Is There a Magnet Effect of Rule-Based Circuit Breakers in Times of High-Frequency Trading?

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Abstract

This paper studies whether rule-based circuit breakers in the form of short-lived volatility interruptions exhibit a magnet effect in times of high-frequency trading. Based on a sample of 3,271 volatility interruptions on two major European venues, we analyze whether trading aggressiveness, trading activity, and volatility accelerate close to volatility interruptions indicating a magnet effect. Although the duration of the interruptions is meaningful given today's high-frequent securities markets, we do not find any evidence for a magnet effect. Rather, our results show that trading aggressiveness, trading activity, and volatility gradually slow down towards the triggering threshold and that price changes even revert in case of downward-triggered interruptions. These findings hold both for different levels of high-frequency trading activity and for disclosed and undisclosed price limits triggering the circuit breaker.

Keywords: Circuit Breaker, Volatility Interruption, Magnet Effect, Gravitational Effect, High-Frequency Trading

JEL Classification: G14, G15, G18

1 Introduction

Exchanges and regulatory authorities worldwide rely on market safeguards known as circuit breakers to ensure integrity and stability of securities markets. Particularly in times of increased automation of financial markets and the large proportion of algorithmic and high-frequency trading, exchange operators and regulators consider circuit breakers as suitable mechanisms to protect securities markets from sudden and large price jumps (Deutsche Boerse Group, 2016; European Parliament and Council, 2014). Moreover, increased volatility in financial markets and various high volatility events such as the May 2010 Flash Crash or the Brexit referendum in June 2016, which led to market turmoil, have accelerated the debate on circuit breakers among regulators, practitioners, and academics alike.

According to an international survey among exchanges, most developed securities markets have circuit breakers in place (Gomber et al., 2017). Moreover, regulators in different jurisdictions have conducted initiatives regarding the implementation or the design of market safeguards. The U.S. Securities and Exchange Commission (SEC), for example, enforced the implementation of the Limit Up-Limit Down pilot plan in 2012 in response to the May 2010 Flash Crash (U.S. Securities and Exchange Commission, 2012). Also, the revised Markets in Financial Instruments Directive (MiFID II), which came into effect in January 2018, makes the implementation of circuit breakers mandatory for trading venues within the European Union (European Parliament and Council, 2014). Most European trading venues rely on volatility interruptions that trigger short-lived instrument-specific call auctions if there is a significant price movement in a financial instrument (Gomber et al., 2017).

Although exchange operators and regulators view circuit breakers as something positive given their broad dissemination in securities markets, the academic perception regarding the effectiveness of circuit breakers is mixed and researchers also discuss possible negative effects of these safeguards. Among them is the so-called "magnet effect" of the price limits which trigger circuit breakers (Subrahmanyam, 1994). The magnet effect hypothesis assumes that traders accelerate their trading intention when prices come closer to the limit which actually pushes prices even further towards the limit and ultimately triggers the circuit breaker. Empirical studies come to contradicting results whether a magnet effect of circuit breakers exists. While papers analyzing longer interruptions mostly find evidence for a magnet effect, studies focusing on shorter interruptions do not. However, most of these studies base their analysis on data sets covering observation periods where no or only few high-frequency trading is present. Yet, high-frequency trading accounts for a large proportion of today's securities trading. According to a study conducted by the European Securities and Markets Authority (2014), high-frequency traders account for 30% to 49% of all trades in European equities markets. Due to increased activity and relative importance of high-frequency traders in securities markets over the past decade, it is of interest to investigate whether circuit breakers in the form of short-lived volatility interruptions exhibit a magnet effect in presence of high-frequency traders. For this group of traders, also a short interruption lasting only a few minutes represents a major constraint on their trading strategies that build upon order updates and trades within milliseconds.

Moreover, the implementation of circuit breakers differs among trading venues. In particular, some venues disclose the price limits triggering the interruption whereas others do not to avoid the magnet effect and to prevent traders from gaming the thresholds (Gomber et al., 2017). Therefore, the non-disclosure of triggering thresholds might mitigate the magnetic characteristic of rule-based circuit breakers since traders are unaware of the exact price limits. Nevertheless, sophisticated traders with access to large amounts of historical data can easily reverse engineer the unknown triggering thresholds and are thus able to derive the price limits of the circuit breaker. Consequently, we additionally investigate whether the disclosure or non-disclosure of the price limits triggering circuit breakers influences the magnet effect of rule-based circuit breakers.

In order to evaluate a potential magnet effect of circuit breakers in times of high-frequency trading, we analyze the trading period right before volatility interruptions on two major European exchanges. The analysis of volatility interruption mechanisms on two different venues not only increases the robustness of our results but also allows us to analyze our second research question. While the volatility interruption mechanisms are very similar on both venues, they differ in one important parameter, which is the disclosure respectively non-disclosure of the triggering thresholds.

Based on highly granular order book and transaction data, we use a sample of 3,271 volatility interruptions that occurred between 2011 and 2015 to analyze whether this rule-based circuit breaker exhibits a magnet effect in presence of high-frequency traders. According to the magnet effect hypothesis, traders are expected to adjust their trading behavior not only by advancing their trades in time, but also by trading more aggressively in proximity to the limits if they possess a magnetic attraction. In particular, a magnet effect would cause an acceleration of price developments, thus leading to larger price changes close to the limits, which ultimately lead to the surpassing of the triggering thresholds. Thus, a potential magnet effect should be observable in the form of higher trading aggressiveness, trading activity, and volatility close to the price limits.

Our results do not provide evidence for a magnet effect of short-lived volatility interruptions even in times of high-frequency trading. Instead of an acceleration of trading activity, trading aggressiveness, and volatility towards the limit, we rather observe trading and price changes to slow down close to the price limits triggering the volatility interruption. This finding holds for interruptions where high-frequency trading activity is high as well as for volatility interruptions where it is low. Moreover, we do not find a difference between volatility interruptions where the actual limits are disclosed to market participants and those interruptions where the market operator does not disclose the stock-specific limits.

The remainder of the paper proceeds as follows: Section 2 presents related literature on circuit breakers in general and on the magnet effect of circuit breakers in particular. Section 3 provides information on the institutional background, the data set, and descriptive statistics. Section 4 outlines the methodological approach as well as the results of our empirical analysis. The results are discussed in Section 5. Section 6 presents the conclusion.

2 Related Literature

2.1 Circuit Breakers in General

Trading venues and regulatory authorities rely on different types of circuit breakers, i.e., market safeguards, to ensure integrity and stability of securities markets. An overview of the terminologies and concepts related to circuit breakers is provided by Abad and Pascual (2013). In general, circuit breakers can be divided into trading halts (also described as circuit breakers in a narrower sense), price limits, and volatility interruptions. In this paper, we focus on volatility interruptions, which suspend continuous trading of individual instruments with short-lived unscheduled call auctions.

There exists a large research stream on circuit breakers providing theoretical rationale and empirical evidence for both positive and negative effects of circuit breakers on market quality. From a theoretical point of view, circuit breakers give traders time to reassess their trading strategies and inventories, thus leading to reduced volatility and orderly trading after the circuit breaker (cooling-off hypothesis, introduced by Ma et al., 1989). Moreover, circuit breakers are beneficial in times of algorithmic trading since they can prevent flash crashes caused by automated submissions of and reactions to disruptive or erroneous orders (Subrahmanyam, 2013).

Nevertheless, circuit breakers have also been criticized by researchers and practitioners. Opponents of circuit breakers put forward that these mechanisms interfere with trading and market liquidity because traders cannot buy and sell instruments as needed and market makers may have problems to manage their inventories (Lauterbach and Ben-Zion, 1993). In addition, trading and/or price constraints induced by circuit breakers delay the incorporation of new information into prices and thus impede the price discovery process (Fama, 1970; Lehmann, 1989). Furthermore, circuit breakers might lead to volatility spillover to other markets and to subsequent trading periods (Subrahmanyam, 1994).

From an empirical point of view, the results concerning the effectiveness of circuit breakers to improve market quality are mixed. While some papers show that circuit breakers indeed reduce volatility (Abad and Pascual, 2010; Lee and Kim, 1995), others do not find evidence for a reduction of volatility (Bildik and Gülay, 2006; Kim et al., 2008). Moreover, some studies even show that volatility increases after a circuit breaker (Christie et al., 2002; Lee et al., 1994) and spills over to subsequent trading periods (Kim and Rhee, 1997). Within this paper, we focus on one specific point of criticism, which is the the so-called magnet effect of the price limits triggering circuit breakers. In the following subsection, we explain and discuss the magnet effect of circuit breakers in detail.

2.2 The Magnet Effect of Circuit Breakers

The magnet effect hypothesis assumes that circuit breakers may cause traders to sub-optimally advance their trades in time once they are concerned about a likely trading constraint (Subrahmanyam, 1994). As a consequence, higher trading aggressiveness close to the price limits increases returns and price volatility, which effectively triggers the circuit breaker. Based on an experimental setup, Ackert et al. (2001) support the model of Subrahmanyam (1994) and provide additional experimental evidence that market participants advance their trades in time by comparing markets with no interruptions and markets with temporary trading halts.

In contrast to other hypotheses concerning circuit breakers, the magnet effect, which is also described as the gravitational effect, refers exclusively to the ex-ante effects of a circuit breaker (Cho et al., 2003). Specifically, the magnet effect predicts a change in trading behavior caused by the price limits of rule-based circuit breakers and describes market participants' herding behavior when there is a possibility of a limit hit (Abad and Pascual, 2013). According to the magnet effect hypothesis, a possible restriction of trading results in more aggressive trading since particularly day traders advance their trades in time to ensure that they can close their positions before the circuit breaker. Especially if hitting a price limit results in a long lasting circuit breaker or a complete trading halt, the magnet effect is reinforced. This trading behavior close to the triggering thresholds leads to ex-ante higher trading volume, more volatility, higher returns, and therefore increases the probability of hitting the price limit. A precondition for this effect is that the rule-based triggers of circuit breakers are publicly known or at least to some extent predictable. Randomizing circuit breakers and keeping price limits undisclosed can mitigate the possibility of a self-fulfilling interruption due to the magnet effect (Subrahmanyam, 1997).

The magnet effect has also been analyzed empirically for different markets, circuit breaker mechanisms, and observation periods. Early empirical work mostly finds no support for a magnet effect of price limits. Arak and Cook (1997) investigate the mornings after large overnight price fluctuations and test whether a magnet or a calming effect is caused by price limits. The authors develop two empirical models to disentangle the effect of price limits from the effect of incoming news and find a price reversal after the morning opening. This price reversal is sensitive to the proximity of prices to limits and provides evidence for a slight calming instead of a magnet effect. Berkman and Steenbeek (1998) study two exchanges, the Osaka Securities Exchange, which has strict price limits in place, and the Singapore International Monetary Exchange with looser limit regimes. They do not find any evidence for a magnetic attraction of price limits or systematic price movements towards the limits. Hall and Kofman (2001) analyze agricultural futures traded at the Chicago Board of Trade and find evidence for a stabilizing effect of price limits instead of magnetic attractions towards the limits. Also, Huang et al. (2001) do not find support for the magnet effect of price limits on the Taiwan Stock Exchange but rather attribute strong price movements to the overreaction of noise traders to new information. Regarding volatility interruptions, Abad and Pascual (2007) find that the probability of hitting a limit is very low even in close proximity to the respective limit. Furthermore, there rather is a reversion in prices since traders become more patient close to the triggering thresholds of the circuit breaker.

The majority of more recent work primarily finds positive evidence for a magnet effect of price limits. Several studies analyzing price limits on the Taiwan Stock Exchange show that they exhibit a magnet effect (Cho et al., 2003; Hsieh et al., 2009; Wong et al., 2009). In particular, Cho et al. (2003) find that upper limits exhibit a significant acceleration when prices converge towards the limit while lower limits show only weak evidence. Using data of price limits on the Korean Stock Exchange, Yan Du et al. (2009) show that acceleration rates increase as the distance to the price limit decreases and find that the effect is stronger for stricter price limits and weaker for quasi-limit hits. Thereby, the authors confirm that the effect is caused by magnetic attraction and not by momentum effects. A magnet effect of price limits is also shown for the Egyptian Stock Exchange and the Kuala Lumpur Stock Exchange (Chan et al., 2005; Tooma, 2011). Goldstein and Kavajecz (2004) investigate trading behavior and strategies on the New York Stock Exchange during the market turbulence and the market-wide trading halts in October 1997. Their findings show that traders alter the timing of their trades resulting in an acceleration of activity towards the circuit breaker, thus providing evidence for a magnet effect.

To the best knowledge of the author, all existing empirical work concerning a potential magnet effect of circuit breakers focuses on observation periods before 2005 (in most cases even before 2000), where no or substantially less high-frequency trading was present. Moreover, existing studies are either based on daily data or intraday aggregations of low granularity, which do not allow to investigate a possible magnet effect of circuit breakers in presence of high-frequency traders, who might react within milliseconds close to the limit hit. Therefore, our paper adds to this research gap by analyzing whether circuit breakers in the form of short-lived volatility interruptions exhibit a magnet effect in presence of high-frequency traders. Since this group of traders acts and reacts within milliseconds, also an interruption of continuous trading for only a few minutes might impede trading strategies of high-frequency traders severely enough leading to a magnet effect of circuit breakers if high-frequency traders are active.

3 Data

3.1 Institutional Background

In order to investigate a potential magnet effect of circuit breakers in presence of high-frequency traders, we analyze short-lived volatility interruptions on Deutsche Boerse's trading platform Xetra and the Spanish stock exchange Bolsa de Madrid (BME). Both markets are order-driven electronic open limit order books. This setup is particularly suitable for our empirical study since it allows us to analyze a possible magnet effect in the presence of high-frequency traders for two different but very similar volatility interruption mechanisms, which increases the robustness of our results. Moreover, we can investigate our second research question whether the disclosure or non-disclosure of triggering thresholds influences a possible magnet effect of circuit breakers. Table 1 shows major design parameters of the volatility interruptions implemented on Xetra and BME.

As described in Table 1, the general setup of volatility interruptions on Xetra and BME is very similar. In both cases, continuous trading is interrupted by an unscheduled call auction once the potential next execution price meets or exceeds the static threshold, which is based on the last auction price, or the dynamic threshold, which is based on the last trade price. During the auction of the volatility interruption, which is equipped with a randomized end, indicative prices and volumes are displayed to market participants. Also, the auction length of the two mechanisms is comparable although the duration of the volatility interruption on Xetra is a bit shorter than the interruption on BME (two minutes compared to five minutes).

Design of Volatility Interruptions on Xetra and BME		
This table provides detailed information about the design of volatility interruptions (volas) on Xetra and BME.		
	Xetra	**BME**
Duration of volas	2:00 min	5:00 min
Random end	0:30 min	0:30 min
Vola extension possible	yes	no
Transparency during volas	indicative price/volume	indicative price/volume
Price ranges		
Static threshold	not disclosed	4-10%[1]
Dynamic threshold	not disclosed	1-8%
Reference prices		
Static threshold	last auction price	last auction price
Dynamic threshold	last trade price	last trade price

Table 1: Design of volatility interruptions on Xetra and BME.

Yet, only the auction phase on Xetra might be extended in case the potential execution price of the auction lies outside of a defined range, which is wider than the dynamic price range. The main difference, however, which is most important for the analysis of a potential magnet effect of short-lived volatility interruptions, is the disclosure respectively non-disclosure of the price limits that trigger the interruption. While these limits are disclosed on BME, they are not publicly known for the mechanism implemented on Xetra (Bolsa de Madrid, 2018; Deutsche Boerse Group, 2015). However, the limits can be approximated based on sufficient historical data.

3.2 Data Set and Descriptive Statistics

We use tick-by-tick order book and trade information collected from Thomson Reuters Tick History for DAX30 and IBEX35[2] stocks traded on Xetra and BME. As the magnet effect is an ex-ante effect, we only consider the data prior to the interruption. Specifically, we analyze a period of 15 minutes prior to each volatility interruption and additionally consider a shorter observation window of five minutes to provide further robustness of our results. We split the data into 30 30-second intervals for the 15-minute observation period and into 30 ten-second intervals for the five-minute observation period. All trade-related variables are computed for each interval while order book information are averaged across the whole 15-minute (five-minute) observation period for each volatility interruption.

[1]For the stock of Bankia S.A., the static threshold was raised up to 30% from May to August 2013 due to extraordinary high volatility.

[2]Two constituents of the IBEX35 index, i.e., the stocks of Abengoa S.A. and Aena S.M.E. S.A., are not included in the analysis due to data issues.

Our data set includes all volatility interruptions in DAX30 and IBEX35 stocks that occurred between January 2011 and September 2015. Volatility interruptions are identified via unscheduled call auctions with suitable duration. Table 2 reports the number of volatility interruptions that occurred in the observation period. Since we consider a time frame of up to 15 minutes before a volatility interruption and in order to exclude possible confounding effects due to scheduled auctions, we exclude those volatility interruptions which started or ended within 15 minutes around opening, intraday[3], or closing auctions. Furthermore, we exclude volatility interruptions where the pre-period overlaps a post-period of 15 minutes of a previous volatility interruption to prevent a potential bias of our results. Moreover, we exclude volatility interruptions with data issues and no observed trade within the 15-minute pre-period. This procedure results in 3,271 volatility interruptions in total, thereof 2,337 volatility interruptions on Xetra and 934 volatility interruptions on BME.

Number of Observed and Considered Volatility Interruptions

Number of volatility interruptions (volas) on each venue during our observation period from January 1st, 2011 to September 30th, 2015 and detailed information about the actual number of interruptions used for our empirical analysis.

	Xetra	**BME**	**Full Sample**
Total number of volas	3,048	1,131	4,179
- Start of vola close to opening auction	248	92	340
- Volas close to intraday auction	108	n.a.	108
- End of vola close to closing auction	110	0	110
- Volas close to end of another vola	240	101	341
- Excluded volas due to data issues	5	4	9
Number of considered volas	**2,337**	**934**	**3,271**
Percentage of the sample	*71.4%*	*28.6%*	*100.0%*

Table 2: Number of observed and considered volatility interruptions.

In contrast to other types of circuit beakers such as market-wide trading halts, which are rather rare events, single-stock volatility interruptions are frequently triggered on both markets Xetra and BME. Therefore, our data set is well-suited to analyze the magnet effect of circuit breakers based on a large number of observations. Table 3 provides descriptive statistics concerning the volatility interruptions included in the analysis. The distribution of considered volatility interruptions over the observation period and over the trading day is provided in Figures A.1 and A.2 in the appendix.

On average, 1.89 volatility interruptions occur in DAX30 stocks on Xetra per trading day. For IBEX35 stocks, the number is slightly lower amounting to 0.76 volatility interruptions per trading day. For each DAX30 (IBEX35) stock, we observe on average 77.90 (28.30) volatility interruptions during our observation period. With

[3] There are no intraday auctions on BME. Consequently, only volatility interruptions that occurred on Xetra are excluded due to being close to intraday auctions.

Descriptive Statistics of the Volatility Interruptions								
This table reports descriptive statistics of all considered volatility interruptions (volas). Mean, median, minimum, and maximum values are computed over all considered volatility interruptions and are not pre-aggregated for each stock.								
	Xetra				**BME**			
	Mean	Median	Min	Max	Mean	Median	Min	Max
Volas per day	1.89	1.00	0.00	50.00	0.76	0.00	0.00	25.00
Volas per stock	77.90	55.50	27.00	281.00	28.30	28.00	2.00	75.00
Duration [seconds]	135	135	120	253	314	314	300	330
Upward volas		1,008 (43%)				454 (49%)		
Downward volas		1.329 (57%)				480 (51%)		

Table 3: Descriptive statistics of the volatility interruptions.

281 volatility interruptions, Commerzbank AG is the stock with the largest number of interruptions while the stock of Ferrovial S.A. is only interrupted twice. A detailed overview of the analyzed index constituents, the number of volatility interruptions per stock, and the stock-specific price limits triggering volatility interruptions is provided in Table A.1 in the appendix. Volatility interruptions on Xetra last on average 135 seconds, which equals the minimum duration of 120 seconds plus the expected value of the 30-second random end. Due to a possible extension of volatility interruptions on Xetra, the interruptions in the sample last up to 253 seconds. However, we only observe five volatility interruptions that last longer than 150 seconds and thus are classified as extensions. The duration of interruptions on BME is between 300 and 330 seconds with a mean of 314 seconds. Concerning the market movement in which the volatility interruptions are triggered, the share of volatility interruptions on Xetra triggered by the lower price limit is with 57% slightly higher than the share of interruptions triggered by the upper price limit (43%). For BME, the number of volatility interruptions is almost evenly split between downward (51%) and upward (49%) triggered interruptions.

The major difference between the volatility interruption mechanisms on Xetra and BME is that the price limits triggering the interruptions on BME are publicly known whereas the respective thresholds on Xetra are not disclosed to market participants. Nevertheless, the stock-specific price limits can be reverse engineered based on comprehensive historic trading data. Specifically, we calculate the static price limits by determining the largest possible deviation from the last auction price, which serves as the reference price for the upper and lower limits, within the 15 minutes before the volatility interruption is triggered. This procedure provides us with a valid approximation of the actual triggering thresholds since we study highly liquid blue chip stocks. In most cases, the largest deviation from the reference price is observed for the price of the last trade prior to the interruption. The constituents of the DAX30 and the IBEX35 index are frequently traded and price changes regularly appear in small increments. Thus, the computed quasi limit is only a small increment away from the actual limit. In addition, we validate our procedure based on the data and the disclosed price limits for volatility interruptions on BME. The validation results show that we are able to correctly approximate 81% of the thresholds. Since the approximated thresholds triggering volatility interruptions on Xetra feature a much lower variation than the thresholds on BME, the percentage of correctly approximated thresholds should be even higher for Xetra.

In order to study possible differences regarding a magnet effect of circuit breakers in presence of high and low high-frequency trading activity, we rely on the order-to-trade ratio (OTR) as a commonly used measure for high-frequency trading since publicly available data feeds do not include a specific flag for high-frequency trading activity (Brogaard et al., 2015; Haferkorn, 2017; Malinova et al., 2016). Furthermore, regulatory authorities also rely on the OTR as a measure for high-frequency trading and have passed acts that enforce trading venues to charge fees for traders with excessive OTRs (Friederich and Payne, 2015; German High-Frequency Trading Act, 2013). We measure the level of high-frequency trading activity based on the OTR during our two different observation periods of 15 and five minutes prior to each volatility interruption in our sample as shown in Equation (1).

$$OTR_i = \frac{Orders_i}{Trades_i}. \tag{1}$$

$Orders_i$ represents the number of orders submitted to Xetra respectively BME during the 15-minute (five-minute) period prior to volatility interruption i while $Trades_i$ is the number of executed trades. Since our data set does not build on order messages but on high-frequent order book snapshots, we indirectly obtain the number of order submissions in each interval following the methodology proposed by He et al. (2015). By comparing the number of orders on each limit to the previous order book situation, we compute the total number of orders that have been submitted[4]. For Xetra, we have to correct our approximation of the number of orders for volatility interruptions that occurred from April 7th, 2014 onwards since the data provider Thomson Reuters changed the data feed for Xetra from a netted feed into

[4]With this procedure, we cannot observe market orders since they are immediately executed without an additional order book update between submission and execution. However, market orders are used to a small percentage in general and especially rarely by high-frequency traders. According to Jarnecic and Snape (2014), only 4.63% of high-frequency traders' orders are market orders.

a more granular feed on April 7th, 2014 (CEF Ultra+[5]). There is no such change for BME during our observation period. Since the OTR shows a few very small and very large outliers, which might result from special market situations right before some of the volatility interruptions, we apply a 95% winsorization to the OTR, i.e., we replace the extreme values at both ends of the distribution with the value of the 2.5th (97.5th) percentile.

Trading Activity and Market Quality prior to Volatility Interruptions

This table provides descriptive statistics regarding average trading activity and market quality 15 and five minutes prior to volatility interruptions. Trading volume and order book depth measured by Depth(10) are reported in million euro. Standard deviation of returns and relative spreads are reported in basis points.

	Xetra				BME			
	Mean	Median	Min	Max	Mean	Median	Min	Max
15 Minutes prior to interruption								
Number of trades	541	416	4	4,573	322	171	2	4,540
Trading volume [mn]	9.40	6.48	0.02	146.02	3.22	0.88	0.00	92.30
OTR	8.37	7.37	2.78	20.87	7.82	4.48	1.24	43.80
Rel. spread [bps]	8.12	6.91	2.14	81.64	25.08	18.18	2.74	162.11
Depth(10) [mn]	0.42	0.32	0.00	3.08	0.08	0.03	0.00	0.97
Std. dev. of returns [bps]	3.76	3.21	0.99	36.75	11.00	7.21	1.18	77.98
5 Minutes prior to interruption								
Number of trades	228	169	0	1,513	134	71	0	2,402
Trading volume [mn]	4.17	2.60	0.00	44.95	1.34	0.36	0.00	64.49
OTR	7.64	6.52	2.28	21.40	7.60	4.10	0.75	48.63
Rel. spread [bps]	8.21	6.89	2.21	96.45	25.22	17.67	2.36	192.10
Depth(10) [mn]	0.41	0.31	0.00	3.95	0.08	0.03	0.00	1.23
Std. dev. of returns [bps]	3.70	3.14	0.00	39.88	10.81	6.32	0.00	96.56

Table 4: Trading activity and market quality prior to volatility interruptions.

Descriptive statistics regarding trading activity and market quality prior to volatility interruptions are provided in Table 4. All variables are reported separately for each market and separately for the 15- and five-minute observation period prior to the interruption. On average, there is more trading activity prior to volatility interruptions on Xetra than prior to interruptions on BME, which holds for both mean number of trades and mean trading volume. Concerning the number of trades, there are on average 541 (228) trades on Xetra and only 322 (134) on BME in the 15 (five) minutes before a volatility interruption is triggered. The mean trading volume prior to volatility interruptions on Xetra amounts to 9.40 (4.17) and on BME to 3.22 (1.34) million euro in the 15-minute (five-minute) observation period. The OTR is quite similar on both markets with 8.37 versus 7.82 in the 15-minute period

[5]Specifically, we correct the number of orders by a factor of 2.12 for volatility interruptions from April 7th, 2014 onwards, which equals the mean change in the number of approximated orders across all DAX30 stocks from the trading day prior to the change in the data feed to April 7th, 2014, which is the day when the change became effective (median = 2.13).

and 7.64 versus 7.60 in the five-minute period. With respect to market quality indicators, liquidity on Xetra is on average higher than on BME shortly before volatility interruptions, which particularly holds for liquidity in terms of order book depth, while volatility is higher on BME.

3.3 Descriptive Analysis of the Magnet Effect

Having described the general characteristics of the data set in the previous subsection, we will now turn to the analysis of the magnet effect of rule-based circuit breakers in times of high-frequency trading in more detail and provide first descriptive findings within this subsection. As already explained, we consider an observation period of 15 (five) minutes prior to each volatility interruption and aggregate all trade-related information into 30-second (ten-second) intervals. In order to investigate whether traders change their behavior close to the price limits triggering volatility interruptions, we rely on five different measures quantifying trading activity, trading aggressiveness, and volatility. Trading activity is quantified by the number of trades and the trading volume in euro in each time interval. Trading aggressiveness is measured via the cumulative log return and the average trade size in each interval. Higher returns indicate that market participants trade more aggressively in a sense that they post more aggressive orders leading to higher market impact and that they are willing to trade at higher (lower) prices in case of a potential upper (lower) limit hit. Volatility is determined based on the standard deviation of returns in each interval.

Figure 1 depicts the development of the above mentioned five variables within the 15 minutes prior to the volatility interruption based on 30-second intervals and averaged across all considered volatility interruptions separately for each market. All variables measuring trading activity, trading aggressiveness, and volatility show a very similar pattern. Specifically, we observe a moderate increase over the 15 minutes prior to the interruption followed by a substantial jump in the last 30-second interval right before the volatility interruption is triggered. Regarding trading activity, a slightly higher increase in number of trades and trading volume is already visible from the fifth minute before the interruption onwards. We find very similar developments of trading activity, trading aggressiveness, and volatility also for the shorter five-minute observation period, which is based on more granular ten-second intervals. These results are shown in Figure A.3 in the appendix. Consequently, the descriptive analysis building on the time-based distance to a volatility interruption shows some indication for a magnet effect due to the substantial jump in trading activity, trading aggressiveness, and volatility right before the interruption although no continuous acceleration over the whole observation window is observable.

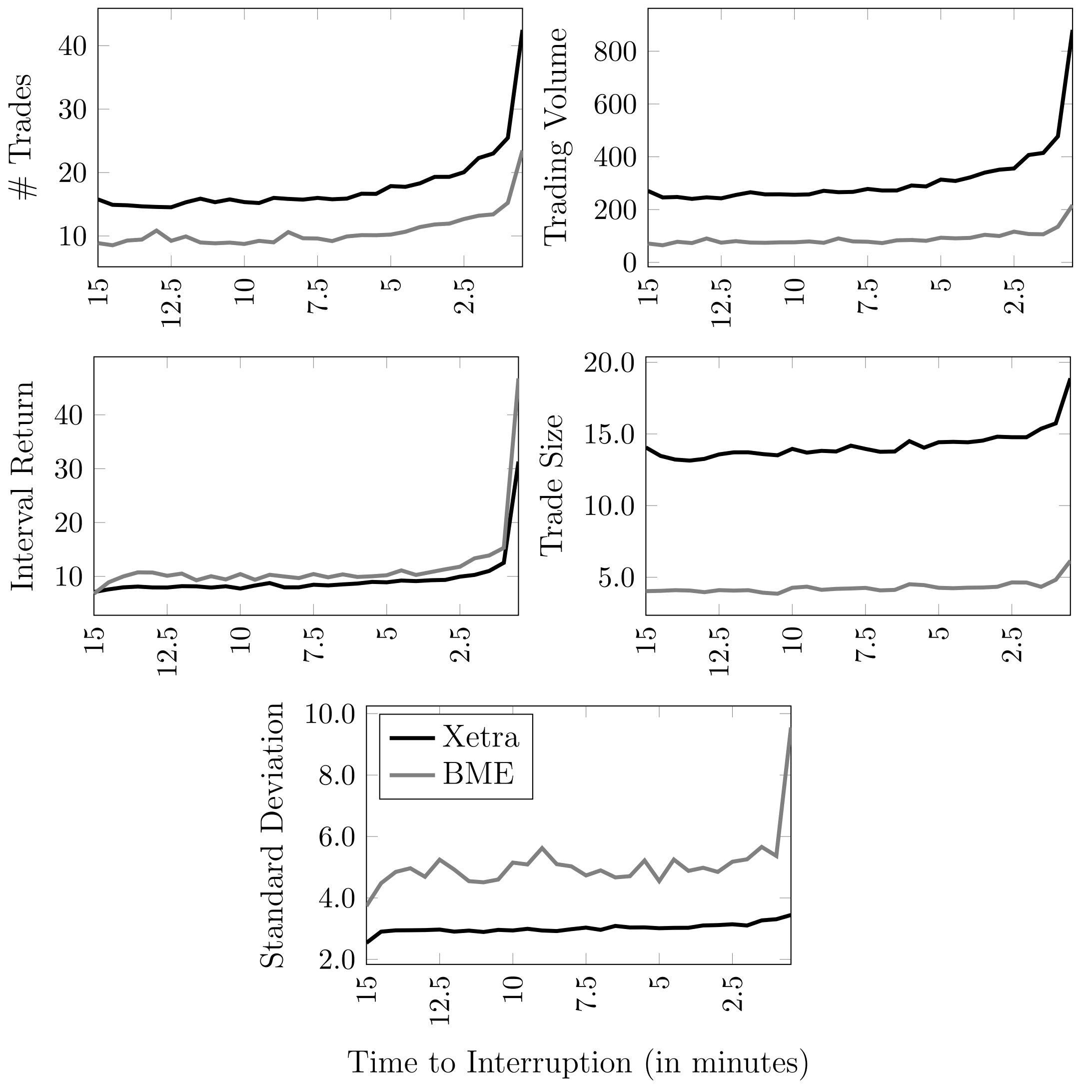

Figure 1: Trading activity, trading aggressiveness, and volatility 15 minutes prior to volatility interruptions averaged across 30-second time intervals. Trading volume and trade size are reported in 1,000 euro. Interval returns and the standard deviation of returns are shown in bps.

However, the time-based distance to the volatility interruption is nothing traders can observe ex-ante since the exact timing of the volatility interruption is unknown and dependent on an incoming order leading to a potential execution price that meets or exceeds the limit. Therefore, we repeat the descriptive analysis by computing the relative distance (measured in bps) of each 30- respectively ten-second time interval to the price limit. We then average across all time intervals that belong to a certain distance interval in steps of 25 bps. The results of this analysis for the 15-minute observation period are shown in Figure 2. Based on the distance to the price limit, no indications for a magnet effect can be observed. Rather, trading activity, cumulative interval returns, and volatility seem to decline the closer trade prices get to the limit triggering the volatility interruption. The average trade size remains on a constant level and also shows no indication for a magnetic attraction of the price limits triggering volatility interruptions. Again, the results remain robust for the five-minute observation period, which is depicted in Figure A.4 in the appendix.

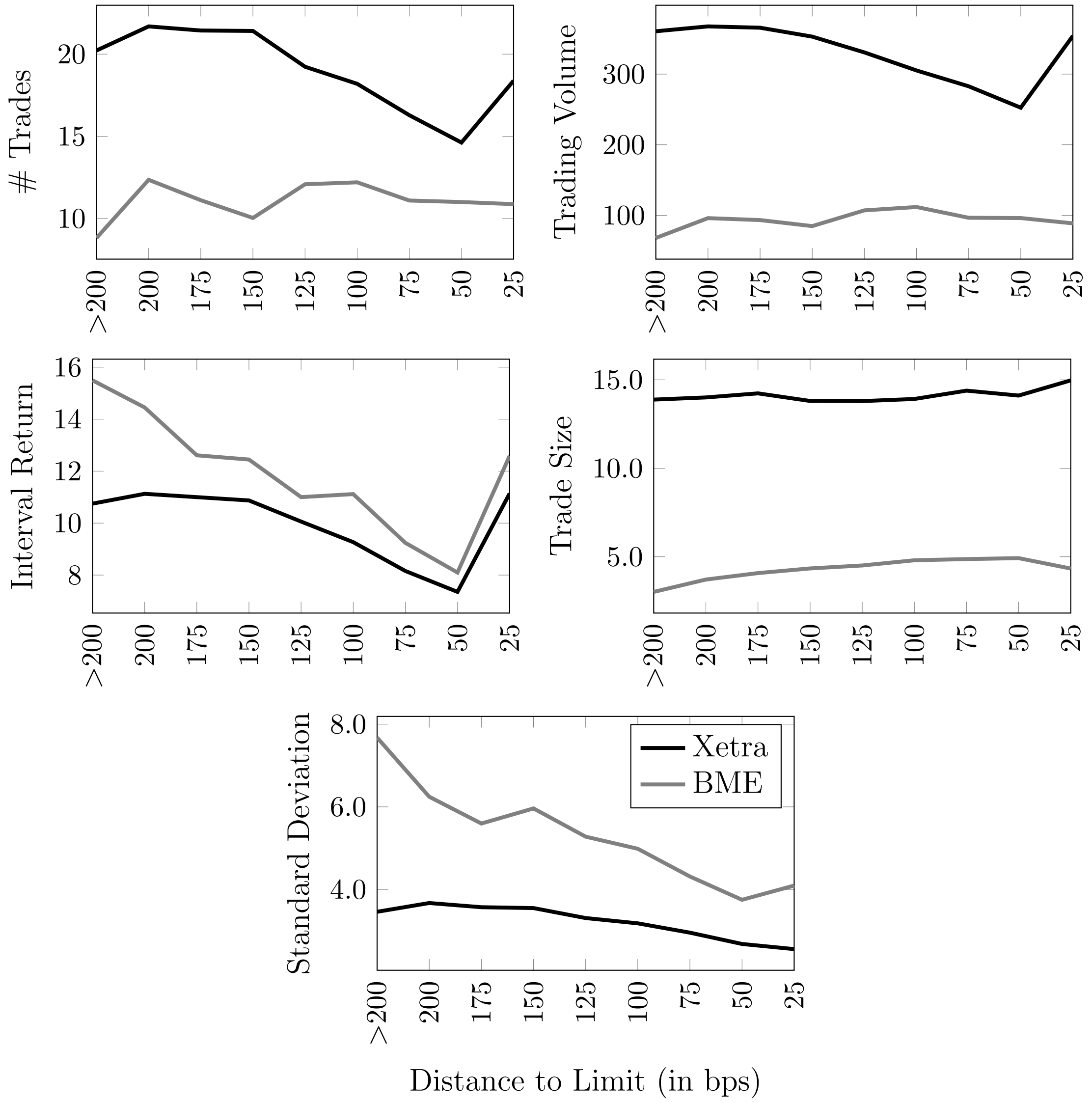

Figure 2: Trading activity, trading aggressiveness, and volatility 15 minutes prior to volatility interruptions aggregated by the distance of each 30-second interval to the limits. Trading volume and trade size are reported in 1,000 euro. Interval returns and the standard deviation of returns are shown in bps.

4 Empirical Analysis

4.1 Research Approach

In a first step, we calculate the relative distance to the upper (lower) price limit for each of the 30- respectively ten-second intervals in case of upward (downward) triggered volatility interruptions. Specifically, the relative distance to the upper price limit is defined as $D_t^{UL} = (UL_t - P_t)/UL_t$, where P_t is the first trade price[6] in time interval t and UL_t is the upper price limit. Similarly, the relative distance to the lower price limit is defined as $D_t^{LL} = (P_t - LL_t)/LL_t$ with LL_t being the lower price limit.

For our empirical analysis, we rely on the method proposed by Abad and Pascual (2007) to analyze a possible magnet effect of volatility interruptions. We examine four value ranges for D_t^{UL} and D_t^{LL} in order to investigate whether trading activity, trading aggressiveness, and volatility accelerate towards the limit. Specifically, we consider the following ranges of distance to the limit (in bps): I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0] and run the regression model, which is shown in Equation (2), for each of our dependent variables measuring trading activity, trading aggressiveness, and volatility in a given time interval t of volatility interruption i.

$$Y_{i,t} = \alpha_0 + \alpha_1 \cdot Y_{i,t-1} + \sum_{k=n}^{n} \beta_k \cdot Controls_i + \sum_{d=0}^{3} (\gamma_{i,d}^U \cdot U_{t-1}^d + \gamma_{i,d}^L \cdot L_{t-1}^d) + \varepsilon_{i,t} \quad (2)$$

As dependent variable $Y_{i,t}$, we use the cumulative return (R_t) as well as the mean trade size (S_t) in each 30- respectively ten-second interval to draw conclusions concerning a possible acceleration of trading aggressiveness. The trading volume in euro (V_t) and the number of trades (T_t) in each time interval are used to measure trading activity. Volatility as the last dependent variable is calculated as the standard deviation of returns (SD_t) in each interval. Since the dependent variables are determined simultaneously in time interval t, the error terms $\varepsilon_{i,t}$ are expected to be contemporaneously correlated[7]. In order to account for this contemporaneous cross-equation error correlation, we estimate Equation (2) for all dependent variables $Y_{i,t}$ by a set of seemingly unrelated regression equations (SURE, Zellner, 1962) using the feasible generalized least squares (FGLS) procedure.

[6] For robustness, we also use the last trade price in each time interval t to determine the relative distance to the upper respectively lower limit of a given 30- respectively ten-second interval and obtain very similar results. The results are available upon request.

[7] We confirm the contemporaneous correlation of the error terms with Breusch-Pagan tests (Breusch and Pagan, 1979) in Section 4.2.

The variable of interest in this regression model is the dummy variable U_{t-1}^{d} (L_{t-1}^{d}) that equals one when the first trade price in the previous time interval is within range D_d before an upper (lower) limit hit. The coefficients $\gamma_{i,d}^{U}$ and $\gamma_{i,d}^{L}$ thus allow us to draw conclusions regarding the existence of a magnet effect of the price limits triggering volatility interruptions. If a magnet effect is present and trading activity, trading aggressiveness, and volatility accelerate towards the limit, we expect $\gamma_{i,3}^{U} < \gamma_{i,2}^{U} < \gamma_{i,1}^{U} < \gamma_{i,0}^{U}$ for upper limit hits. For lower limit hits, we expect $\gamma_{i,3}^{L} > \gamma_{i,2}^{L} > \gamma_{i,1}^{L} > \gamma_{i,0}^{L}$ regarding cumulative returns (since they become more negative if a magnet effect is present in case of downward triggered volatility interruptions) and $\gamma_{i,3}^{L} < \gamma_{i,2}^{L} < \gamma_{i,1}^{L} < \gamma_{i,0}^{L}$ for the other four measures analyzed in this study.

In order to control for different levels of liquidity prior to volatility interruptions, we include the average relative spread, order book depth and order imbalance for the period prior to each volatility interruption as control variables.[8] Moreover, we control for the cumulative trading volume until the respective time interval of each interruption to account for systematic differences between volatility interruptions triggered in a very active or inactive trading environment. We run the regression model for both the 15-minute and the five-minute observation period prior to the interruption. Moreover, we repeat the regression for volatility interruptions triggered in case of high and low high-frequency trading activity and for interruptions with disclosed and undisclosed thresholds.

4.2 Results

Table 5 reports the estimated $\gamma_{i,d}^{U}$ and $\gamma_{i,d}^{L}$ coefficients for the full sample of 3,271 volatility interruptions based on the 15-minute observation period. We do not find support for a magnet effect of price limits triggering rule-based circuit breakers in the form of volatility interruptions even in times of relevant high-frequency trading activity. This holds for both upward and downward triggered volatility interruptions. Instead of speeding up as the limit approaches, price changes slow down progressively the closer the interval is to the limit in case of upper limit hits, i.e., $\gamma_{i,3}^{U} > \gamma_{i,2}^{U} > \gamma_{i,1}^{U} > \gamma_{i,0}^{U} > 0$. For lower limit hits, returns not only move towards zero but our results indicate that prices even revert within the closest interval to the price limit, i.e., $\gamma_{i,3}^{L} < \gamma_{i,2}^{L} < \gamma_{i,1}^{L} < 0 < \gamma_{i,0}^{L}$. These findings are in line with those of Abad and Pascual (2007).

Besides cumulative returns of the 30-second intervals, also mean trade size, number of trades, trading volume, and volatility progressively decrease the closer the

[8] Order book depth is measured by Depth(X) with X = 10 bps around the midpoint as proposed by Degryse et al. (2015). Referring to Chordia et al. (2002), we calculate order imbalance as $\frac{|Depth(10)_{Ask} - Depth(10)_{Bid}|}{Depth(10)}$.

respective interval is to the limit. Moreover, the estimated coefficients indicate that trade sizes, trading activity, and volatility are smaller respectively lower for time intervals within the price ranges up to 200 bps than for intervals which are farther away from the triggering threshold. These observations hold for both upper and lower limit hits, i.e., $0 > \gamma^U_{i,3} > \gamma^U_{i,2} > \gamma^U_{i,1} > \gamma^U_{i,0}$ and $0 > \gamma^L_{i,3} > \gamma^L_{i,2} > \gamma^L_{i,1} > \gamma^L_{i,0}$. The results of the more granular ten-second intervals based on the shorter observation period of five minutes prior to the volatility interruption are almost identical and reported in Table A.2 in the appendix.

Trading Behavior Close to Volatility Interruptions (15 Minutes)

This table reports the results of the regression model described in Equation (2) for the full sample of 3,271 volatility interruptions. The dummy variables U_d (L_d) indicate how far a 30-second interval is away from the price limit in case of an upper (lower) limit hit. The ranges of distance to the limit (in bps) are I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0]. Controls for liquidity, order imbalance, and cumulative trading volume are included. We provide t statistics in parentheses. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Trading Aggressiveness		Trading Activity		Volatility
	Return (R_t)	Trade Size (S_t)	Trades (T_t)	Volume (V_t)	Volatility (SD_t)
U_3	6.379***	-0.509***	-3.126***	-56.51***	-0.457***
	(19.86)	(-3.75)	(-11.01)	(-9.36)	(-5.99)
U_2	5.651***	-0.596***	-4.066***	-77.93***	-0.529***
	(20.50)	(-5.12)	(-16.67)	(-15.04)	(-8.07)
U_1	4.692***	-0.967***	-5.126***	-93.59***	-0.644***
	(18.75)	(-9.14)	(-23.11)	(-19.86)	(-10.83)
U_0	3.098***	-1.498***	-6.406***	-110.4***	-1.375***
	(11.91)	(-13.59)	(-27.71)	(-22.50)	(-22.14)
L_3	-2.232***	-0.425***	-2.426***	-52.41***	-0.334***
	(-7.73)	(-3.48)	(-9.49)	(-9.64)	(-4.86)
L_2	-1.554***	-0.825***	-3.668***	-77.24***	-0.493***
	(-5.96)	(-7.47)	(-15.86)	(-15.71)	(-7.93)
L_1	-0.709**	-1.132***	-4.660***	-95.36***	-0.599***
	(-2.80)	(-10.56)	(-20.77)	(-19.99)	(-9.94)
L_0	1.371***	-1.902***	-5.858***	-113.0***	-1.223***
	(4.81)	(-15.73)	(-23.16)	(-21.02)	(-18.00)
Adj. R^2	0.019	0.366	0.434	0.451	0.219
N			94,859		

Breusch-Pagan test: The null of independence is rejected at the 1% level ($p = 0.000$).

Table 5: Trading behavior close to volatility interruptions based on the full sample and the 15-minute observation period.

To shed further light on our primary research question of whether rule-based circuit breakers exhibit a magnet effect in times of high-frequency trading, we divide our sample into volatility interruptions that were triggered when high-frequency trading activity was high and those interruptions that were triggered when high-frequency trading activity was low. Therefore, we rely on the OTR as a measure of high-frequency trading activity and divide our full sample of 3,271 interruptions by the median OTR. We then run our regression model described in Equation (2) separately for both sub-samples. Table 6 reports the estimated coefficients $\gamma_{i,d}^{U}$ and $\gamma_{i,d}^{L}$. Again, we do not find any evidence for a magnet effect of rule-based circuit breakers in the form of short-lived volatility interruptions. Specifically, the results show that the slowing down respectively reversion of price changes and the decrease in trading aggressiveness, trading activity, and volatility towards the limits hold for interruptions triggered in phases both with a lot of high-frequency trading activity and less high-frequency trading activity. The implications of the results are identical to those of the full sample shown in Table 5. For robustness, similar results are obtained using the more granular data based on the five-minute observation period as well as splitting the data set for each market separately into events with high and low OTR. These results are provided in Tables A.3 - A.5 in the appendix.

Results Subdivided by High and Low High-Frequency Trading Activity (15 Minutes)

This table reports the results of the regression model described in Equation (2) for sub-samples with high and low high-frequency trading activity. The dummy variables U_d (L_d) indicate how far a 30-second interval is away from the price limit in case of an upper (lower) limit hit. The ranges of distance to the limit (in bps) are I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0]. Controls for liquidity, order imbalance, and cumulative trading volume are included. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

		Trading Aggressiveness		Trading Activity		Volatility
HFT	Coef.	Return (R_t)	Trade Size (S_t)	Trades (T_t)	Volume (V_t)	Volatility (SD_t)
High	U_3	5.601***	-0.647***	-1.975***	-34.18***	-0.487***
	U_2	5.085***	-0.701***	-2.478***	-46.26***	-0.715***
	U_1	4.485***	-1.005***	-3.390***	-62.59***	-0.771***
	U_0	3.012***	-1.464***	-4.990***	-84.43***	-1.454***
	L_3	-2.054***	0.034	-1.465***	-21.88***	-0.366***
	L_2	-1.466***	-0.809***	-2.192***	-43.70***	-0.588***
	L_1	-0.709**	-1.074***	-3.536***	-64.76***	-0.762***
	L_0	1.345***	-1.914***	-4.665***	-85.09***	-1.230***
Low	U_3	7.257***	-0.262	-3.392***	-64.02***	-0.393**
	U_2	6.375***	-0.266	-4.709***	-93.33***	-0.260*
	U_1	5.035***	-0.665***	-6.155***	-111.2***	-0.489***
	U_0	3.300***	-1.224***	-7.303***	-124.8***	-1.269***
	L_3	-2.449***	-0.749***	-2.458***	-67.26***	-0.179
	L_2	-1.697***	-0.659***	-4.214***	-97.11***	-0.264*
	L_1	-0.685	-1.040***	-4.855***	-114.0***	-0.291**
	L_0	1.466**	-1.776***	-6.425***	-131.7***	-1.146***

Breusch-Pagan tests: The null of independence is rejected at the 1% level ($p = 0.000$).

Table 6: Trading behavior close to volatility interruptions subdivided by high and low high-frequency trading activity based on the 15-minute observation period.

In a last step, we analyze whether the disclosure or non-disclosure of the thresholds triggering volatility interruptions has an influence on the magnetic attraction of these price limits. Therefore, we again divide our sample into sub-samples. As already discussed, the major difference between the volatility interruption mechanisms implemented on Xetra and BME is that only BME publishes the price limits triggering volatility interruptions. Consequently, we run the regression model separately for both markets and compare the estimated coefficients $\gamma_{i,d}^{U}$ and $\gamma_{i,d}^{L}$. The results are reported in Table 7. Again, our results show that rule-based circuit breakers in the form of short lived volatility interruptions do not exhibit a magnet effect. In particular, the evidence against a magnet effect is independent of whether the price limits triggering the interruption are disclosed to market participants or not. Although a magnet effect of rule-based circuit breakers is theoretically more pronounced when the triggering thresholds are publicly known (Subrahmanyam, 1997), our results also indicate a slowing down of trading activity and price changes in case of interruptions with disclosed price limits. We obtain similar results using the shorter observation period of five minutes as shown in Table A.6 in the appendix.

Results Subdivided by Disclosed and Undisclosed Price Limits (15 Minutes)

This table reports the results of the regression model described in Equation (2) for sub-samples with disclosed and undisclosed price limits. The dummy variables U_d (L_d) indicate how far a 30-second interval is away from the price limit in case of an upper (lower) limit hit. The ranges of distance to the limit (in bps) are I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0]. Controls for liquidity, order imbalance, and cumulative trading volume are included. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

		Trading Aggressiveness		Trading Activity		Volatility
Price Limits	Coef.	Return (R_t)	Trade Size (S_t)	Trades (T_t)	Volume (V_t)	Volatility (SD_t)
Disclosed	U_3	6.999***	0.083	-2.647***	-15.75**	-1.189***
	U_2	5.801***	-0.043	-3.348***	-29.98***	-1.154***
	U_1	4.590***	-0.259*	-4.437***	-42.87***	-1.312***
	U_0	2.555***	-0.717***	-5.304***	-49.00***	-2.464***
	L_3	-3.267***	-0.110	-1.418**	-15.96**	-0.754**
	L_2	-1.735*	-0.142	-2.246***	-24.04***	-1.160***
	L_1	-1.116	-0.459***	-3.233***	-40.30***	-1.067***
	L_0	1.556*	-0.926***	-4.257***	-47.33***	-2.207***
Undisclosed	U_3	5.948***	-0.619***	-3.548***	-73.07***	-0.182***
	U_2	5.384***	-0.570***	-4.636***	-97.76***	-0.297***
	U_1	4.541***	-0.909***	-5.782***	-115.8***	-0.378***
	U_0	3.291***	-1.215***	-7.464***	-146.0***	-0.715***
	L_3	-1.899***	-0.505**	-2.800***	-67.06***	-0.156***
	L_2	-1.516***	-0.926***	-4.225***	-97.26***	-0.258***
	L_1	-0.638**	-1.104***	-5.517***	-118.1***	-0.424***
	L_0	1.006***	-1.738***	-6.998***	-151.7***	-0.622***

Breusch-Pagan tests: The null of independence is rejected at the 1% level ($p = 0.000$).

Table 7: Trading behavior close to volatility interruptions subdivided by disclosed and undisclosed price limits based on the 15-minute observation period.

In general, our results show that the magnet effect, an often claimed negative effect of circuit breakers that leads to an acceleration of trading aggressiveness, trading activity, and volatility prior to the interruption, does not exist for short-lived volatility interruptions. This finding also holds when high-frequency traders, for whom the short-lived unscheduled auction still represents a major constraint on their trading strategies, are highly active. Moreover, a magnet effect cannot be observed even if the thresholds triggering the volatility interruption are publicly disclosed.

5 Discussion

While several academic papers analyzing short-lived circuit breakers do not find evidence in support of a magnet effect, these studies focus on time periods where no or substantially less high-frequency trading was present. For high-frequency traders, however, who react to new information within milliseconds and who regularly offset their inventories, also a seemingly short interruption of continuous trading for only two to five minutes represents a significant constraint on their trading possibilities. Thus, the question arises whether short-lived circuit breakers in the form of volatility interruptions exhibit a magnet effect in times of high-frequency trading.

Based on our analysis, we do not find evidence for a magnet effect of short-lived volatility interruptions implemented on two major European exchanges even in times of high-frequency trading. Instead of an acceleration of trading activity, trading aggressiveness, and volatility towards the price limits triggering the interruption, we rather observe these measures to slow down close to the limits. The slowing down of price changes and trading activity holds both for the full sample as well as for sub-samples of events with high and low high-frequency trading activity before the volatility interruption. In particular, our results support the findings of Abad and Pascual (2007) although we focus on shorter time intervals (i.e., a more granular aggregation based on 30 respectively ten seconds instead of five minutes) and a recent data set that includes substantial amounts of high-frequency trading volume.

Moreover, our results suggest that volatility interruptions do not exhibit a magnet effect independent of whether the price limits triggering volatility interruptions are publicly known or not. This finding is in line with Clapham et al. (2017), who show that the effectiveness of volatility interruptions to reduce volatility is not affected by the disclosure or non-disclosure of the triggering thresholds. Since professional market participants with access to comprehensive historical market data or sufficient experience are able to approximate the thresholds even if they are not disclosed, the disclosure of the price limits provides a level playing field for all market participants. Our results show that the disclosure of the limits does not reduce the effectiveness of the market safeguard due to a magnet effect. In line with this result, the majority of trading venues already publish the thresholds of their circuit breaker mechanisms (Gomber et al., 2017).

Our results are also relevant for practitioners such as exchange operators and regulators. We provide evidence that short-lived volatility interruptions do not seem to exhibit a magnet effect, which would potentially weaken the positive effects of the safeguard, even in today's high-frequent markets. Thus, our analysis provides further arguments for exchanges and regulators to implement respectively enforce the implementation of circuit breakers. Since a magnet effect representing a potential downside of these mechanisms can also not be observed in times of high-frequency trading, circuit breakers qualify as meaningful mechanisms to prevent sudden unexpected price movements in highly automated securities markets.

There are also some limitations connected to our study. Since Deutsche Boerse does not disclose the stock-specific price limits that trigger volatility interruptions, we have to reverse engineer them. Nevertheless, our procedure to approximate the thresholds based on the trade price that is farthest away from the reference price prior to the interruption appears to provide us with a valid approximation of the actual price limits since we study highly liquid blue chip stocks. In most cases, this is the price of the last trade prior to the interruption. The stocks which are analyzed in this study are frequently traded and price changes regularly appear in small increments. Thus, the actual limit is only a small increment away from the approximated limit. Moreover, we validate our procedure based on data for stocks traded on BME, where the actual price limits of the volatility interruptions are disclosed. Furthermore, our data set does not contain a flag indicating high-frequency trading activity so that we have to rely on the OTR as a proxy for the amount of high frequency trading. Nevertheless, this measure is very common in research concerning high-frequency trading (Brogaard et al., 2015; Haferkorn, 2017; Malinova et al., 2016) and is also used in regulatory acts aimed at restricting high-frequency trading activity (Friederich and Payne, 2015).

Regarding future research opportunities, the analysis of a potential magnet effect of circuit breakers in times of high-frequency trading can be extended to different types of circuit breakers. Since our analysis focuses on volatility interruptions that initiate an unscheduled call auction showing at least some pre-trade transparency in the form of indicative prices and execution volumes, our results are not necessarily transferable to other types of circuit breakers. Thus, future research could analyze a potential magnet effect of market-wide or single-stock trading halts based on data sets with relevant volumes of high-frequency traders. Also, future research might consider the possibility of market participants to trade on alternative trading venues or over the counter during a circuit breaker on the venue under investigation.

6 Conclusion

To the best knowledge of the author, this is the first paper testing the magnet effect of rule-based circuit breakers in presence of high-frequency traders. Specifically, we investigate whether the stock-specific price limits of volatility interruptions implemented on two major European exchanges exhibit a magnet effect. Volatility interruptions represent a rule-based circuit breaker as suggested by Madhavan (1992), which switches continuous trading into an unscheduled auction to avoid large price jumps and to handle market phases of high uncertainty. Although these unscheduled call auctions last only two to five minutes, they represent a major constraint for market participants such as high-frequency traders that react within milliseconds during continuous trading according to their different strategies. Therefore, we investigate whether these short-lived, rule-based circuit breakers exhibit a magnet effect in times of high-frequency trading, which accounts for a substantial part of overall trading volume in today's securities markets. Moreover, we analyze whether a non-disclosure of the actual limits mitigates a potential magnet effect although market participants with access to comprehensive historical market data can reverse engineer and estimate the price limits.

Based on a recent sample of 3,271 volatility interruptions on the German stock exchange Deutsche Boerse and the Spanish stock exchange Bolsa de Madrid, we do not find evidence for a magnet effect of short-lived volatility interruptions even in times of substantial high-frequency trading activity. Instead of an acceleration of trading activity, trading aggressiveness, and volatility towards the limit, we observe trading and price changes rather to slow down close to the limits triggering volatility interruptions. This finding holds for interruptions where high-frequency trading activity is high as well as for volatility interruptions where it is low. Moreover, we do not find a difference between volatility interruptions where the actual limits are disclosed to market participants and those interruptions where the market operator does not disclose the stock-specific limits. Consequently, market operators could publish the actual limits to create a level playing field among highly professional market participants that are able to estimate the limits based on historical data and participants that cannot without weakening the effectiveness of the market safeguard. In general, our findings provide further evidence that even in today's high-frequent securities markets, volatility interruptions do not exhibit a magnet effect, which is a regularly discussed potential negative effect of rule-based circuit breakers. Thus, volatility interruptions might serve as suitable market safeguards to handle phases of market stress as suggested by Madhavan (1992).

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Appendix

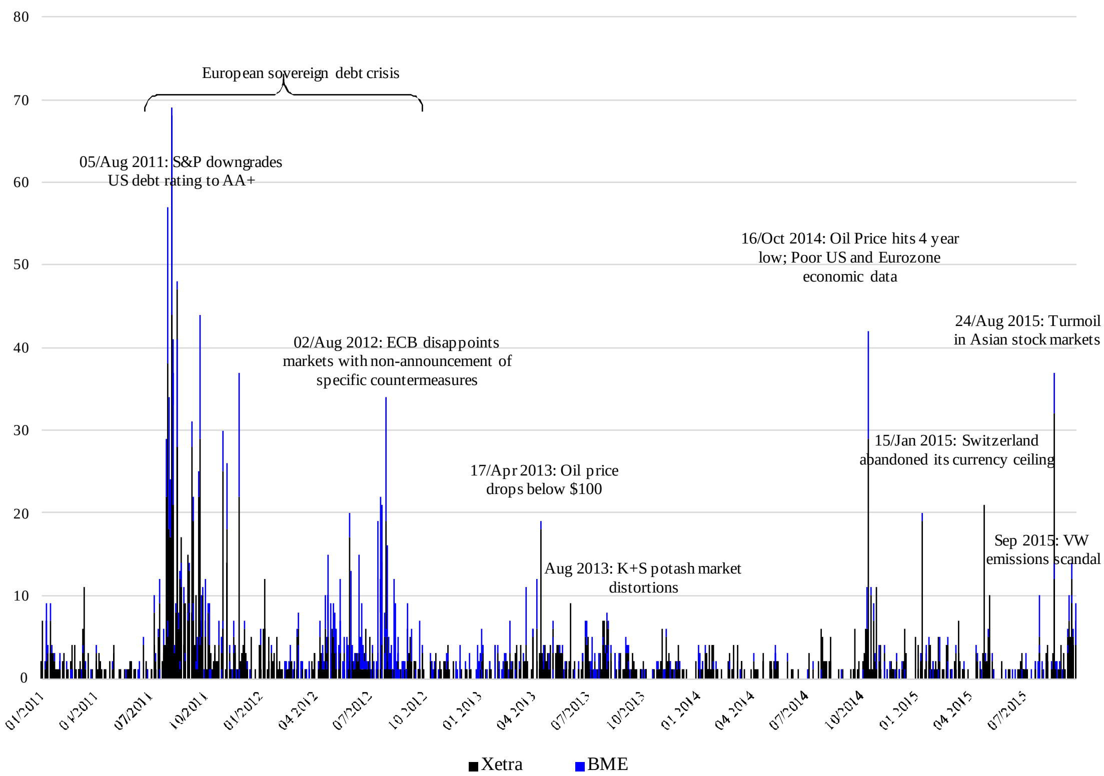

Figure A.1: Distribution of volatility interruptions over the observation period and major events leading to spikes in the number of interruptions per day.

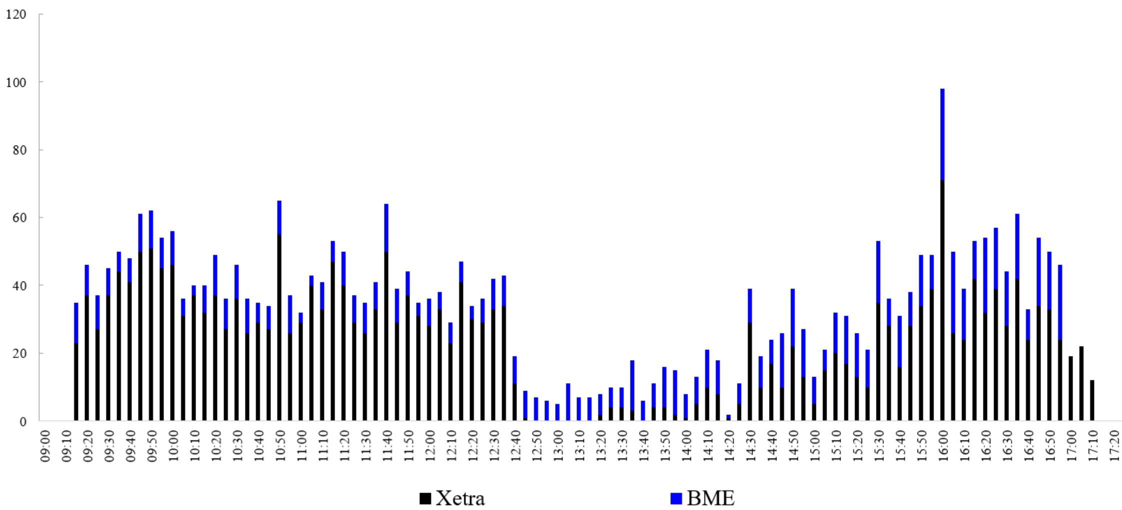

Figure A.2: Distribution of volatility interruptions over the trading day.

Considered Index Constituents, Number of Volatility Interruptions, and Price Limits												
This table provides all considered DAX30 and IBEX35 constituents, the number of analyzed volatility interruptions (volas) per stock during our observation period, and the corresponding price limits triggering volatility interruptions.												
Xetra							BME					
		Up		Down					Up		Down	
Instrument	Volas	Mean	Max	Mean	Min		Instrument	Volas	Mean	Max	Mean	Min
ADSGn.DE	48	3%	4%	-3%	-4%		ABE.MC	11	4%	5%	-5%	-5%
ALVG.DE	54	4%	4%	-3%	-4%		ACS.MC	36	5%	7%	-5%	-7%
BASFn.DE	52	3%	4%	-3%	-4%		ACX.MC	30	5%	5%	-5%	-5%
BAYGn.DE	57	3%	5%	-3%	-5%		AMA.MC	5	6%	6%	-5%	-6%
BEIG.DE	29	3%	3%	-3%	-4%		ANA.MC	38	5%	7%	-5%	-7%
BMWG.DE	94	3%	4%	-3%	-4%		BBVA.MC	28	6%	6%	-6%	-6%
CBKG.DE	281	3%	4%	-3%	-6%		BKIA.MC	71	9%	20%	-9%	-30%
CONG.DE	65	4%	6%	-4%	-6%		BKT.MC	30	6%	7%	-6%	-7%
DAIGn.DE	90	3%	4%	-3%	-4%		CABK.MC	30	5%	6%	-5%	-6%
DB1Gn.DE	52	3%	4%	-3%	-4%		DIDA.MC	7	8%	8%	-6%	-7%
DBKGn.DE	149	3%	5%	-3%	-5%		ELE.MC	19	4%	5%	-5%	-5%
DPWGn.DE	38	3%	4%	-3%	-4%		ENAG.MC	7	n.a.	n.a.	-4%	-5%
DTEGn.DE	39	3%	4%	-3%	-4%		FCC.MC	75	5%	7%	-5%	-7%
EONGn.DE	86	3%	4%	-3%	-4%		FER.MC	2	n.a.	n.a.	-6%	-6%
FMEG.DE	32	3%	4%	-3%	-4%		GAM.MC	56	6%	8%	-6%	-8%
FREG.DE	41	3%	4%	-3%	-4%		GAS.MC	24	5%	5%	-4%	-5%
HEIG.DE	107	3%	4%	-3%	-4%		GRLS.MC	21	5%	5%	-5%	-5%
HNKG_p.DE	27	3%	4%	-3%	-4%		IBE.MC	22	5%	6%	-5%	-6%
IFXGn.DE	114	3%	4%	-3%	-5%		ICAG.MC	10	7%	7%	-7%	-7%
LHAG.DE	137	3%	4%	-3%	-4%		IDR.MC	33	6%	10%	-4%	-6%
LING.DE	37	3%	4%	-3%	-4%		ITX.MC	10	6%	6%	-5%	-6%
LXSG.DE	87	4%	6%	-4%	-6%		MAP.MC	40	5%	6%	-5%	-6%
MRCG.DE	36	3%	4%	-3%	-4%		MTS.MC	35	5%	6%	-5%	-6%
MUVGn.DE	32	3%	4%	-3%	-4%		OHL.MC	33	6%	6%	-6%	-6%
RWEG.DE	108	3%	4%	-3%	-4%		POP.MC	44	6%	8%	-6%	-7%
SAPG.DE	28	3%	4%	-3%	-4%		REE.MC	11	4%	5%	-5%	-5%
SDFGn.DE	139	3%	4%	-3%	-4%		REP.MC	29	5%	6%	-5%	-5%
SIEGn.DE	37	3%	4%	-3%	-4%		SABE.MC	38	6%	6%	-6%	-6%
TKAG.DE	128	3%	4%	-3%	-4%		SAN.MC	24	5%	6%	-6%	-6%
VOWG_p.DE	113	3%	4%	-3%	-4%		SCYR.MC	57	8%	8%	-7%	-8%
							TEF.MC	12	5%	10%	-5%	-5%
							TL5.MC	26	6%	7%	-6%	-7%
							TRE.MC	20	6%	7%	-6%	-7%
No. of volas	2,337							934				

Table A.1: Considered index constituents, number of volatility interruptions, and price limits triggering volatility interruptions.

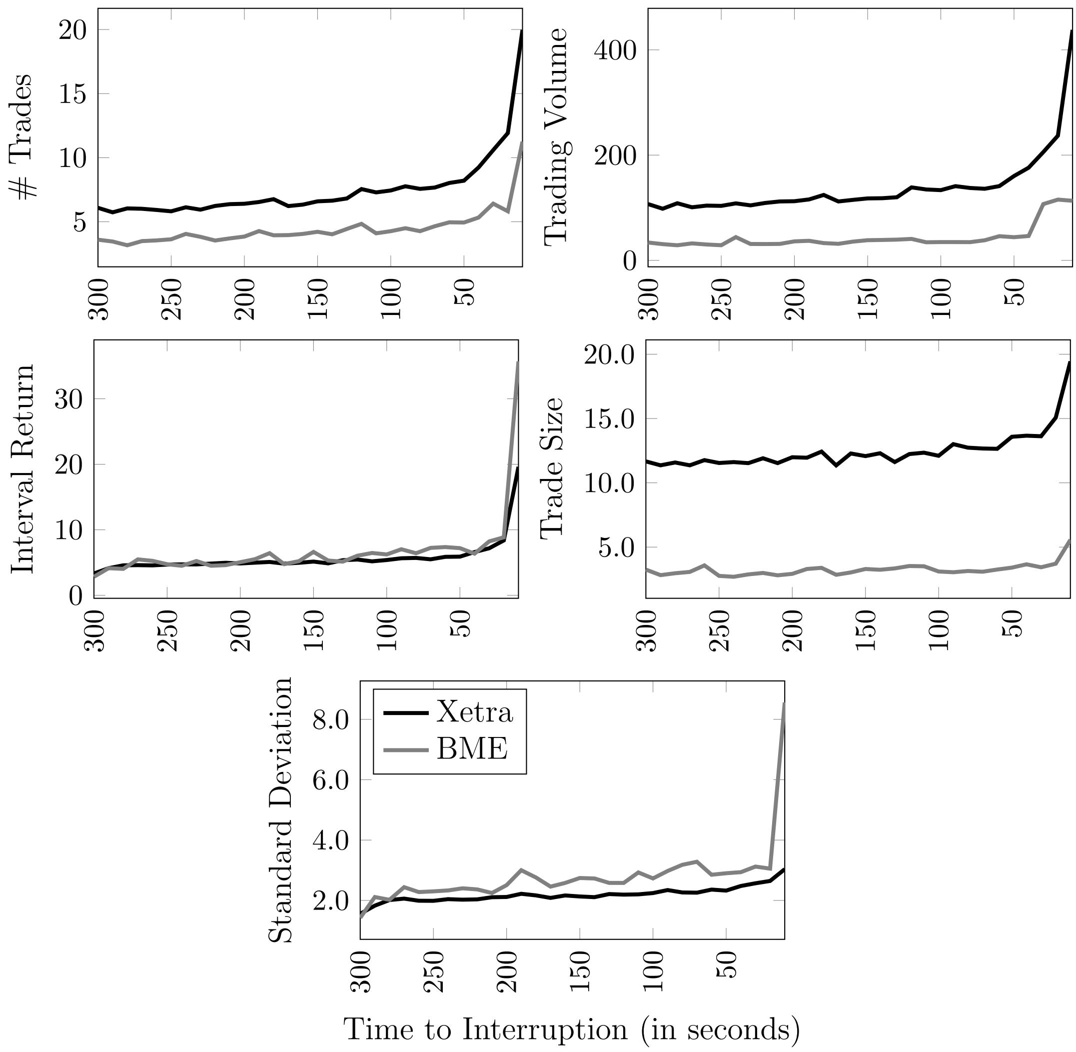

Figure A.3: Trading activity, trading aggressiveness, and volatility five minutes prior to volatility interruptions averaged across ten-second time intervals. Trading volume and trade size are reported in 1,000 euro. Interval returns and the standard deviation of returns are shown in bps.

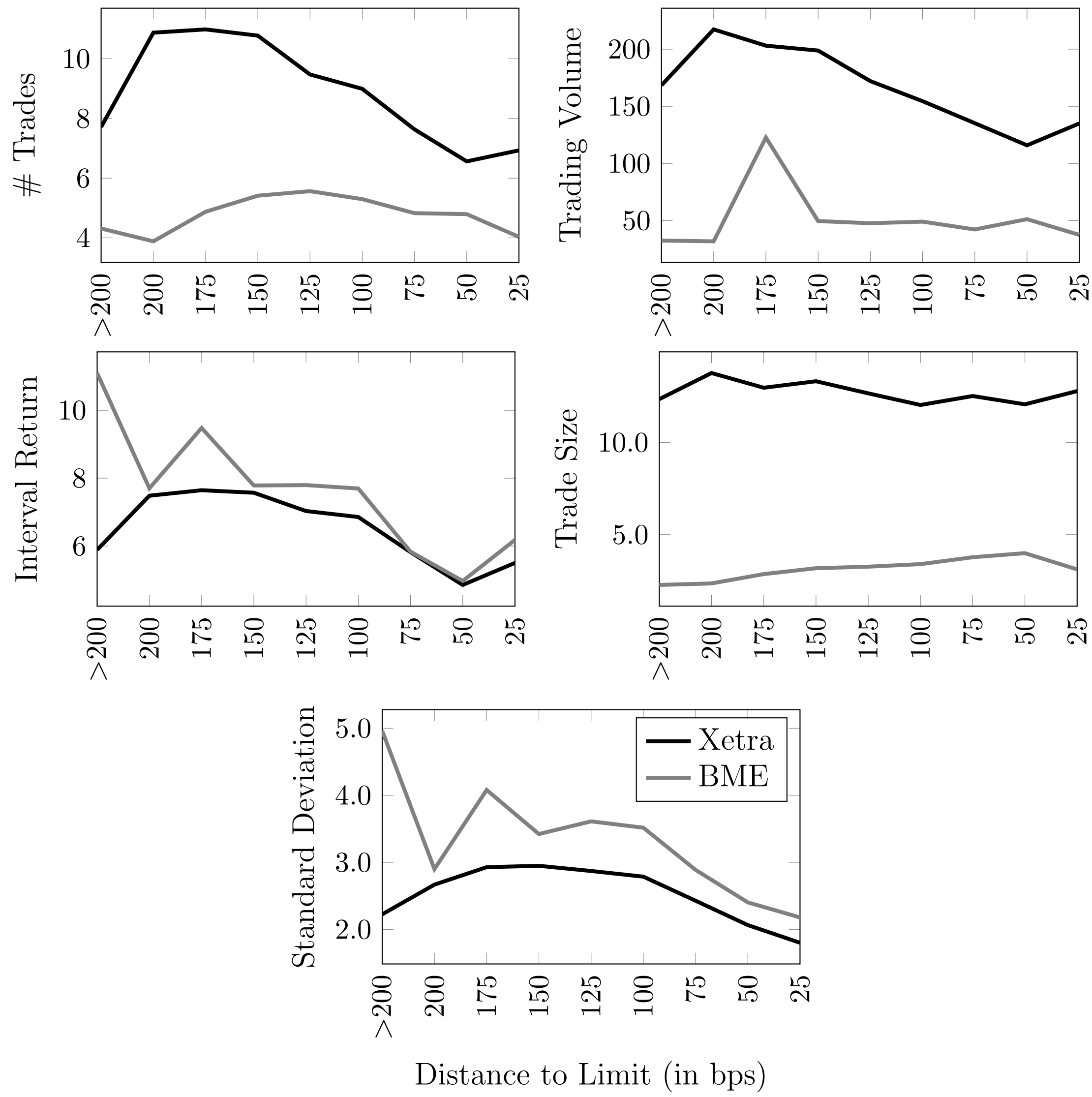

Figure A.4: Trading activity, trading aggressiveness, and volatility five minutes prior to volatility interruptions aggregated by the distance of each ten-second interval to the limits. Trading volume and trade size are reported in 1,000 euro. Interval returns and the standard deviation of returns are shown in bps.

Trading Behavior Close to Volatility Interruptions (5 Minutes)					
This table reports the results of the regression model described in Equation (2) for the full sample of 3,271 volatility interruptions. The dummy variables U_d (L_d) indicate how far a ten-second interval is away from the price limit in case of an upper (lower) limit hit. The ranges of distance to the limit (in bps) are I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0]. Controls for liquidity, order imbalance, and cumulative trading volume are included. We provide t statistics in parentheses. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.					
	Trading Aggressiveness		Trading Activity		Volatility
	Return (R_t)	Trade Size (S_t)	Trades (T_t)	Volume (V_t)	Volatility (SD_t)
U_3	6.408***	-0.384	-2.223***	-48.48***	-0.356***
	(20.73)	(-1.61)	(-10.07)	(-7.41)	(-4.06)
U_2	5.723***	-0.0635	-2.858***	-63.63***	-0.434***
	(23.11)	(-0.33)	(-16.15)	(-12.14)	(-6.18)
U_1	4.646***	-0.927***	-3.719***	-81.71***	-0.625***
	(23.47)	(-6.08)	(-26.23)	(-19.48)	(-11.14)
U_0	3.051***	-2.273***	-4.783***	-101.3***	-1.157***
	(17.22)	(-16.63)	(-37.55)	(-26.94)	(-23.00)
L_3	-1.259***	-0.265	-1.564***	-53.18***	-0.109
	(-4.85)	(-1.33)	(-8.43)	(-9.66)	(-1.48)
L_2	-0.381	-0.501**	-2.451***	-64.70***	-0.371***
	(-1.81)	(-3.08)	(-16.25)	(-14.47)	(-6.21)
L_1	0.406*	-1.221***	-3.276***	-82.61***	-0.550***
	(2.14)	(-8.35)	(-24.09)	(-20.52)	(-10.22)
L_0	1.646***	-2.483***	-4.484***	-106.7***	-1.079***
	(8.93)	(-17.43)	(-33.84)	(-27.24)	(-20.60)
Adj. R^2	0.025	0.237	0.305	0.234	0.139
N			93,699		
Breusch-Pagan test: The null of independence is rejected at the 1% level ($p = 0.000$).					

Table A.2: Trading behavior close to volatility interruptions based on the full sample and the five-minute observation period.

Results Subdivided by High and Low High-Frequency Trading Activity (5 Minutes)

This table reports the results of the regression model described in Equation (2) for sub-samples with high and low high-frequency trading activity. The dummy variables U_d (L_d) indicate how far a ten-second interval is away from the price limit in case of an upper (lower) limit hit. The ranges of distance to the limit (in bps) are I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0]. Controls for liquidity, order imbalance, and cumulative trading volume are included. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

		Trading Aggressiveness		Trading Activity		Volatility
HFT	Coef.	Return (R_t)	Trade Size (S_t)	Trades (T_t)	Volume (V_t)	Volatility (SD_t)
High	U_3	5.276***	-0.586	-1.350***	-33.65***	-0.359***
	U_2	5.023***	-0.544	-1.591***	-41.48***	-0.550***
	U_1	4.026***	-1.210***	-2.308***	-58.54***	-0.680***
	U_0	2.577***	-2.253***	-3.241***	-73.91***	-1.180***
	L_3	-1.851***	-0.347	-0.877***	-45.77***	-0.099
	L_2	-0.706**	-0.905***	-1.516***	-52.11***	-0.460***
	L_1	0.195	-1.397***	-2.093***	-62.58***	-0.645***
	L_0	1.264***	-2.523***	-3.041***	-81.02***	-1.123***
Low	U_3	7.041***	-0.117	-2.289***	-43.83***	-0.338*
	U_2	6.079***	0.398	-3.112***	-64.50***	-0.257*
	U_1	5.088***	-0.489*	-4.004***	-83.73***	-0.498***
	U_0	3.369***	-1.934***	-5.150***	-103.1***	-1.038***
	L_3	-0.997*	-0.209	-1.346***	-50.62***	-0.006
	L_2	-0.339	-0.097	-2.276***	-62.67***	-0.168
	L_1	0.339	-0.920***	-3.194***	-86.64***	-0.341***
	L_0	1.799***	-2.159***	-4.663***	-111.8***	-0.923***

Breusch-Pagan tests: The null of independence is rejected at the 1% level ($p = 0.000$).

Table A.3: Trading behavior close to volatility interruptions subdivided by high and low high-frequency trading activity based on the five-minute observation period.

Results Subdivided by Market and High and Low HFT Activity (15 Minutes)						
This table reports the results of the regression model described in Equation (2) for sub-samples with high and low high-frequency trading activity separately for each market. The dummy variables U_d (L_d) indicate how far a 30-second interval is away from the price limit in case of an upper (lower) limit hit. The ranges of distance to the limit (in bps) are I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0]. Controls for liquidity, order imbalance, and cumulative trading volume are included. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.						
		Trading Aggressiveness		Trading Activity		Volatility
HFT	Coef.	Return (R_t)	Trade Size (S_t)	Trades (T_t)	Volume (V_t)	Volatility (SD_t)
			Xetra			
High	U_3	5.239***	-0.701**	-1.782***	-32.02***	-0.325***
	U_2	4.956***	-0.775***	-2.521***	-48.85***	-0.456***
	U_1	4.400***	-1.012***	-3.509***	-68.35***	-0.554***
	U_0	3.156***	-1.154***	-5.393***	-97.44***	-0.920***
	L_3	-1.751***	-0.143	-1.645***	-29.96***	-0.248***
	L_2	-1.526***	-0.923***	-2.209***	-43.17***	-0.434***
	L_1	-0.751**	-1.097***	-3.809***	-71.70***	-0.638***
	L_0	1.129***	-1.794***	-4.935***	-98.16***	-0.772***
Low	U_3	6.783***	-0.010	-4.009***	-88.84***	-0.017
	U_2	6.014***	0.475*	-5.420***	-120.1***	-0.097*
	U_1	4.898***	0.117	-7.106***	-143.0***	-0.146***
	U_0	3.800***	0.144	-9.194***	-186.4***	-0.396***
	L_3	-2.101***	-0.387	-2.861***	-79.67***	-0.045
	L_2	-1.578***	-0.344	-5.108***	-129.0***	-0.060
	L_1	-0.511	-0.456*	-6.182***	-143.9***	-0.202***
	L_0	0.832	-0.761*	-8.718***	-200.3***	-0.439***
			BME			
High	U_3	6.353***	0.170	-1.421**	-10.55	-1.108**
	U_2	5.398***	-0.082	-1.893***	-22.17***	-1.470***
	U_1	4.292***	-0.285	-3.035***	-31.42***	-1.642***
	U_0	1.873**	-0.921***	-3.930***	-36.04***	-2.957***
	L_3	-3.425***	0.037	-0.935*	-13.29*	-0.576
	L_2	-2.258**	0.033	-1.291***	-14.07**	-1.148***
	L_1	-1.799*	-0.336*	-2.599***	-29.43***	-0.992***
	L_0	0.916	-1.008***	-3.436***	-34.17***	-2.390***
Low	U_3	7.474***	0.041	-3.601***	-20.65*	-1.005**
	U_2	6.047***	-0.005	-4.487***	-37.87***	-0.512
	U_1	4.756***	-0.200	-5.547***	-53.80***	-0.775**
	U_0	3.028**	-0.433***	-6.442***	-62.87***	-1.600***
	L_3	-3.437*	-0.293	-0.950	-14.22	-0.394
	L_2	-1.501	-0.312	-2.542**	-33.98***	-0.500
	L_1	-0.698	-0.524***	-3.182***	-52.08***	-0.442
	L_0	1.957	-0.786***	-4.486***	-62.22***	-1.420***
Breusch-Pagan tests: The null of independence is rejected at the 1% level ($p = 0.000$).						

Table A.4: Trading behavior close to volatility interruptions subdivided by high and low high-frequency trading activity based on the 15-minute observation period reported separately for each market.

Results Subdivided by Market and High and Low HFT Activity (5 Minutes)

This table reports the results of the regression model described in Equation (2) for sub-samples with high and low high-frequency trading activity separately for each market. The dummy variables U_d (L_d) indicate how far a 10-second interval is away from the price limit in case of an upper (lower) limit hit. The ranges of distance to the limit (in bps) are I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0]. Controls for liquidity, order imbalance, and cumulative trading volume are included. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

		Trading Aggressiveness		Trading Activity		Volatility
HFT	Coef.	Return (R_t)	Trade Size (S_t)	Trades (T_t)	Volume (V_t)	Volatility (SD_t)
				Xetra		
High	U_3	5.116***	-1.014*	-1.508***	-37.44***	-0.319***
	U_2	4.917***	-0.502	-1.599***	-37.86***	-0.301***
	U_1	4.018***	-1.340***	-2.402***	-54.08***	-0.523***
	U_0	2.813***	-2.245***	-3.374***	-69.98***	-0.851***
	L_3	-1.765***	-0.455	-1.029***	-27.49***	0.086
	L_2	-0.674**	-0.873**	-1.602***	-37.73***	-0.322***
	L_1	0.060	-1.351***	-2.210***	-50.02***	-0.519***
	L_0	1.111***	-2.440***	-3.197***	-69.45***	-0.796***
Low	U_3	6.037***	-0.230	-2.495***	-57.31***	-0.116
	U_2	5.716***	0.635	-3.780***	-84.98***	0.023
	U_1	4.780***	0.203	-4.515***	-104.4***	-0.258***
	U_0	3.551***	-0.693*	-5.831***	-137.7***	-0.395***
	L_3	-1.162***	-0.573	-1.679***	-63.11***	0.074
	L_2	-0.510	-0.243	-2.667***	-77.57***	-0.016
	L_1	0.340	-0.962***	-4.086***	-107.5***	-0.146***
	L_0	1.403***	-1.313***	-5.457***	-143.5***	-0.310***
				BME		
High	U_3	6.520***	0.569	-0.489	32.12	0.625
	U_2	3.965***	0.764**	-0.441	11.09	-0.824**
	U_1	2.745***	-0.175	-1.615***	10.81	-0.911***
	U_0	0.655	-0.810***	-2.488***	4.196	-1.880***
	L_3	-3.695***	-0.050	-0.862**	-33.30	-0.610
	L_2	-2.636***	-0.090	-0.954***	8.962	-0.482
	L_1	-1.216	-0.297	-1.320***	20.37	-0.905***
	L_0	0.268	-0.989***	-2.297***	-3.097	-1.771***
Low	U_3	8.998***	-0.112	-2.126***	-16.77	-1.294**
	U_2	7.356***	-0.032	-2.371***	-19.88**	-0.917*
	U_1	6.243***	-0.249	-3.341***	-25.37***	-0.770**
	U_0	3.912***	-0.956***	-4.655***	-53.19***	-1.539***
	L_3	0.494	0.175	-0.441	-16.63	-0.053
	L_2	1.675	-0.625	-1.751**	-24.69**	-0.724*
	L_1	1.408	-0.017	-1.073*	-26.71***	-0.372
	L_0	2.974***	-1.566***	-3.892***	-53.62***	-1.434***

Breusch-Pagan tests: The null of independence is rejected at the 1% level ($p = 0.000$).

Table A.5: Trading behavior close to volatility interruptions subdivided by high and low high-frequency trading activity based on the five-minute observation period reported separately for each market.

Results Subdivided by Disclosed and Undisclosed Price Limits (5 Minutes)						
This table reports the results of the regression model described in Equation (2) for sub-samples with disclosed and undisclosed price limits. The dummy variables U_d (L_d) indicate how far a ten-second interval is away from the price limit in case of an upper (lower) limit hit. The ranges of distance to the limit (in bps) are I_3 = [200,150), I_2 = [150,100), I_1 = [100,50), I_0 = [50,0]. Controls for liquidity, order imbalance, and cumulative trading volume are included. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.						
		Trading Aggressiveness		Trading Activity		Volatility
Price Limits	Coef.	Return (R_t)	Trade Size (S_t)	Trades (T_t)	Volume (V_t)	Volatility (SD_t)
Disclosed	U_3	8.085***	0.115	-1.460***	-8.388	-0.648*
	U_2	6.200***	0.313	-1.690***	-10.82	-0.996***
	U_1	5.029***	-0.343*	-2.734***	-14.70	-0.955***
	U_0	2.850***	-1.017***	-3.770***	-37.10***	-1.892***
	L_3	-1.028	-0.010	-0.860*	-42.60**	-0.400
	L_2	-0.032	-0.419*	-1.665***	-30.09*	-0.755***
	L_1	0.705	-0.325	-1.679***	-18.10	-0.904***
	L_0	2.242***	-1.358***	-3.360***	-46.31***	-1.845***
Undisclosed	U_3	5.759***	-0.727*	-2.515***	-57.79***	-0.222***
	U_2	5.451***	-0.121	-3.333***	-74.55***	-0.186***
	U_1	4.429***	-0.938***	-4.112***	-92.74***	-0.454***
	U_0	3.124***	-2.170***	-5.213***	-115.20***	-0.726***
	L_3	-1.358***	-0.627*	-1.800***	-57.28***	0.045
	L_2	-0.510**	-0.663**	-2.718***	-71.38***	-0.181***
	L_1	0.285	-1.405***	-3.832***	-92.94***	-0.375***
	L_0	1.343***	-2.360***	-4.976***	-118.10***	-0.641***
Breusch-Pagan tests: The null of independence is rejected at the 1% level ($p = 0.000$).						

Table A.6: Trading behavior close to volatility interruptions subdivided by disclosed and undisclosed price limits based on the five-minute observation period.