, \sup\left(|r_{c,s}| : t \leq s \leq T\right) < \bar{r}\right)$ where $\bar{r}$ is the price limit expressed as a return and ε is 1%. Unless the measure of market quality q is independent of the subsequent price process, $q_{c,t}$ will not represent a satisfactory control group as it will be impossible to decompose the effect of the suspension from that of the censoring. For measures of market quality that directly depend on prices, such as volatility, trading costs and spreads, then by construction, this independence condition cannot hold. For other measures, such as volume or number of trades, it is plausible that censoring is not independent; the trade arrival process within a security can affect its price and vice versa.

In order to demonstrate how this censoring issue can lead to erroneous conclusions about the effects of circuit breakers, we compare the market quality for FTSE-100 stocks that trade through a hypothetical price limit of ±7% with those stocks with a maximum daily absolute return of 6%, as would be analogous to comparing trading behavior of halted stocks with near-halt stocks. Since for this group of securities, there is no actual barrier at this level, we can consider any significant effect to be due to the censoring issue depicted above. Details of the regression specifications as well as parameter estimates are contained in the appendix. Most importantly, the dummy variable indicating whether a stock is in the event or the control is highly significant in many of the regressions, especially for events at the −7% "barrier", for measures of volatility and volume traded (table A.1 in the appendix).

In order to circumvent this issue, we only use the near-halt regression discontinuity technique to identify the effect of a halt in one security on the trading activity for other securities, not the event security itself. This eliminates the mechanical dependency of the outcome variables on the treatment classification although the issue of second-order censoring is potentially important, whereby our control group contains a greater proportion of stocks that are reverting back towards the opening price which may bias our inference. This issue becomes more important as the interval we analyze increases and so we only use this technique to identify the effect over the five minute windows before and after events.

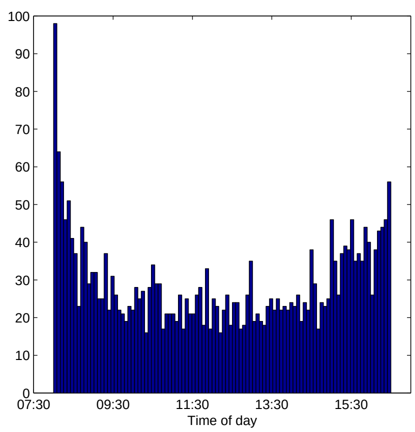
5 Data description

Our dataset contains all trades executed on the London Stock Exchange (LSE) from the 1st of July 2011 until the 31st of August 2011, a total of forty-four trading days. There were 3,781 securities listed on the LSE including shares, exchange-traded funds and products, bonds, warrants and structured products. The price, volume, and trade time to the nearest second are recorded for every transaction, as well as the trade type identifying the trade as being one of 26 alternative classifications, such as ordinary trades, automated trades, late corrections, contra trades and so on. Our analysis focuses on automated trades, those that are executed on the electronic order book of the LSE, and uncrossing trades that match limit and market orders placed during a suspension of continuous trading and precede the resumption of continuous trading.

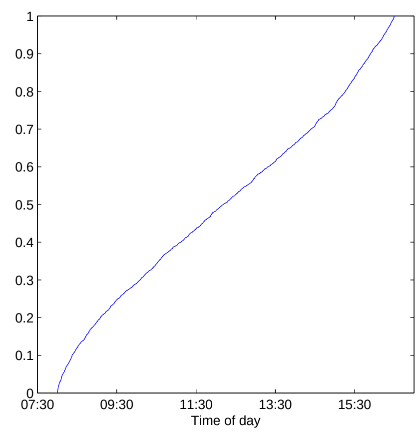
The sample period was chosen as it covers a time of unusual turbulence in global stock markets and therefore contains a relatively large number of circuit breaker events. In total there were 2,931 unscheduled auction periods on the LSE during this period. Figure 3 contains a histogram of all events on the LSE in our sample period and the empirical CDF of these data.

Figure 3: All unscheduled AESP during sample period

Figure 3a contains a histogram of all unscheduled auction periods on the LSE from the 1st of July 2011 until 31st of August 2011, sorted into 100 bins. Figure 3b is the empirical cumulative distribution function (CDF) of the data in figure 3a.



(a) Histogram of all events



(b) Empirical CDF for all events

There are a number of limitations with the dataset that are important to note. Firstly, the counterparties to each trade are not identified and hence it is not possible to track specific trading institutions over time nor to consider transactions between specific types of traders (e.g. high frequency traders or investment banks). Secondly, trades are not assigned as either buyer initiated or seller initiated. Thirdly, the dataset does not include information detailing the state of the order book during the sample period and hence does not identify the best bid and offer, the order imbalance or the depth in the order book prior to a trade. Lastly, as mentioned above, trade times are assigned to the nearest whole second which implies that there is a non-trivial degree of aggregation of trade times to this level of precision.

Industry sectors for FTSE-100 securities were obtained from Bloomberg. There were ten categories with up to 24 securities in each sector. The largest sector by number of firms is *financials* and the smallest is *information technology*. A breakdown of the sectors is contained in table 2. Unscheduled auctions were most common in the *financials* and *materials* sectors.

Table 2: Bloomberg industry sectors

Number of stocks and number of circuit breaker events by Bloomberg sector for the FTSE-100 during the sample period, 1st July 2011 to 31st August 2011.

Sector name	**Stocks**	**Events**
Consumer Discretionary	13	1
Consumer Staples	11	0
Energy	10	1
Financials	24	16
Health Care	4	0
Industrials	13	2
Information Technology	3	0
Materials	14	7
Telecomm'n Services	4	1
Utilities	6	0

In order to describe the returns processes for the FTSE-100 stocks in our sample, we perform heteroskedasticity-robust variance ratio tests as derived in Lo and MacKinlay (1989). These test whether or not the variance of the returns process defined over different intervals are consistent with the hypothesis that the log of prices follows a random walk. Specifically, for a random walk

$$X_t = \mu + X_{t-1} + \varepsilon_t \tag{16}$$

where σ^2 is the variance of the first differences of this process, and for any subsequence of $\{X_t\}_{t=1}^{T}$ that takes the form $\{X_1, X_{1+q}, X_{1+2q}, ...\}$ for some integer $q \geq 2$, then $\sigma_q^2/q\sigma^2 = 1$ where σ_q^2 is the variance of the subsequence (see Castura et al. (2010) for an application of this to high frequency US equity data). Variance ratios less than one indicate negative serial correlation, while variance ratios greater than one represent positive serial correlation, and possibly a momentum process. Both cases would indicate a deviation from the random walk assumption and hence a deviation from price efficiency in the sense that returns would have a predictable component.

The results of our variance ratio tests for one minute returns and $q = 5, 10$ are contained in table 3. In figure 4 we plot the significant variance ratios against the log of mean daily trading value. At both the five and ten minute aggregation levels, we find evidence of negative serial correlation in high frequency returns, with all but one of the significant test statistics taking a value less than one. Since we are performing our tests at high frequencies, it is likely that market-microstructure factors such as bid-ask bounce and discrete prices are contributing to the mean-reverting nature of the price process (Castura et al., 2010). Regardless, these data indicate that there are deviations from full price efficiency that may justify (or reflect) the presence of circuit breakers.

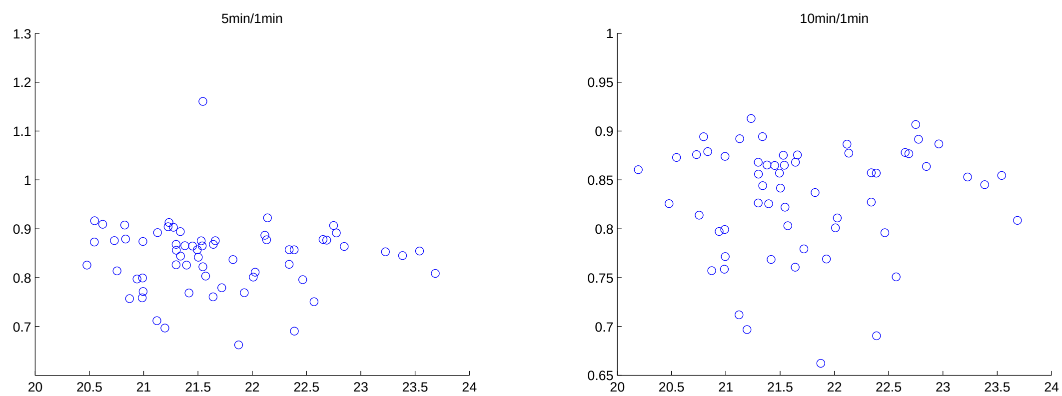
Table 3: Variance Ratio Summary Statistics

Results for variance ratio (VR) tests comparing the variance of 5-min with the variance of 1-min returns and the variance of 10-min returns with the variance 1-min returns for all FTSE-100 stocks in our sample. VRs less than one indicate negative serial correlation in the returns process, while VRs greater than one represent positive serial correlation. The table contains the mean VR, median VR, number of significant VRs less thane one and number of VRs greater than one.

Intervals	**Mean**	**Median**	**Significant < 1**	**Significant > 1**
5min/1min	0.9047	0.9122	63	1
10min/1min	0.8731	0.8771	60	0

Figure 4: Significant variance ratios vs. mean daily value traded

Variance ratio statistics for returns time-series for each FTSE-100 stock during our sample period plotted against log of mean daily value traded. The left hand panel contains the variance ratios for 5-min vs. 1-min returns and the right hand panel contains the variance ratios for 10-min vs. 1-min returns.



6 Results

6.1 Time-series regressions and variance ratio tests for high-frequency returns

As a first step towards understanding how circuit breakers affect the trading process, we perform time-series regressions for the 5 minute returns in all FTSE-100 stocks over our sample period.

These regressions incorporate the inverse distance from the current price to the upper and lower price limits in both the mean and the variance equations of the returns process. These are similar in spirit to those used as evidence of the magnet effect in Cho et al. (2003) although our specification differs from that of Cho et al. (2003) in a number of ways. Firstly, we correct for the well-documented intraday periodicity of returns, secondly, we use the E-GARCH model as opposed to the GARCH framework to explicitly account for the leverage effect, and thirdly we use a continuous distance metric whereas Cho et al. (2003) use a dummy if the price is within a threshold value of the limit price.

The specification for these regressions is as follows:

$$\begin{aligned}
r_t &= \alpha + \theta\varepsilon_{t-1} + \kappa^L dist_{t-1}^L + \kappa^U dist_{t-1}^U + \varepsilon_t \\
\varepsilon_t &\sim \mathcal{N}\left(0, \sigma_t^2\right) \\
\log\left(\sigma_t^2\right) &= \omega + \beta\log\left(\sigma_{t-1}\right) + \rho\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\left(\frac{2}{\pi}\right)}\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} + ... \\
&\quad \lambda^L dist_{t-1}^L + \lambda^U dist_{t-1}^U
\end{aligned} \tag{17}$$

where r_t is the 5 minute log return, the inverse distance metrics are defined as

$$dist_t^i = 0.1^{1/2} - \min\left\{\left|\frac{p_t^i - p_t}{p_t}\right|^{1/2}, 0.1^{1/2}\right\} \; for \; i = L, U \tag{18}$$

and p_t^L, p_t^U are the lower and upper price limits at time t respectively. The distance metrics are bounded: $dist_t^L, dist_t^U \in \left[0, 0.1^{1/2}\right]$ and attain their respective maximums when the price is adjacent to that limit price. Further, only one of the two distance metrics is greater than zero at any given t.

Essentially, equation (17) is a standard MA(1) - E-GARCH specification augmented with our inverse distance metrics $dist_t^i$ in both the mean and the variance equations. The parameter γ corresponds to the usual asymmetric component of the volatility process in the E-GARCH model, while the parameters $\left(\kappa^L, \kappa^U\right)$ and $\left(\lambda^L, \lambda^U\right)$ correspond to the effect of proximity to the limit on expected deseasonalized returns and their volatility respectively. Since the variables $dist_t^i$, $i = L, U$ are inverse distance metrics, positive coefficients correspond to increases in the mean and variance as proximity to the limits increase.

In order to account for the commonly observed (U-shaped) periodicity of the intraday returns process, we apply the deseasonalizing method described in Andersen and Bollerslev (1998) where intraday dynamics of the volatility of returns are estimated using a Fourier Flexible Form (FFF).

The general form of the model used is

$$r_{t,n} - \bar{r}_{t,n} = \sigma_{t,n} s_{t,n} Z_{t,n} \tag{19}$$

where $r_{t,n}$ is the log return from period $n-1$ to n on day t, $\bar{r}_{t,n}$ is the expected log return, $Z_{t,n}$ is an i.i.d mean zero error term with unit variance, $s_{t,n}$ represents the intraday periodicity of the volatility of returns (calendar effects) and $\sigma_{t,n}$ denotes the remaining (potentially persistent) volatility component. It is the $s_{t,n}$ term specifically that we wish to control for when running the regressions in (17). This term is potentially important: if volatility is systematically higher later in the day (i.e. a U-shaped volatility process), and circuit breakers are more likely to be triggered later in the day regardless of market quality (due to static price limits), we may erroneously conclude that the increase in volatility associated with proximity to a price limit is due to a magnet effect.

Andersen and Bollerslev (1998) suggest using ARCH models at the daily frequency to get an estimate of $\sigma_{t,n}$ and the sample mean of returns to estimate $\bar{r}_{t,n}$ (assuming that these are constant throughout the trading day). Squaring and taking logs of (19) gives the regression form for estimating (19):

$$\hat{x}_{t,n} \equiv 2\log\left|r_{t,n} - \bar{r}\right| - \log\hat{\sigma}_t = \hat{c} + f(\theta, n) + \hat{u}_{t,n} \tag{20}$$

where $\hat{c}$ is an estimate of $\mathbb{E}\left[\log Z_{t,n}^2\right]$ and $u_{t,n} = \log Z_{t,n}^2 - \mathbb{E}\left[\log Z_{t,n}^2\right]$. The term $f(\theta, n)$ is a parametric representation of $\mathbb{E}\left[\log s_{t,n}\right]$ which the authors estimate using a Fourier Flexible Form (FFF). In the case of our data, using

$$f(\theta, n) = \sum_{q=0}^{Q} \mu_q n^q + \sum_{p=1}^{P}\left(\delta_{c,p}\cos\frac{p2\pi}{N}n + \delta_{s,p}\sin\frac{p2\pi}{N}n\right) \tag{21}$$

with tuning parameters $Q = 2$ and $P = 5$ provides a good fit for many stocks in our sample.[10] We use an MA(1)-E-GARCH model to estimate $\hat{\sigma}_t$ for the daily returns. These are then used with the absolute log returns to generate a regressand for equation (20) and the intraday periodicity are estimated using the FFF in (21). Then the raw five minute returns are normalized using $\hat{s}_{t,n}$ and we estimate equation (17) for these deseasonalized returns via maximum likelihood with initial errors for each days assumed to equal zero and initial variances set equal to the mean variance for the deseasonalized processes.

In table (4) we report the mean and median parameter estimates for $\left(\kappa^L, \kappa^U, \lambda^L, \lambda^U\right)$ as well as the number of significant negative and positive coefficients across all FTSE-100 stocks. Figure (5) plots the t-statistics for these parameters against the log of mean daily value traded for each stock.

[10] Andersen and Bollerslev (1998) actually use a Fourier Flexible Form (FFF) of the type $f(\theta, n) = \mu_0 + \sum_{p=1}^{P}\left(\delta_{c,p}\cos\frac{p2\pi}{N}n + \delta_{s,p}\sin\frac{p2\pi}{N}n\right)$ where $n = (1, 2, ..., N)$ is the intraday period. The form we use here is actually from Andersen et al. (2000), however it gives a superior fit to that of Andersen and Bollerslev (1998).

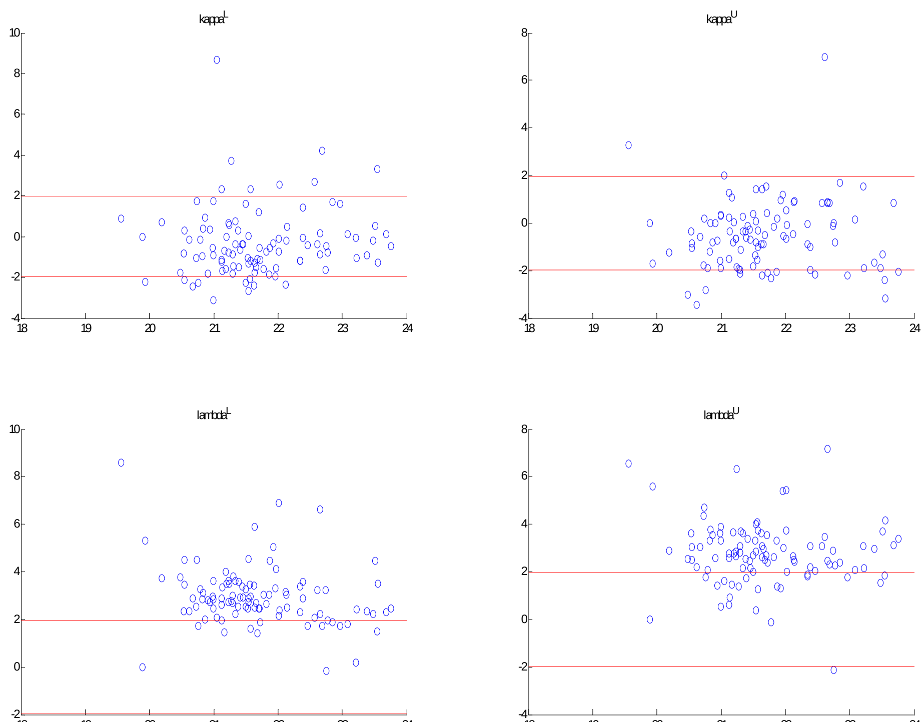
Table 4: Augmented E-GARCH Distance Parameters Summary Statistics

Summary statistics for time series regressions for the mean and conditional variance of the 5-min deseasonalized returns for all FTSE-100 stocks during the sample period. The regression model is the standard MA(1)-EGARCH model augmented with metrics for the inverse distance to the upper and lower static price limits included in both the mean and variance equations (see (17) and (18) for full specification). The table reports the mean, median, the number of positive significant parameter estimates and the number of negative significant parameter estimates both for the upper and lower distance metrics for the mean equation $\left(\kappa^L, \kappa^U\right)$ and the variance equation $\left(\lambda^L, \lambda^U\right)$.

Parameter	**Mean**	**Median**	**Significant < 0**	**Significant > 0**
κ^L	0.00438	-0.00123	10	8
κ^U	-0.00112	-0.00010	14	3
λ^L	0.49846	0.49683	0	85
λ^U	0.41880	0.48454	1	79

Figure 5: Augmented E-GARCH distance t-statistics vs. log of mean daily value traded

Parameter estimates for the distance metrics in the augmented MA(1)-EGARCH model of 5-min returns plotted against the log mean value traded per day for each FTSE-100. The upper panels contain the plots for the distance metric parameter estimates in the mean equation for each stock $\left(\kappa^L, \kappa^U\right)$ and the lower panels contain the parameter estimates for the distance metrics in the variance equations $\left(\lambda^L, \lambda^U\right)$. Horizontal bars indicate 5% critical values.



For the mean equation we see that the distance metric is not consistently significantly different from zero, indicating that the mean of the returns process does not generally respond one way or another as proximity to the barriers increases. For the variance equation, we see that the volatility of the deseasonalized returns process is generally increasing with proximity to both the upper and lower price limits. While these results may reflect the presence of a magnet effect, it may also be the case that the E-GARCH framework does not allow for a sufficiently flexible relationship between returns-on-open and volatility, and our inverse distance metrics are simply picking up some of this misspecification.

6.2 The effect of suspension length on market quality

We now present the results of our regressions that determine the causal impact of the length of trading suspensions on subsequent market quality, as described in section 4.1. Both ordinary least squares and quantile regressions for the 25^{th}, 50^{th} and 75^{th} quantiles are performed for the three market quality variables. The regression model for both the OLS and quantile regressions is

$$y_{i,post} = x'_{i,pre}\beta + \gamma l_i + \varepsilon_{i,pst} \tag{22}$$

where $y_{i,post}$ is the measure of market quality recorded from the resumption of continuous trading to the end of the fixed interval (5 or 30 minutes), $x_{i,pre}$ is a vector of controlling variables recorded in the fixed interval prior to the suspension including realized variance (level), volume, number of trades, time of day and its square and a constant term, l_i is the randomized auction length (from 0-30s) and $\varepsilon_{i,pst}$ is an error term assumed to satisfy $\mathbb{E}\left[\varepsilon_{i,pst}|x_{i,pre}, l_i\right] = 0$. Due to the fact that l_i is by design a random variable, the error term is certainly uncorrelated with the uncrossing time. The parameter of interest is γ, the marginal effect of auction length on expected market quality in the case of the OLS regressions, or the marginal effect of auction length on the conditional q^{th} quantile of market quality for $q = \{0.25, 0.5, 0.75\}$. Heteroscedascity-robust standard errors in computed in the case of the OLS regressions.

The sample of events includes all securities on the LSE that have static price limits of 10%, that trade at least 100 times per day on average during July and August 2011, and incurred exactly one trading halt that day due to a static breach before uncrossing without a price monitoring or market order extension. We also filter out events that occurred either within 5 or 30 minutes of the open or close depending on the length of the interval in question. This sample is then split into events at the upper limit and the lower limit to allow the parameter estimates to vary across these two categories of events and all variables are Winsorized at the 1% level. The estimates for γ in both the OLS and quantile regressions for upper and lower events are contained in table 5. All parameter estimates and standard errors are contained in tables A.2 - A.4 in the appendix.

The estimates for the length parameter in lower limit events in tables 5a and 5b indicate that

Table 5: Auction length parameter estimates

Coefficient estimates for the effect of auction length on volume, number of trades and change in realized variance following a static limit breach in all securities in our sample that trade at least 100 times per day on average. The regression model is $y_{i,post} = x'_{i,pre}\beta + \gamma l_i + \varepsilon_{i,pst}$ where $y_{i,post}$ is the measure of market quality recorded from the resumption of continuous trading to the end of the fixed interval (5 or 30 minutes), $x_{i,pre}$ is a vector of controlling variables recorded in the fixed interval prior to the suspension including realized variance, volume, number of trades, time of day and its square and a constant term, l_i is the randomized auction length (from 0-30s) and $\varepsilon_{i,pst}$ is an error term. Both OLS with robust standard errors and quantile regressions for the 25th, 50th and 75th quantiles with bootstrapped standard errors are reported and separate regressions are estimated for events at lower and upper limits respectively. The sample excludes all overlapping events, securities with multiple events in a given trading day and events that occur within either five or thirty minutes of the opening or closing auction depending on the interval being examined. Tables 5a and 5b report the estimates for lower limit events over 5-min and 30-min intervals respectively, and tables 5c and 5d report the estimates for upper limit events.

(a) Lower limit events $Time = 5\ mins$, $Freq = 10s$

	OLS (Robust)			**25% Quant. Reg**		**50% Quant. Reg**		**75% Quant. Reg**		
	coef.		**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**		**t-stat**
ΔRV	0.01005	(*)	1.71	-0.0016	-0.94	-0.0029	-0.46	0.01778	(**)	2.17
Vlm	-5.3807		-1.58	-0.2901	-0.47	0.08086	0.13	-0.2196		-0.27
No. Trds	0.11652		0.30	-0.0228	-0.2	0.16454	0.86	0.28821		0.86
No. Obs	164									

(b) Lower limit events $Time = 30\ mins$, $Freq = 30s$

	OLS (Robust)			**25% Quant. Reg**		**50% Quant. Reg**		**75% Quant. Reg**		
	coef.		**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**		**t-stat**
ΔRV	0.02482	(**)	2.22	-0.0007	-0.17	0.01209	0.98	0.02435	(*)	1.73
Vlm	2.24428		0.42	-1.0486	-0.65	0.0153	0.02	1.27504		0.51
No. Trds	0.67058		0.44	0.19712	0.44	0.1289	0.27	0.18538		0.22
No. Obs	144									

(c) Upper limit events $Time = 5\ mins$, $Freq = 10s$

	OLS (Robust)		**25% Quant. Reg**		**50% Quant. Reg**		**75% Quant. Reg**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
ΔRV	0.00447	0.38	0.00096	0.4	0.00041	0.05	0.01217	0.84
Vlm	-1.30426	-0.59	0.19566	0.62	0.43971	0.50	-1.81517	-0.93
No. Trds	0.27518	0.93	0.10421	1.09	0.04395	0.26	0.04765	0.15
No. Obs	111							

(d) Upper limit events $Time = 30\ mins$, $Freq = 30s$

	OLS (Robust)		**25% Quant. Reg**		**50% Quant. Reg**		**75% Quant. Reg**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
ΔRV	0.00527	0.25	-0.0042	-0.64	-0.0029	-0.23	-0.0018	-0.11
Vlm	-1.01952	-0.40	0.22601	0.31	-0.02447	-0.02	-2.61866	-1.21
No. Trds	0.44173	0.62	0.12008	0.38	0.12574	0.31	0.30745	0.53
No. Obs	101							

for these events, the length of the uncrossing period has a significant positive effect on ΔRV in the OLS regressions over the 30 minute interval and the regression for the 75th quantile over the 5 minute interval. The same parameter is significant at the 10% level for the OLS regression over the 5 minute interval and the regression for the 75th quantile over the 30 minute interval. Auction length does not have a significant effect on the mean or any quantile for the volume or number of trades after lower limit events over either 5 or 30 minutes. That this effect is still present after thirty minutes also suggests that the impact of longer auctions is felt over relatively long periods, compared with the length of the auction itself. The fact that the length variable is not significant in the regressions for the 25th or 50th quantiles but is significant for the 75th quantile indicates that the effect of longer suspensions manifests at the upper tail of the volatility distribution; price paths are more likely to be very volatile compared with normal trading, but for many events the auction length is unlikely to have a material effect.

These results suggest that the magnitude of market microstructure noise or price inefficiency in the realized price process is larger after longer auctions following breaches of the lower price limit. That this effect is present despite there being no significant effect on the volume or number of trades suggests that the increase is being driven by lower levels of liquidity, as higher volatility is not being caused by an increase in the intensity of the trade arrival process. Our results might also be interpreted as supportive of the volatility spillover hypothesis, however since neither the volume or trading frequency is larger following longer halts, it is not clear that the increase in realized variance is being driven by market participants delaying order submission until continuous trading resumes.

Considering the estimates for events at the upper limit in tables 5c and 5d, the length variable is no longer significant in any specification indicating that, in contrast to the results for lower limit events, longer auctions do not lead to greater price inefficiency or a deterioration in liquidity. That the auction length only affects market quality for lower limit events may reflect the fact that due to asymmetric volatility profiles for equity prices (whereby volatility tends to increase in a falling market), the probability of a type-I error (an unwarranted suspension) is arguably higher in falling markets. It is plausible that the fraction of market participants with negative exposure to a falling stock price is much larger than those with a negative exposure to a rising stock price as the former group will contain long-only asset managers who do not take directional short positions in the equity market, as well as speculators and other participants who trade to hedge an exposure. It is also likely supply in the lending market for many of the securities in our sample is relatively limited, further restricting the fraction of investors with positive exposure to a price depreciation. Then, a type-I error in a falling market, whereby a market is suspended when it ought not to be, would affect a larger fraction of the market and may manifest in increased volatility upon resumption of continuous trading.

6.3 The effect of a suspension on related securities

The regressions in this section are designed to identify the effect of a stock entering a trading halt on the market quality of other stocks in that sector (referred to as spillover effects), as described in section 4.2. Identification is achieved by examining the effect of a particular stock entering a trading halt on other stocks, and comparing this with the effect of a particular stock trading within 1% of a limit but not entering an auction phase on the other stocks.[11]

The sample includes all non-overlapping halts and near-halts (stocks that trade within 1% of the limit but do not enter an auction phase) in the FTSE-100 over the sample period. Each stock is assigned to one of ten industrial sectors as designated by Bloomberg market services (see table 2). The sample constitutes a panel-like dataset with observations on all stocks (excluding the event stock) in the FTSE-100 during each of the events, halts and near halts, in the sample period. The regression model is

$$y_{ij} = x_{ij}'\beta + \gamma^h D_{ij}^{h,in} + \gamma^{nh} D_{ij}^{nh,in} + \lambda^h D_{ij}^{h,out} + \lambda^{nh} D_{ij}^{nh,out} + \upsilon_i + \eta_j + u_{ij} \tag{23}$$

where the subscripts i and j refer to an index of stocks and events respectively. The variable y_{ij} is a market quality measure of interest (the set of which were defined in section 4), x_{ij} is a vector of controlling variables, $D_{ij}^{h,in}$ is a dummy variable taking the value 1 if event j is a halt in the sector of stock i and zero otherwise, $D_{ij}^{nh,in}$ is a dummy taking the value 1 if event j is a near-halt in the sector of stock i and zero otherwise and $D_{ij}^{h,out}, D_{ij}^{nh,out}$ are the equivalent variables for halts and near-halts in sectors outside of the sector of i^{th} stock. The error terms comprise of stock-specific and event-specific effects, υ_i and η_j, and u_{ij} is an error term assumed to satisfy $\mathbb{E}\left[u_{ij}|x_{ij}, D_{ij}^h, D_{ij}^{nh}\right] = 0$.

The parameters of interest are those that correspond to the halt and near-halt dummies both within and outside of stock i's sector. These capture the effect of a halt and a near-halt respectively on the market quality of the stocks both within the event sector and in non-event sectors following an event. We are specifically interested in the hypotheses:

$$\begin{array}{lccc} H_0: & \gamma^h & = & \gamma^{nh} \\ H_1: & \gamma^h & \neq & \gamma^{nh} \end{array} \tag{24}$$

$$\begin{array}{lccc} H_0: & \lambda^h & = & \lambda^{nh} \\ H_1: & \lambda^h & \neq & \lambda^{nh} \end{array} \tag{25}$$

as well as the joint test of (24) and (25). The test described in (24) corresponds to the hypotheses that the effect of a halt on the market quality statistic of interest within a given sector is identical to that of a near-halt, and therefore that halts do not have a significant effect on market quality.

[11] As noted previously, this method would not be valid for determining the effect of auctions on the halted stock itself due to censoring on the outcome variable and regressions highlighting this are included in the appendix.

The test described in (25) corresponds to the same hypothesis but for stocks outside of the event sector. In both cases, we are also interested in the direction of the inequality under the alternative.

The model is estimated both using OLS with heteroscedasticity-robust standard errors, corresponding to the case where $\upsilon_i = \eta_j = 0 \ \forall \ i, j$, and using the two-way random effects model corresponding to the case where υ_i and η_j are not forced to be equal to zero, but are assumed to be uncorrelated to the regressors. In the latter case we estimate the model using feasible GLS (FGLS) with first-stage residuals computed using OLS.[12]

The sample is again split into events at the lower-limit and events at the upper-limit. Regressions are performed for both groups over the five minute interval following an event, corresponding to the period when a halted security would be suspended from automated trading. While our identification strategy is not affected by the direct censoring issue referred to in section 4.2.1, there are possible second-order censoring effects that may become important as the post-event interval is increased. Specifically, the control group may contain a higher proportion of "orderly" trading days as many of the event securities in the control group may have mean-reverted (and therefore appreciated in value for lower limit events or depreciated for upper limit events) following the time of the event. This effect is likely to become more significant as the interval we analyze increases and so we restrict our analysis to the actual lockout period of five minutes.

There were a total of 28 non-overlapping events in our sample, with 101 securities (excluding the event stock) observed during each event. The breakdown of events by sector are contained in table 6.

[12]It is not possible to use the two-way fixed estimator to identify the total effect of an event (halt or near-halt) on stocks within or outside of the event sector since this estimator would remove any stock or event invariant coefficients. In order to identify the total effect of an event (either halt or near-halt) either within or outside the event sector, we must either jointly estimate all four dummy variables $D_{i,j}^{x \times y}$ for $x = \{h, nh\}$ and $y = \{in, out\}$, or to estimate constants and an event invariant halt or near-halt dummy that would load additively into the total effect of event type x in or out of the event sector. As a robustness check, we also estimate a restricted version of (23) where $D^{h,out} = D^{h,in} = D^h$ and $D^{nh,out} = D^{nh,in} = D^{nh}$ (i.e. the event effect is assumed to be homogeneous for stocks within and outside of the event sector) that can be estimated in the presence of a stock-specific fixed effects. Results using this estimation technique are consistent with those of obtained using OLS and two-way random effects estimation and are available on request.

Table 6: Non-overlapping events by industry sector

Halts and near-halts in FTSE-100 stocks sorted by Bloomberg industry sector. Halts are defined as unscheduled auction periods caused by breaches of the static limit reference price. Near-halts are defined as events whereby a stock price is within 1% of the static price limit but never breaches the limit level and an unscheduled auction period does not occur.

		Upper limit events		**Lower limit events**	
Sector name	**Stocks**	**Halts**	**Near-halts**	**Halts**	**Near-Halts**
Consumer Discretionary	13	0	0	0	0
Consumer Staples	11	0	0	0	0
Energy	10	0	0	1	0
Financials	24	3	2	5	1
Health Care	4	0	0	0	0
Industrials	13	1	1	1	1
Information Technology	3	0	0	0	0
Materials	14	3	1	1	5
Telecomm'n Services	4	0	1	1	0
Utilities	6	0	0	0	0

The controlling variables include volume, number of trades and the realized variance in the fixed interval prior to the event and we now include the return-on-open of the non-event stocks.[13] The sample is again Winsorized at the 1% level.

6.3.1 Lower limit events

Tables 7a and 7b contain estimates for the dummy parameters for lower limit events obtained using two-way random effects and OLS with robust standard errors, as well as *p*-values for Wald test statistics of the hypotheses outlined in (24) and (25) for events at the lower limit. All parameter estimates for the lower limit events are contained in table A.5a in the appendix.

[13] For the regressions in section 6.2 these returns are all between 9% and 10% and so are not included.

Table 7: Spillover parameter estimates and tests

Parameter estimates for the halt and near-halt coefficients for volume, number of trades and change in realized variance. The regression model is $y_{ij} = x'_{ij}\beta + \gamma^h D_{ij}^{h,in} + \gamma^{nh} D_{ij}^{nh,in} + \lambda^h D_{ij}^{h,out} + \lambda^{nh} D_{ij}^{nh,out} + \upsilon_i + \eta_j + u_{ij}$ where the subscripts i and j refer to an index of stocks and events respectively, the variable y_{ij} is a market quality measure of interest (change in realized variance, volume and number of trades), x_{ij} is a vector of controlling variables, $D_{ij}^{h,in}$ is a dummy variable taking the value 1 if event j is a halt in the sector of stock i and zero otherwise, $D_{ij}^{nh,in}$ is a dummy taking the value 1 if event j is a near-halt in the sector of stock i and zero otherwise and $D_{ij}^{h,out}$, $D_{ij}^{nh,out}$ are the equivalent variables for halts and near-halts in sectors outside of the sector of i^{th} stock, υ_i is a stock specific random effect, η_j is an event specific random effect and u_{ij} is an exogenous error term. The model is estimated using both two-way random effects and OLS with heteroscedasticity robust standard errors. Columns two to five report the coefficient estimates for halts and near-halts within the event sector and outside the event sector respectively, columns six to eight report the p-value of Wald tests that the parameters within the event sector are equal, that the parameters outside the event sector are equal and the joint test for these two hypotheses. Tables 7a and 7b report these results for events occurring at the lower limit and tables 7c and 7d report these results for events at the upper limits.

(a) Lower limit events - two-way random effects estimates

	Coefficient estimates				**Hypothesis test p-values**		
Dep. Variable	γ^h	γ^{nh}	λ^h	λ^{nh}	$\gamma^h = \gamma^{nh}$	$\lambda^h = \lambda^{nh}$	*Joint*
ΔRV	0.5797$^{(**)}$	1.2133$^{(**)}$	0.4530$^{(**)}$	0.5389$^{(**)}$	0.01$^{(**)}$	0.44	0.04$^{(**)}$
Vlm	35.079$^{(**)}$	7.5623	11.530$^{(**)}$	9.2250	0.15	0.70	0.28
No. Trds	24.308$^{(**)}$	10.507	15.587$^{(**)}$	16.555$^{(**)}$	0.07$^{(*)}$	0.78	0.16

(b) Lower limit events - OLS (robust s.e.) estimates

	Coefficient estimates				**Hypothesis test p-values**		
Dep. Variable	γ^h	γ^{nh}	λ^h	λ^{nh}	$\gamma^h = \gamma^{nh}$	$\lambda^h = \lambda^{nh}$	*Joint*
ΔRV	0.5454$^{(**)}$	1.1408$^{(**)}$	0.3970$^{(**)}$	0.4765$^{(**)}$	0.07$^{(*)}$	0.39	0.14
Vlm	34.549$^{(*)}$	9.7623	12.061$^{(**)}$	10.624	0.17	0.86	0.38
No. Trds	22.356$^{(**)}$	7.2497	13.829$^{(**)}$	13.951$^{(**)}$	0.07$^{(*)}$	0.97	0.19

(c) Upper limit events - two-way random effects estimates

	Coefficient estimates				**Hypothesis test p-values**		
Dep. Variable	γ^h	γ^{nh}	λ^h	λ^{nh}	$\gamma^h = \gamma^{nh}$	$\lambda^h = \lambda^{nh}$	*Joint*
ΔRV	2.9714$^{(**)}$	0.2486	1.7648$^{(**)}$	0.3331	0.00$^{(**)}$	0.00$^{(**)}$	0.00$^{(**)}$
Vlm	45.979$^{(**)}$	-31.436$^{(*)}$	14.139$^{(**)}$	8.1094	0.00$^{(**)}$	0.35	0.00$^{(**)}$
No. Trds	23.487$^{(**)}$	-3.0820	20.137$^{(**)}$	11.028$^{(**)}$	0.00$^{(**)}$	0.03$^{(**)}$	0.00$^{(**)}$

(d) Upper limit events - OLS (robust s.e.) estimates

	Coefficient estimates				**Hypothesis test p-values**		
Dep. Variable	γ^h	γ^{nh}	λ^h	λ^{nh}	$\gamma^h = \gamma^{nh}$	$\lambda^h = \lambda^{nh}$	*Joint*
ΔRV	2.1394$^{(**)}$	-0.3279	0.7769$^{(**)}$	-0.2019	0.00$^{(**)}$	0.00$^{(**)}$	0.00$^{(**)}$
Vlm	50.516$^{(**)}$	-30.131	18.573$^{(**)}$	10.723	0.00$^{(**)}$	0.38	0.00$^{(**)}$
No. Trds	57.389$^{(**)}$	44.482	30.084$^{(**)}$	119.14$^{(**)}$	0.00$^{(**)}$	0.04$^{(**)}$	0.00$^{(**)}$

Considering the results using the random-effects estimator for the change in realized variance, the halts parameter for other stocks in the event sector is significantly smaller than the near-halts parameter in the event sector at the 5% level, indicating that for stocks within the event sector, the halt leads to a reduction in the magnitude of market microstructure noise in the trading process. For stocks outside of the event sector, the halt and near-halt parameters are not significantly different. The joint test of both hypotheses is also rejected at the 5% level. For volume and number trades, the halt parameters are larger than the near-halt parameters both within and outside the event sector, however the difference is only significant at the 10% level for the number of trades within the event sector. The OLS estimates are consistent with those obtained using the random effects estimator, although for the change in realized variance, the joint test can no longer rejected and the within sector test is only rejected at the 10% level.

Table 8a contain Wilcoxon non-parametric rank sum tests for equal medians in the two groups and t-tests for equal means. The first row of results compare the medians and means for the simple difference in realized variance from before and after the two types of events while the second and third rows refer to the percentage change in the volume and number of trades from before and after events of either types.. The t-test for equal means are significant at the 5% level for the percentage change in volume and number of trades, while the Wilcoxon tests are only rejected at the 10% level for difference in realized variance.

Table 8: Wilcoxon Rank Sum and two sample t-tests

Wilcoxon non-parametric rank sum tests for equal medians and t-test for equal means for the difference in realized variance, and percent changes in volume and number of trades during halts and near-halts. The second, third and fourth columns contain the median for halts, the median for near-halts and the associated p-value for the Wilcoxon test that these values are equal respectively. The fourth, fifth and sixth columns contain the sample mean for halts, the sample mean for near-halts and the p-value for the t-test for equality of means. Table 8a report these statistics for events at the lower limit and table 8b report these statistics for events at the upper limit.

(a) Lower limit events

	Wilcoxon rank sum test			**t-test for equal means**		
Dep. Variable	**halt med.**	**near-halt med.**	**p-value**	**halt mean**	**near-halt mean**	**p-value**
ΔRV	-0.0001	0.00164	0.05	-0.0016	0.0060	0.24
$\Delta\%$ *Vlm*	0.23367	0.04841	0.26	1.3431	0.2538	0.04
$\Delta\%$ *No. Trds*	0.22283	0.05634	0.12	0.7672	0.1807	0.04

(b) Upper limit events

	Wilcoxon rank sum test			**t-test for equal means**		
Dep. Variable	**halt med.**	**near-halt med.**	**p-value**	**halt mean**	**near-halt mean**	**p-value**
RV	0.0011	-0.0005	0.08	0.04318	0.0024	0.08
$\Delta\%$ *Vlm*	0.4100	-0.0543	0.01	0.9118	0.4705	0.17
$\Delta\%$ *No. Trds*	0.2929	-0.1429	0.01	0.6204	0.3164	0.14

Taken together, we interpret these results as evidence that suspensions do not lead to a significant deterioration in market quality of related securities (those in the event sector) in the FTSE-100. Indeed the results indicate that during the suspension the price paths for these related securities become more orderly as the suspension leads to a statistically significant drop in the ΔRV without a significant changes in volume and the number of trades, and hence the magnitude of market microstructure noise and price inefficiency in the realized price process decreases in the related securities. The suspensions do not have a significant effect on the change in realized variance, number of trades or volume of trades outside the event sector. In relation to the discussion presented in section 4.2, we find evidence that the transitory transmission of price instability across securities is meaningful and that the suspension mechanism can potentially help to ameliorate contagion across stocks in falling markets. The estimates for the volume and number of trades regressions provide evidence that suspensions do not lead to very large transfers of trading activity from the halted stock to related securities, which we might have expected to observe if market participants hedge exposure in the suspended security by trading related securities.

6.3.2 Upper limit events

Parameter estimates and hypothesis test results for upper limit events are contained in tables 7c and 7d, and Wilcoxon rank-sum tests and t-tests for equal means are contained in tables 8b. All parameter estimates for the upper limit events are contained in table A.5b in the appendix. Unlike our analysis for the effect of auction length within a given security, we continue to observe a consistently statistically significant effect for suspensions in stocks that have hit upper price limits. Interestingly, for the change in realized variances following an upper limit event, we see a significant increase both within the event sector and other stocks outside the event sector, indicating that the magnitude of market microstructure noise increases for all stocks following a trading suspension. We also observe a significant increase in both the volume and number of trades at the 5% level within the event sector, and a significant effect at the 5% level for number of trades outside the event sector. These test results are consistent across both the OLS and two-way random effects specifications. For the tests of equal means and medians, the only rejections at the 5% level are for the median of the changes in volume and number of trades.

These results again indicate the highly asymmetric effect of circuit breakers on trading behavior. In falling markets, we see a significant decrease in the magnitude of market microstructure noise and price inefficiencies in related securities when the most volatile security is removed from continuous trading. Conversely, when stock prices are rising and hence asset values are appreciating, we observe significant trading spillovers (volume and number of trades rising) and an increase in market microstructure noise for all securities after a suspension. One potential explanation for this observation is that events at the lower limit are associated with higher market wide volatility which can in turn lead to a rapid deterioration of market wide liquidity due to interactions between volatility, margins and funding conditions for market makers (as per Brunnermeier and Pedersen

(2009)). Removing the volatile stock helps to reduce the likelihood of a flip from normal trading to the "bad" equilibrium of tight funding and poor liquidity. Events at the upper limit are less likely be contemporaneous with high volatility and so the benefit of the preventative role of circuit breakers is dominated by other, negative effects. Other explanations may lie in the differing compositions of market participants with negative exposures to price appreciation and price depreciation and other asymmetries in the effectiveness of circuit breakers when market-wide volatility is high (perhaps due to changes in the relative probability of type-I and type-II errors). In any case, we believe that considering the results from upper and lower limit events together, circuit breakers are playing an important role in preventing the short-term transmission of deteriorating prices and market quality across securities in falling markets.

7 Conclusion

This paper uses proprietary data to investigate the efficacy of circuit breakers on the London Stock Exchange during July and August 2011. We answer two related questions. Firstly, using exogenous variation in the length of the uncrossing time that follows all suspensions of continuous trading on the LSE, we estimate the marginal effect of auction length on subsequent market quality for all LSE securities that trade 100 times per day or more on average during our sample period. We allow for these effects to differ between circuit breakers triggered by breaches of upper and lower static price limits respectively. Our results show that, for lower limit events, market quality is significantly poorer after longer suspensions (a greater degree of price inefficiency and market microstructure noise for a given volume and frequency of trading) but we find no significant effects for upper limit events. Furthermore, quantile regressions indicate that the length of the suspension after lower limit events affects the upper tail of the subsequent distribution of market microstructure noise.

The second empirical question addressed is the effect of a suspension in one security on subsequent market quality in other securities, both in the same industrial sector and in other sectors. To do so we compare the effect of trading suspensions in FTSE-100 stocks on subsequent market quality for other stocks with the effect of near-limit events, whereby a stock trades to within 1% of a limit price but ultimately does not breach this level. Again we allow parameter estimates to vary across breaches of upper and lower static limit prices, and our regression design allows for both stock and event unobserved random effects. We find that trading halts in FTSE-100 stocks due to breaches of lower static limit prices leads to a significant improvement in market quality (i.e. less market microstructure noise and price inefficiency) in other stocks in the same industrial sector without broadly significant increases in trading intensity. We interpret this as evidence that trading suspensions help to ameliorate the spread of market microstructure effects across stocks in falling markets and argue that circuit breakers play an important role in preventing contagion of poor market quality on the LSE in such conditions. Conversely, breaches of the upper limit lead to large trading spillovers (increased trading intensity) and an increase in microstructure noise for other securities. The results for upper limit events are arguably of lesser concern for policy makers concerned with preventing contagion due to the observed empirical asymmetric correlations in equity markets whereby cross-asset return correlations tend to be higher in bear markets (e.g. Longin and Solnik (2001) and Cappiello et al. (2006)).

We also provide evidence that a common identification technique used in some papers in the literature may suffer from an important source of bias. Specifically we argue that censoring on the outcome variable (the price path) implies that inference based on comparing halts with near-halts within a particular security can be biased. To demonstrate the salience of this issue, we perform regressions of market quality on whether or not a FTSE-100 stock breaches an arbitrary limit of $\pm 7\%$ compared with those with a maximum absolute daily return in excess of 6% but not greater than 7%. These show that the arbitrary barrier is significant at the 5% level for majority of the regressions at the lower limit as well as some of the regressions at the upper limit.

With better data it would be possible to extend the analysis presented in this paper in a number of directions. Firstly, without access to information detailing the state of the order book over the trading day, we are unable to perform inference regarding the effect of trading suspensions on variables such as effective and realized spreads and average trading costs. Further as we are unable to identify the counterparties to each trade, we cannot make any conclusions regarding the trading patterns of different classes of investors (such as high frequency traders or investment banks) around trading suspensions. We also would like to understand how trading may or may not migrate to alternative venues such as multilateral trading facilities (MTFs) during a suspension in the primary market as many important MTFs do not have pre-specified systems in place in order to coordinate with the primary exchange during a suspension (Gomber et al., 2013).

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Appendix

Parameter estimates using an artificial barrier

To demonstrate the saliency of the censoring issue discussed in section 4.2.1, we create an artificial static price limit for all FTSE-100 stocks in our sample at 7%. The true static price limit for these stocks is $\pm 10\%$. We then identify all stocks with absolute returns on open greater than 7%, and all stocks that have a maximum absolute return on open of greater than 6% but less than 7%. For each stock in either classification we calculate the change in realized variance, total volume traded and the total number of transactions over both 5 and 30 minutes and regress these measures on a set of controlling variables. The regression model is

$$y_{i,post} = x'_{i,pre}\beta + \gamma h_i + \varepsilon_{i,pst} \tag{.1}$$

where $y_{i,post}$ is either the volume or number of trades after the artificial event or the change in realized variance from before and after the artificial event, $x_{i,pre}$ is the set of controlling variables (volume, number of trades and realized variance over the fixed interval prior to the event, time of day and a constant term), h_i is a binary variable taking the value 1 if the event was a breach of the artificial limit and 0 if the event was in the control group and $\varepsilon_{i,pst}$ is an error term assumed to satisfy $\mathbb{E}\left[\varepsilon_{i,pst}|x_{i,pre}, h_i\right] = 0$. Consistent with other regression analysis in this paper, the sample is split into upper and lower events (i.e. those that occur at $+7\%$ and those at -7%) and all variables are Winsorized at the 1% level.

We are interested in the significance of the parameter γ on the dummy variable. Since in this case there is no interruption to the trading process at the assigning price level, the significance of this parameter indicates the importance of the censoring of the dependent variable when comparing the treated and the control groups. Inference that ignores this censoring issue and instead assigns all significance to the effect of the circuit breaker can be biased. In this case, the bias can be seen to be significant as for the regressions at the lower limit, the "halt" dummy is significant at the 5% level for all three dependent variables at both the 5 and 30 minute intervals, excluding volume at the 30 minute interval, for which the parameter is significant at the 10% level (see table A.1a). Volatility, volume and number of trades are all significantly higher in the "halt" group compared with the "near-halt" group. For the events at the upper limit, the dummy is significant at the 5% level for realized volatility and number of trades during the 5 minute interval (see table A.1b).

Table A.1: Parameter estimates for artificial barrier

All coefficient estimates for OLS regressions of volume, number of trades and change in realized variance on a vector of controlling variables and a dummy variable indicating whether or not the return on open has exceeded the artificial barrier level of 7%. The regression model is $y_{i,post} = x'_{i,pre}\beta + \gamma h_i + \varepsilon_{i,pst}$ where $y_{i,post}$ is either the change in realized variance, the volume or the number of trades, $x_{i,pre}$ is the set of controlling variables (volume, number of trades and realized variance over the fixed interval prior to the event, time of day and a constant term), h_i is a binary variable taking the value 1 if the event was a breach of the artificial limit and 0 if the event was in the control group and $\varepsilon_{i,pst}$ is an error term. Table A.1a reports these coefficients for lower limit events and table A.1b reports these coefficients for upper limit events.

(a) Lower limit events

	Change in Realized variance				**Volume**				**Number of Trades**			
	5mins/10s		**30mins/30s**		**5mins/10s**		**30mins/30s**		**5mins/10s**		**30mins/30s**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Constant	0.0832	4.00	0.1784	2.55	0.3249	1.54	-0.755	-1.20	34.672	1.03	-334.3	-1.90
Time	-0.005	-3.90	-0.011	-2.40	-0.018	-1.20	0.0766	1.76	-1.58	-0.70	28.789	2.65
Volume	0.0001	2.14	0.000	0.57	0.001	8.16	0.001	17.70	0.0089	0.84	0.0143	2.14
No. Trds	0.000	-0.60	0.000	1.57	0.000	-1.30	0.000	-1.10	0.8093	8.25	0.8424	12.70
Prior RV	-0.528	-8.00	-0.487	-6.40	-0.814	-1.30	-1.03	-1.20	-96.14	-1.00	-162.8	-1.00
Halt	0.0071	1.57	0.0501	3.78	0.1173	2.05	0.2592	1.75	33.806	2.67	180.21	4.51
No. Obs	163		141		163		141		163		141	
R-sq	0.5102		0.3944		0.7289		0.9256		0.6431		0.8100	

(b) Upper limit events

	Change in Realized variance				**Volume**				**Number of Trades**			
	5mins/10s		**30mins/30s**		**5mins/10s**		**30mins/30s**		**5mins/10s**		**30mins/30s**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Constant	-0.059	-1.20	-0.056	-0.40	0.4502	0.92	-5.568	-2.40	-14.71	-0.20	-775	-3.50
Time	0.0028	0.93	0.0027	0.29	-0.027	-0.80	0.3503	2.14	1.836	0.43	53.681	3.37
Volume	0	-1.20	0	-1.60	0.0007	4.84	0.001	7.97	-0.004	-0.20	-0.002	-0.20
No. Trds	0.0001	1.12	0.0001	1.63	0.0001	0.14	0.0013	2.14	0.8146	7.48	1.056	14.30
Prior RV	-0.113	-0.50	-0.14	-0.60	-0.295	-0.70	0.7364	0.62	10.871	0.11	517.75	3.02
Halt	0.0208	1.78	0.0452	1.43	0.1396	1.44	0.6547	1.21	43.755	2.50	47.597	0.72
No. Obs	75		70		75		70		75		70	
R-sq	0.0276		0.042		0.8069		0.8537		0.7461		8215	

Table A.2: Auction length parameter estimates: Change in Realized variance

All coefficient estimates for the regression model $y_{i,post} = x'_{i,pre}\beta + \gamma l_i + \varepsilon_{i,pst}$ where $y_{i,post}$ is the change in realized variance from the fixed interval before and after an auction (5 or 30 minutes), $x_{i,pre}$ is a vector of controlling variables recorded in the fixed interval prior to the suspension including realized variance, volume, number of trades, time of day and its square and a constant term, l_i is the randomized auction length (from 0-30s) and $\varepsilon_{i,pst}$ is an error term. The sample includes all events in securities that trade at least 100 times per day on average. Both OLS with robust standard errors and quantile regressions for the 25th, 50th and 75th quantiles with bootstrapped standard errors are reported. Tables A.2a and A.2b report these estimates for lower and upper limit events respectively.

(a) Lower limit events

	Time=5 mins, Freq=10s								**Time=30 mins, Freq=30s**							
	OLS (Rob)		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**		**OLS (Rob.)**		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Constant	2.207	1.04	-0.036	-0.06	0.282	0.21	2.370	0.7	3.707	1.09	-1.455	-1.20	-0.061	-0.02	11.74	1.69
Time	-0.3	-0.89	0.042	0.43	0.025	0.12	-0.341	-0.64	-0.52	-0.97	0.310	1.62	0.116	0.19	-1.706	-1.60
Time sq.	0.012	0.90	-0.002	-0.59	-0.002	-0.22	0.014	0.67	0.021	1.00	-0.013	-1.79	-0.006	-0.25	0.065	1.61
Volume	0.000	0.89	0.000	0.14	0.000	0.8	0.000	0.32	0.00	0.10	0.000	0.14	0.000	-0.29	0.000	-0.07
No. Trds	-0.001	-2.47	0.000	-0.34	-0.001	-1.38	-0.001	-0.98	-0.001	-1.98	0.000	-0.02	0.000	-0.2	0.000	-0.73
Prior RV	0.22	1.56	-0.973	-8.66	-0.941	-4.64	-0.656	-1.81	-0.58	-3.84	-0.715	-10.87	-0.684	-3.07	-0.453	-1.75
Length	0.01	1.71	-0.002	-0.94	-0.003	-0.46	0.018	2.17	0.025	2.22	-0.001	-0.17	0.012	0.98	0.024	1.73
No. Obs	164		164		164		164		144		144		144		144	

(b) Upper limit events

	Time=5 mins, Freq=10s								**Time=30 mins, Freq=30s**							
	OLS (Rob)		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**		**OLS (Rob.)**		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Constant	5.540	1.01	-1.001	-0.83	0.588	0.16	6.046	0.64	-0.114	-0.01	-0.367	-0.12	1.825	0.39	-3.556	-0.33
Time	-0.857	-0.99	0.155	0.84	-0.084	-0.15	-0.825	-0.56	0.043	0.03	0.108	0.23	-0.24	-0.32	0.779	0.45
Time sq.	0.035	1.04	-0.006	-0.85	0.0036	0.17	0.030	0.52	0.0025	0.04	-0.005	-0.26	0.010	0.33	-0.032	-0.45
Volume	0.001	4.28	0.001	2.14	0.001	3.1	0.002	2.36	0.001	1.72	0.000	0.50	0.000	1.10	0.001	1.41
No. Trds	-0.007	-3.00	-0.002	-0.83	-0.004	-1.64	-0.006	-1.62	-0.003	-2.06	0.000	-0.40	-0.001	-0.98	-0.004	-2.47
Prior RV	-0.157	-0.52	-0.465	-2.16	-0.258	-0.67	-0.030	-0.05	-0.292	-0.92	-0.806	-3.28	-0.173	-0.37	0.508	0.99
Length	0.004	0.38	0.001	0.4	0.000	0.05	0.012	0.84	0.005	0.25	-0.004	-0.64	-0.003	-0.23	-0.002	-0.11
No. Obs	111		111		111		111		101		101		101		101	

Table A.3: Auction length parameter estimates: Volume

All coefficient estimates for the regression model $y_{i,post} = x'_{i,pre}\beta + \gamma l_i + \varepsilon_{i,pst}$ where $y_{i,post}$ is the volume traded from the resumption of continuous trading to the end of the fixed interval (5 or 30 minutes), $x_{i,pre}$ is a vector of controlling variables recorded in the fixed interval prior to the suspension including realized variance, volume, number of trades, time of day and its square and a constant term, l_i is the randomized auction length (from 0-30s) and $\varepsilon_{i,pst}$ is an error term. The sample includes all events in securities that trade at least 100 times per day on average. Both OLS with robust standard errors and quantile regressions for the 25th, 50th and 75th quantiles with bootstrapped standard errors are reported. Tables A.3a and A.3b report these estimates for lower and upper limit events respectively.

(a) Lower limit events

	Time=5 mins, Freq=10s								**Time=30 mins, Freq=30s**							
	OLS (Rob)		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**		**OLS (Rob.)**		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Constant	1956	2.48	86.68	0.33	88.30	0.29	492.3	0.73	3105	1.45	2.668	0.00	-156.9	-0.38	-1195.5	-1.10
Time	-280.2	-2.42	-14.89	-0.36	-13.198	-0.29	-73.57	-0.75	-500.2	-1.52	-6.070	-0.07	24.52	0.39	192.78	1.16
Time sq.	10.21	2.39	0.620	0.39	0.501	0.3	2.768	0.78	19.95	1.59	0.405	0.12	-0.905	-0.38	-7.289	-1.15
Volume	1.924	8.99	0.766	1.72	1.938	3.79	2.255	3.77	1.205	17.11	1.127	11.39	1.321	4.38	2.1000	4.80
No. Trds	-0.994	-1.14	0.032	0.06	-0.451	-0.89	-0.027	-0.04	-0.080	-0.38	-0.039	-0.18	-0.258	-0.75	-0.446	-1.49
Prior RV	-122.7	-2.80	-16.44	-0.26	-64.11	-1.08	-36.78	-0.65	-2.247	-0.04	-30.74	-0.52	-1.274	-0.05	-16.03	-0.58
Length	-5.381	-1.58	-0.290	-0.47	0.081	0.13	-0.210	-0.27	2.244	0.42	-1.049	-0.65	0.015	0.02	1.275	0.51
No. Obs	164		164		164		164		144		144		144		144	

(b) Upper limit events

	Time=5 mins, Freq=10s								**Time=30 mins, Freq=30s**							
	OLS (Rob)		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**		**OLS (Rob.)**		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Constant	-505.67	-0.78	-30.25	-0.2	-84.51	-0.32	-207.3	-0.38	-2179	-2.27	-308.3	-0.58	-380.4	-0.55	-542.2	-0.52
Time	82.55	0.77	5.296	0.22	12.77	0.3	37.02	0.39	353.9	2.28	46.024	0.59	53.21	0.5	90.45	0.56
Time sq.	-2.834	-0.65	-0.213	-0.23	-0.420	-0.25	-1.147	-0.29	-13.62	-2.19	-1.684	-0.58	-1.750	-0.43	-3.148	-0.51
Volume	0.520	2.27	0.287	1.15	0.704	1.5	1.897	3.08	1.274	5.91	0.905	3.44	1.669	4.16	2.033	5.39
No. Trds	1.192	1.02	0.037	0.1	-0.166	-0.18	-0.500	-0.36	-0.121	-0.24	-0.067	-0.28	-0.263	-0.84	-0.469	-0.96
Prior RV	54.960	1.48	15.16	0.89	25.72	0.62	24.29	0.47	12.37	0.51	-7.853	-0.64	-7.439	-0.31	-5.260	-0.16
Length	-1.304	-0.59	0.196	0.62	0.440	0.50	-1.815	-0.93	-1.020	-0.40	0.226	0.31	-0.025	-0.02	-2.619	-1.21
No. Obs	111		111		111		111		101		101		101		101	

Table A.4: Auction length parameter estimates: Number of trades

All coefficient estimates for the regression model $y_{i,post} = x'_{i,pre}\beta + \gamma l_i + \varepsilon_{i,pst}$ where $y_{i,post}$ is the number of trades from the resumption of continuous trading to the end of the fixed interval (5 or 30 minutes), $x_{i,pre}$ is a vector of controlling variables recorded in the fixed interval prior to the suspension including realized variance, volume, number of trades, time of day and its square and a constant term, l_i is the randomized auction length (from 0-30s) and $\varepsilon_{i,pst}$ is an error term. The sample includes all events in securities that trade at least 100 times per day on average. Both OLS with robust standard errors and quantile regressions for the 25th, 50th and 75th quantiles with bootstrapped standard errors are reported. Tables A.4a and A.4b report these estimates for lower and upper limit events respectively.

(a) Lower limit events

	Time=5 mins, Freq=10s								**Time=30 mins, Freq=30s**							
	OLS (Rob)		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**		**OLS (Rob.)**		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Constant	-70.06	-0.66	11.90	0.35	-13.44	-0.25	-39.41	-0.47	-190.1	-0.51	-52.63	-0.32	-39.99	-0.24	-143.5	-0.54
Time	13.98	0.82	-1.926	-0.35	1.891	0.24	7.678	0.56	32.26	0.50	6.857	0.26	6.739	0.26	25.098	0.59
Time sq.	-0.548	-0.82	0.087	0.4	-0.050	-0.17	-0.300	-0.56	-1.109	-0.42	-0.224	-0.22	-0.257	-0.25	-0.917	-0.54
Volume	0.031	1.76	0.015	0.61	0.053	1.71	0.002	0.09	0.037	3.97	0.0366	2.00	-0.002	-0.1	0.015	0.8
No. Trds	0.824	7.36	0.696	6.55	0.909	4.30	1.461	6.62	0.836	10.67	0.724	5.43	1.175	7.24	1.191	12.02
Prior RV	-10.86	-2.72	-5.392	-1.6	-6.265	-1.48	-9.521	-1.84	-7.680	-0.63	-4.835	-0.86	-0.735	-0.14	-5.157	-0.59
Length	0.117	0.30	-0.023	-0.2	0.165	0.86	0.288	0.86	0.671	0.44	0.197	0.44	0.129	0.27	0.185	0.22
No. Obs	164		164		164		164		144		144		144		144	

(b) Upper limit events

	Time=5 mins, Freq=10s								**Time=30 mins, Freq=30s**							
	OLS (Rob)		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**		**OLS (Rob.)**		**25% Q. Reg**		**50% Q. Reg**		**75% Q. Reg**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Constant	-125.6	-1.67	0.778	0.03	2.075	0.06	-19.78	-0.32	-403.3	-1.53	-84.62	-0.66	-116.9	-0.68	18.68	0.08
Time	20.875	1.69	0.525	0.12	0.141	0.02	3.511	0.34	63.76	1.52	13.73	0.68	17.766	0.67	-2.863	-0.08
Time sq.	-0.796	-1.63	-0.031	-0.17	0.006	0.02	-0.102	-0.24	-2.439	-1.50	-0.524	-0.67	-0.623	-0.61	0.145	0.1
Volume	0.012	0.67	-0.001	-0.12	-0.006	-0.19	-0.003	-0.04	0.052	1.50	-0.001	-0.04	0.021	0.4	0.086	0.9
No. Trds	0.790	4.65	0.424	2.22	0.829	3.47	1.448	3.13	0.973	6.95	0.788	6.36	0.964	6.49	1.395	3.78
Prior RV	-1.721	-0.81	-0.441	-0.13	-0.296	-0.08	-0.287	-0.05	-4.048	-1.32	-3.390	-1.16	-0.038	-0.01	-4.842	-0.82
Length	0.275	0.93	0.104	1.09	0.044	0.26	0.048	0.15	0.442	0.62	0.121	0.38	0.126	0.31	0.307	0.53
No. Obs	111		111		111		111		101		101		101		101	

Table A.5: Spillover parameter estimates

Parameter estimates for the regression model $y_{ij} = x'_{ij}\beta + \gamma^h D_{ij}^{h,in} + \gamma^{nh} D_{ij}^{nh,in} + \lambda^h D_{ij}^{h,out} + \lambda^{nh} D_{ij}^{nh,out} + \upsilon_i + \eta_j + u_{ij}$ where the subscripts i and j refer to an index of stocks and events respectively, the variable y_{ij} is a market quality measure of interest (realized variance, volume and number of trades), x_{ij} is a vector of controlling variables, $D_{ij}^{h,in}$ is a dummy variable taking the value 1 if event j is a halt in the sector of stock i and zero otherwise, $D_{ij}^{nh,in}$ is a dummy taking the value 1 if event j is a near-halt in the sector of stock i and zero otherwise and $D_{ij}^{h,out}, D_{ij}^{nh,out}$ are the equivalent variables for halts and near-halts in sectors outside of the sector of i^{th} stock, υ_i is a stock specific random effect, η_j is an event specific random effect and u_{ij} is an exogenous error term. The model is estimated using both two-way random effects and OLS with heteroscedasticity robust standard errors. Table A.5a reports the parameter estimates for lower limit events and table A.5b reports these results for upper limit events.

(a) Lower limit events

	Change in Realized Variance				**Volume**				**Number of trades**			
	Random Effects		**OLS (Robust)**		**Random Effects**		**OLS (Robust)**		**Random Effects**		**OLS (Robust)**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Volume	0.0005	2.73	0.0005	2.00	0.9242	67.80	0.9291	22.50	0.0091	1.76	0.0079	0.93
No. Trds	0.0016	2.49	0.0017	2.41	-0.01	-0.20	-0.018	-0.30	0.8444	44.50	0.8654	28.80
Prior RV	-46.23	-19.00	-44.00	-10.00	-21.87	-0.10	61.333	0.29	-81.52	-1.10	-101.3	-1.40
Return	-12.14	-5.40	-12.42	-5.00	-263.9	-1.80	-152.2	-0.60	-124.6	-1.90	-166.7	-2.30
Halt (Out)	0.453	4.88	0.3970	4.19	11.53	2.15	12.061	2.01	15.588	5.57	13.829	6.33
Nr Hlt (Out)	0.539	4.67	0.4765	3.82	9.2251	1.39	10.624	1.16	16.555	4.75	13.951	4.45
Halt (In)	0.5797	3.65	0.5454	3.09	35.079	3.07	34.549	1.82	24.309	5.18	22.356	4.97
Nr Hlt (In)	1.2134	5.25	1.1408	4.34	7.5624	0.44	9.7623	0.69	10.507	1.54	7.2497	1.01
No. Obs	1515		1515		1515		1515		1515		1515	
R-sq	0.205		0.198		0.823		0.829		0.688		0.717	

(b) Upper limit events

	Change in Realized Variance				**Volume**				**Number of trades**			
	Random Effects		**OLS (Robust)**		**Random Effects**		**OLS (Robust)**		**Random Effects**		**OLS (Robust)**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
Volume	0.0007	2.24	0.0002	0.30	1.0099	68.50	1.0084	24.00	0.0186	2.48	0.0158	1.20
No. Trds	-0.002	-1.60	0.0003	0.13	-0.25	-4.00	-0.266	-2.80	0.817	26.70	0.8491	16.10
Prior RV	-45.48	-7.20	5.1204	0.42	817.52	3.80	618.3	1.65	128.17	1.22	176.07	1.00
Return	14.938	2.63	17.557	2.32	588.58	2.76	600.39	1.97	261.27	2.55	263.38	2.29
Halt (Out)	1.7648	6.23	0.7769	4.38	14.14	2.32	18.573	2.93	20.137	5.60	17.352	5.69
Nr Hlt (Out)	0.3332	1.00	-0.202	-1.40	8.1094	1.23	10.724	1.60	11.028	2.81	9.1643	2.95
Halt (In)	2.9715	7.58	2.1394	4.19	45.979	3.70	50.516	3.02	23.487	3.87	20.99	3.77
Nr Hlt (In)	0.2487	0.44	-0.328	-1.10	-31.44	-1.70	-30.13	-1.50	-3.082	-0.40	-7.227	-1.00
No. Obs	1010		1010		1010		1010		1010		1010	
R-sq	0.108		0.045		0.868		0.856		0.583		0.617	