# Managing Excess Volatility: Design and Effectiveness of Circuit Breakers

Benjamin Clapham[a], Peter Gomber[b], Martin Haferkorn[c], and Sven Panz[d]

[a] *Goethe University Frankfurt, clapham@wiwi.uni-frankfurt.de*

[b] *Goethe University Frankfurt, gomber@wiwi.uni-frankfurt.de*

[c] *Goethe University Frankfurt, haferkorn@wiwi.uni-frankfurt.de*

[d] *Goethe University Frankfurt, panz@wiwi.uni-frankfurt.de*

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**Abstract**

We investigate different designs of circuit breakers implemented on European trading venues and examine their effectiveness to manage excess volatility and to preserve liquidity. Specifically, we empirically analyze volatility and liquidity around volatility interruptions implemented on the German and Spanish stock market, which differ regarding specific design parameters. We find that volatility interruptions in general significantly decrease volatility in the post interruption phase. Unfortunately, this decrease in volatility comes at the cost of decreased liquidity. Regarding design parameters, we find tighter price ranges and shorter durations to support volatility interruptions in achieving their goals.

**Keywords:** Circuit Breaker, Volatility Interruption, Volatility, Liquidity, Market Design

**JEL Classification:** G14, G15, G18, G28

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# 1 Introduction

Since the October 1987 stock market crash, circuit breakers in financial markets attract the attention of academics, regulators, and practitioners. In response to the crash, the New York Stock Exchange (NYSE) implemented the first circuit breaker based on the proposals of the Brady commission (Brady, 1988), which investigated the causes and consequences of the events in 1987. Circuit breakers are volatility safeguards that shall protect markets from extreme price fluctuations, excessive volatility and overreactions. Especially in the context of today's highly automated trading and the large number of transactions conducted by algorithmic and high-frequency trading (HFT) firms (Brogaard et al., 2014; European Securities and Markets Authority, 2014; Hendershott and Riordan, 2013), circuit breakers aim at ensuring market stability.

Phases of high volatility and large price swings in very short time spans (flash crash events) have become an increasing phenomenon in recent years highlighting the importance of circuit breakers. The most prominent of these events are the May 2010 Flash Crash in the US (Kirilenko et al., 2016), the October 2014 flash rally in US sovereign bond prices, the market turmoil after the removal of the Swiss franc-euro peg in January 2015, immense fluctuations of equity prices in August 2015, and the triggering of the market-wide circuit breaker in China right after its implementation in January 2016 (Latter, 2016). As a consequence, circuit breakers and their design gained public and regulatory attention which also led to regulatory initiatives regarding the introduction and the configuration of these mechanisms. The US Securities and Exchange Commission (SEC), for instance, established single-stock trading halts besides the existing market-wide trading halt in the US after the May 2010 Flash Crash. In China, regulatory authorities induced trading venues to implement a market-wide trading halt in January 2016. However, this circuit breaker was removed after it was triggered twice in the first four days being in effect. The Chinese case highlights that design and configuration of circuit breakers need to be well-conceived and carefully reviewed in order to ensure that the safeguard achieves the desired goal of calming markets in volatile phases.

Theoretical and empirical research on circuit breakers has come to mixed results on whether these mechanisms are effective in improving market quality and whether their benefits outweigh potential drawbacks. Nevertheless, the implementation of circuit breakers has become common practice among most trading venues worldwide (Gomber et al., 2017). Yet, designs and configurations of those circuit breakers differ substantially which might be an explanation for the ambiguous empirical results. Therefore, an analysis of different circuit breaker implementations enables to assess which circuit breaker configurations are most effective in providing market stability.

Consequently, we conduct an empirical analysis to investigate the effectiveness of two different circuit breaker mechanisms in reducing volatility and preserving liquidity. In doing so, we focus on volatility interruptions which are a specific type of circuit breakers that are primarily implemented by European venues. In contrast to trading halts, volatility interruptions switch continuous trading of individual stocks to an unscheduled call auction in case of extreme volatility. After a market-clearing call auction price is determined, continuous trading resumes. The selected volatility interruptions in this paper are comparable in their fundamental set-up but specific and important design parameters vary, which enables us to investigate these parameters in detail. Moreover, research on European volatility interruptions is scarce so the analysis conducted in this paper contributes to this research gap.

Specifically, our analysis focuses on two differing volatility interruption mechanisms implemented at Deutsche Boerse and the Spanish stock exchange Bolsa de Madrid to analyze their effectiveness in improving market quality, i.e., lowering volatility and preserving liquidity. By evaluating major design parameters such as the width of triggering thresholds, the publication of these thresholds, and the duration of the interruption, we are able to discuss and draw conclusions which configuration of these parameters performs best in reaching the goals of market stability and investor protection. The results are highly relevant for regulators, market participants, and market operators alike and provide new empirical insights to the existing literature on circuit breakers.

The paper is structured as follows. Section 2 presents the basic terminology regarding circuit breakers as well as related literature on their effectiveness. Section 3 gives information on the venues covered in this analysis, presents the data set, and shows descriptive statistics. Section 4 provides the research methodology and the results of our empirical analysis concerning the impact of circuit breakers on volatility and liquidity. The results are discussed in Section 5. Finally, section 6 concludes.

# 2 Literature Review

## 2.1 Terminology concerning Circuit Breakers

Trading venues have implemented different types of circuit breakers to ensure market stability. Abad and Pascual (2013) as well as Gomber et al. (2013) provide an overview on terminologies and concepts of circuit breakers. In general, the term circuit breakers describe all mechanisms that are intended to prevent extreme price swings and to protect liquidity providers by restricting or pausing trading. Circuit breakers can be divided into trading halts (also described as circuit breakers in a narrower sense) and price limits that define specific price ranges in which trades are allowed. Trading halts suspend trading of a particular instrument (single-instrument circuit breaker) or the whole market (market-wide circuit breaker) for a pre-defined time period. Price limits, on the other hand, either lead to an order rejection or trigger unscheduled call auctions which interfere continuous trading if a pre-defined limit is reached or breached. Our empirical study concentrates on these rule-based, unscheduled call auctions, which are known as volatility interruptions. Different to trading halts, volatility interruptions do not completely suspend all trading activity but collect orders in the call phase and display indicative prices and volumes to provide transparency and orientation for traders. In the empirical part of this study, we analyze design aspects of volatility interruptions on European equity markets and their effects on volatility and liquidity.

## 2.2 Theoretical Background and Empirical Findings

The first research papers on circuit breakers were published after the October 1987 stock market crash. The Brady Commission, which was appointed in the US to investigate the causes of the crash, recommended that limits should define how much a security can rise or fall and noted that circuit breakers represent meaningful mechanisms to facilitate price discovery and to calm down extreme market movements (Brady, 1988). Greenwald and Stein (1988), Kyle (1988), Lehmann (1989), and Moser (1990) were among the first who analyzed the effects of circuit breakers on financial markets. They conclude that circuit breakers have both positive and negative effects on market quality and price discovery leading to several follow-up studies on the pro and contra arguments.

Proponents of circuit breakers regularly emphasize the possibility for traders to reassess their inventories and trading strategies as proposed by the cooling-off hypothesis of Ma et al. (1989). Also, a halt reduces the risk for liquidity providers, i.e., limit order traders, to be picked off by informed traders (Copeland and Galai, 1983). Greenwald and Stein (1991) propose a model showing that circuit breakers may support markets in absorbing large volume shocks. As a response to the May 2010 Flash Crash, Subrahmanyam (2013) reviews the literature on circuit breakers regarding their relevance for algorithmic trading. Although he finds no evidence for the effectiveness of trading halts to reduce volatility, he argues that they might prevent disruptive or erroneous orders, which becomes increasingly important in an environment of fully automated order submissions.

Opponents, on the other hand, argue that circuit breakers interfere with market liquidity (Lauterbach and Ben-Zion, 1993) and delay the efficient incorporation of information into market prices (as described by Glosten and Milgrom, 1985 as well as Fama, 1970) thereby deferring price discovery (Lehmann, 1989). Moreover, circuit breakers might lead to a volatility spillover to other markets and to subsequent trading periods (Subrahmanyam, 1994). Rule-based circuit breakers might additionally cause a “gravitational” or “magnet” effect describing an acceleration of asset prices towards the threshold due to a fear of illiquidity (Cho et al., 2003; Goldstein and Kavajecz, 2004; Subrahmanyam, 1994). In a multi-period model, Slezak (1994) shows that circuit breakers spread uncertainty over a longer period of time and delay the release of private information leading to higher risk premia and price volatility.

Further theoretical research focuses on the ability of circuit breakers to limit daily liabilities of market participants and the costs of portfolio adjustments (Kim and Yang, 2004) as well as their positive effect on overall welfare (Westerhoff, 2003). Additionally, the effect of circuit breakers on market runs (Draus and van Achter, 2012) and the ability of circuit breakers to prevent market manipulation (Kim and Park, 2010) as well as abusive pricing by dealers (Edelen and Gervais, 2003) are investigated. Price-triggered circuit breakers can benefit liquidity providers as they protect them from incurring large losses and possible bankruptcy (Subrahmanyam, 1995).

Madhavan (1992) provides the theoretical rationale for volatility interruptions. He proposes a model of a rule-based circuit breaker that switches from continuous trading to a call auction in highly volatile markets. He shows that continuous trading may not be sensible during periods of severe information asymmetries and corresponding high volatility. A complete trading halt could worsen the prevailing information asymmetries because, once halted, resuming the continuous trading process may be difficult or even impossible. Instead, Madhavan (1992) suggests a temporary switch to a call auction to avoid market failure. Moreover, he shows that call auctions are more robust to problems of information asymmetry and aggregate information efficiently if the number of participants is large enough. Regarding the optimal range of triggering thresholds, Subrahmanyam (1997) points out that price ranges which are too narrow will jeopardize the functioning of the market as it is interrupted too often while only few interruptions occur if ranges are too wide. This shows that the effectiveness of circuit breakers depends on their parametrization.

Circuit breakers have also been analyzed empirically. However, empirical studies on circuit breakers come to contradicting results on whether these mechanisms are effective in reducing volatility, preserving liquidity and contributing to price discovery. These divergent results can partly be explained by the various designs of circuit breakers implemented on different analyzed markets. Nevertheless, most empirical studies doubt that circuit breakers fulfill their requirement of lowering volatility at appropriate costs.

Lee and Kim (1995) do find a reduction in volatility due to price limits on the Korean stock market. They control for other potentially influential variables on volatility based on a cross-sectional analysis and construct portfolios to isolate the impact of price limits from other factors like beta, price level, and firm size. Abad and Pascual (2010) study the volatility interruption on the Spanish market and find that market conditions after the volatility interruption remain unstable but volatility and trading activity revert to normal levels within 90 minutes. Zimmermann (2014) finds that the volatility interruption on Deutsche Boerse contributes significantly to the price discovery process leading to a reduction in volatility after the call auction. Lu (2016) examines the effect of price limits on cross-listed stocks on the Hong Kong and Chinese stock exchanges. For actively traded stocks, he rejects a possible volatility spillover as well as a delay in price discovery.

On the other hand, various studies find no empirical evidence for a reduction in volatility (Bildik and Gülay, 2006; Kim et al., 2008; Phylaktis et al., 1999) or even identify an increase in volatility after the circuit breaker (Chen, 1993; Farag, 2014; Lee et al., 1994). Similarly, Corwin and Lipson (2000) consistently observe a significant increase in volatility following security-specific NYSE trading halts. Additionally, they find decreased liquidity, measured by order book depth, around the halt and high amounts of order submissions as well as cancellations during and after the halt. Regarding Nasdaq trading halts, Christie et al. (2002) show that spreads and volatility increase significantly after short-lived interruptions while this effect is less strong for halts that reopen trading on the next day. Other empirical studies support that circuit breakers lead to a volatility spillover in time (Kim and Rhee, 1997) and across different stocks in case of single-stock circuit breakers (Brugler and Linton, 2016).

Due to contrary findings of empirical studies and different circuit breaker implementations on trading venues, the design parameters of circuit breakers need to be investigated further. Some researchers provide first insights on the influence of specific design parameters on the effectiveness of circuit breakers. Berkman and Lee (2002) analyze the effects of a change in price limits on the Korean Stock Exchange and conclude that tighter limits may have positive effects by reducing volatility and increasing trading volume. Contrary, Kim (2001) tests the relation between volatility and different regimes of price limits that were implemented on the Taiwan Stock Exchange and finds that there is no reduction in volatility when price limits are more restrictive. Chan et al. (2005) find evidence on the Kuala Lumpur Stock Exchange (today Bursa Malaysia) that even wide price limits delay the arrival of information through informed traders, increase order imbalances, and do not improve information asymmetry. Ryoo and Smith (2002) test execution prices after circuit breakers for the random walk hypothesis. Using multiple variance ratio tests, they discover that a widening of daily price limits increases the number of stocks following a random walk and therefore the efficiency of the market. Thus, narrower price limits do not enhance the price discovery process. The duration of the cooling-off period is analyzed by Chou et al. (2013) who look at the time period a securitys price at the Taiwan Stock Exchange stays at the limit and find that the endogenous limit-hit duration depends on stock-specific risk factors.

However, the aforementioned studies do not empirically test differently calibrated but similar circuit breaker concepts relative to each other to reveal the influence of design parameters such as the width of price limits or the efficiency of upward or downward triggered circuit breakers. Moreover, they only investigate one specific parameter and do not analyze the interaction of multiple parameters relevant for the circuit breaker. With our empirical study, we aim to fill this research gap by analyzing and discussing differently calibrated volatility interruptions on Deutsche Boerse's electronic trading platform Xetra and Bolsa de Madrid. Moreover, we empirically analyze whether a potential volatility reduction due to circuit breakers comes at a cost and derive proposals regarding the design of circuit breakers.

# 3 Institutional Background and Data

In this chapter, we provide general information about the trading venues and their volatility interruption mechanisms, introduce our data set, and discuss descriptive statistics.

## 3.1 Venue Information

Table 1 illustrates the design and parameters of scheduled auctions and volatility interruptions (i.e., unscheduled auctions) on Deutsche Boerse's electronic trading platform Xetra and Bolsa de Madrid (BME). The two considered venues have implemented opening and closing auctions of different lengths to determine the daily opening or closing price. Xetra additionally runs an intraday auction to enable trading of larger blocks without market impact, information leakage, or signaling. These scheduled auctions are equipped with a random end.

Volatility interruptions on Xetra and BME trigger an unscheduled call auction whenever the static or dynamic price range is reached or breached. The static threshold describes the maximum allowed deviation of prices in continuous trading compared to the last auction price while the dynamic threshold sets the maximum allowed deviation of each price from the previous trade. The fundamental setup of the volatility interruptions with static and dynamic price ranges is identical on both venues but important design parameters vary. One of these characteristics is the duration of the interruption. While volatility interruptions on Xetra last at least two minutes, interruptions on BME take significantly longer and last at least five minutes. On both venues, the unscheduled call auction of the volatility interruption is equipped with a random end of up to 30 seconds. In contrast to BME, volatility interruptions on Xetra can be extended in case of persisting large price deviations during the call auction of the volatility interruption.[1] Similar to scheduled auctions, indicative prices and volumes are displayed during the volatility interruption reflecting the aggregate supply and demand at each point in time.

| **Main Parameters of Volatility Interruptions on Xetra and BME** | | |
|---|---|---|
| This table provides detailed information about the duration and design parameters of volatility interruptions (volas) as well as scheduled auctions on Xetra and BME. * represents an addition of 30 seconds, in which the call auction ends randomly. | | |
| | **Xetra** | **BME** |
| Opening Auction | 8:50am - 9:00am* | 8:30am - 9:00am* |
| Intraday Auction | 1:00pm - 1:02pm* | - |
| Closing Auction | 5:30pm - 5:35pm* | 5:30pm - 5:35pm* |
| Duration of Volas | 2:00min* | 5:00min* |
| Vola Extension Possible | yes | no |
| Transparency during Scheduled Auctions and Volas | indicative price/volume | indicative price/volume |
| **Parameters** | | |
| Static Threshold | not disclosed | 4-10% |
| 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

Another difference between both mechanisms concerns the thresholds that trigger a volatility interruption. As Table 1 indicates, Deutsche Boerse does not disclose the stock-specific thresholds while BME publishes them. Moreover, when reverse-engineering the thresholds for volatility interruptions on Xetra, both width and distribution of thresholds vary substantially between Xetra and BME. On Xetra, these thresholds are individually and regularly adjusted based on the historical volatility of the specific stock (Deutsche Boerse Group, 2015). To account for expected periods of higher volatility, Deutsche Boerse uses so-called “Fast Markets” where price ranges of volatility interruptions are enlarged. “Fast Markets” are activated irregularly on a discretionary basis and this status displayed to market participants. BME uses categories of price ranges to which individual securities are allocated. The standardized categories of possible values vary between 4% and 10% for static thresholds and between 1% and 8% for dynamic thresholds. Despite these categories, BME reserves the right to adjust the thresholds for a certain share, market

[1] The volatility interruption is extended if, at the end of the auction, the potential price exceeds a pre-defined range, which is broader than the dynamic price range. The extension of the volatility interruption is terminated manually (Deutsche Boerse Group, 2015).

segment, or even for the whole market if necessary (Bolsa de Madrid, 2012). These differences in the duration of the interruption as well as the width and disclosure of the thresholds enable us to compare the effectiveness of volatility interruptions based on their different configurations.

## 3.2 Data Set

For our empirical analysis, we rely on Thomson Reuters Tick History data comprising tick-by-tick order book and trade information for the stocks in the main blue chip indices traded at Xetra (DAX30) and BME (IBEX35). We identify volatility interruptions by selecting all auctions which occurred outside the scheduled auction periods in the observation period from January 2011 until the end of September 2015. The time range of more than four years comprises multiple periods of distress for European financial markets (e.g., the sovereign debt crisis between 2011 and 2012) as well as company-specific distress (e.g., the Volkswagen emission scandal in 2015). Therefore, we are able to analyze volatility interruptions triggered by general market turmoil as well as volatility interruptions caused by price fluctuations due to company-specific news.

To avoid the consideration of misclassified volatility interruptions, we only consider those auctions with a suitable duration and those which were not delayed opening auctions (e.g., due to technical problems) or earlier closing auctions (e.g., on New Years Eve). Additionally, we verified the number as well as the start and end point applying a separate data set provided by Deutsche Boerse. In summary, the following information is provided on a millisecond basis for every stock: First, all executed trades with time stamp, price, and volume 15 minutes before the start and 15 minutes after the end of each volatility interruption. Second, all order book snapshots consisting of ten levels on the bid and ask side for the same time periods.

## 3.3 Volatility Interruptions

Table 2 shows the number of volatility interruptions that occurred in the observation period. Due to the fact that we consider a time frame of 15 minutes before the start of the volatility interruption and 15 minutes after the end of a volatility interruption, we exclude those volatility interruptions which started or ended within 15 minutes around the opening, intraday, or closing auction. Furthermore, we exclude volatility interruptions where the post-period overlapped the pre-period of the next volatility interruption to prevent confounding effects. Also, we exclude volatility interruptions with no observed trade within the pre- or post-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 used for our empirical analysis. | | |
| | **Xetra** | **BME** |
| **Total number of volas** | 3,048 | 1,131 |
| - Start of vola close to opening auction | 248 | 92 |
| - Vola close to intraday auction | 108 | n.a. |
| - End of vola close to closing auction | 110 | 0 |
| - Overlapping volas | 240 | 101 |
| - Excluded volas due to data issues | 5 | 4 |
| **Number of considered volas** | **2,337** | **934** |
| *Percentage of the sample* | *71.4%* | *28.6%* |

Table 2: Number of Observed and Considered Volatility Interruptions

In Table 3, descriptives for all considered volatility interruptions are depicted separately for each market. Due to a possible extension of volatility interruptions on Xetra, the duration lasts between 120 and 253 seconds. However, we only observe five volatility interruptions lasting longer than 150 seconds, which can be specified as extensions. The mean duration of volatility interruptions on Xetra lasts 135 seconds which equals the minimum duration of 120 seconds plus half of the random end (30 seconds). The duration of Spanish volatility interruptions is between 300 and 330 seconds with a mean of 314 seconds.

The mean absolute auction yield is computed as the relative difference between the auction price and the last trade price before the volatility interruption in absolute terms. With 0.50%, this yield is higher on the Spanish market compared to the German market with 0.20%. This can be traced back to the significantly longer auction period. The executed volume in the auction of the volatility interruption, however, amounts to 0.50mn euro on Xetra and 0.23mn euro on BME.

In 50% of all interruptions on Xetra, the auction yield shows an inverse sign compared to the price trend before the interruption. This indicates that price changes before the auction were exaggerated and are corrected through the volatility interruption. On BME, the price trend is reversed in 41% of the cases during the auction. On both venues, the total number of downward triggered volatility interruptions is slightly higher than the number of upward triggered interruptions. For BME, the sample is almost balanced with respect to interruptions in downward and upward market movements.

| Volatility Interruption Descriptives | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| This table reports descriptive statistics of all considered volatility interruptions (volas). The absolute auction yield is calculated as the relative difference between the last trade price before the volatility interruption and the auction price of the interruption in absolute terms. Mean, median, min, and max are computed over all considered volatility interruptions and are not pre-aggregated for each stock. Please note that the reported variables are computed for those volatility interruptions which are considered in the final analysis. | | | | | | | | |
| | **Xetra** | | | | **BME** | | | |
| | Mean | Med | Min | Max | Mean | Med | 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 | 29.20 | 29.50 | 2.00 | 75.00 |
| Duration [seconds] | 135 | 135 | 120 | 253 | 314 | 314 | 300 | 330 |
| Abs. Auction Yield [%] | 0.20 | 0.11 | 0.00 | 4.91 | 0.50 | 0.22 | 0.00 | 5.56 |
| Auction Volume [mn] | 0.50 | 0.24 | 0.00 | 14.39 | 0.23 | 0.08 | 0.00 | 5.65 |
| Auction Trend Change | 50% | | | | 41% | | | |
| Upward Volas | 1,008 (43%) | | | | 454 (49%) | | | |
| Downward Volas | 1.329 (57%) | | | | 480 (51%) | | | |

Table 3: Descriptive Statistics of the Volatility Interruptions

The maximum number of considered volatility interruptions per day spikes to 50 for Xetra on August 9th, 2011 and can be traced back to the European sovereign debt crisis and the associated financial turmoil. The same holds for BME, where the maximum number of volatility interruptions spikes on August 10th, 2011 reaching 25 volatility interruptions. Concerning the total number of volatility interruptions per stock, stocks of larger financial institutions caused the highest number of volatility interruptions. A detailed overview of the number of volatility interruptions per stock can be found in the appendix (see Tables 8 - 9). Spikes in the total number of volatility interruptions during our observation period can be grouped into three different categories (see Figure 1). First, ongoing market-wide financial distress such as the European sovereign debt crisis from mid 2011 until the end of 2012 or the market turmoil in Asia in August 2015. Second, ad hoc events or news triggering market-wide distress like disappointing ECB announcements (see August 2012), the peg abandonment on January 15th, 2015 of the Swiss franc or the release of negative economic data (e.g., the oil price drop on April 17th, 2013). Third, single-stock turbulences caused by ad hoc events or news for specific companies such as the emission scandal of Volkswagen in September 2015 or the enormous loss of market value of K+S in August 2013 due to distortions at the potash market.

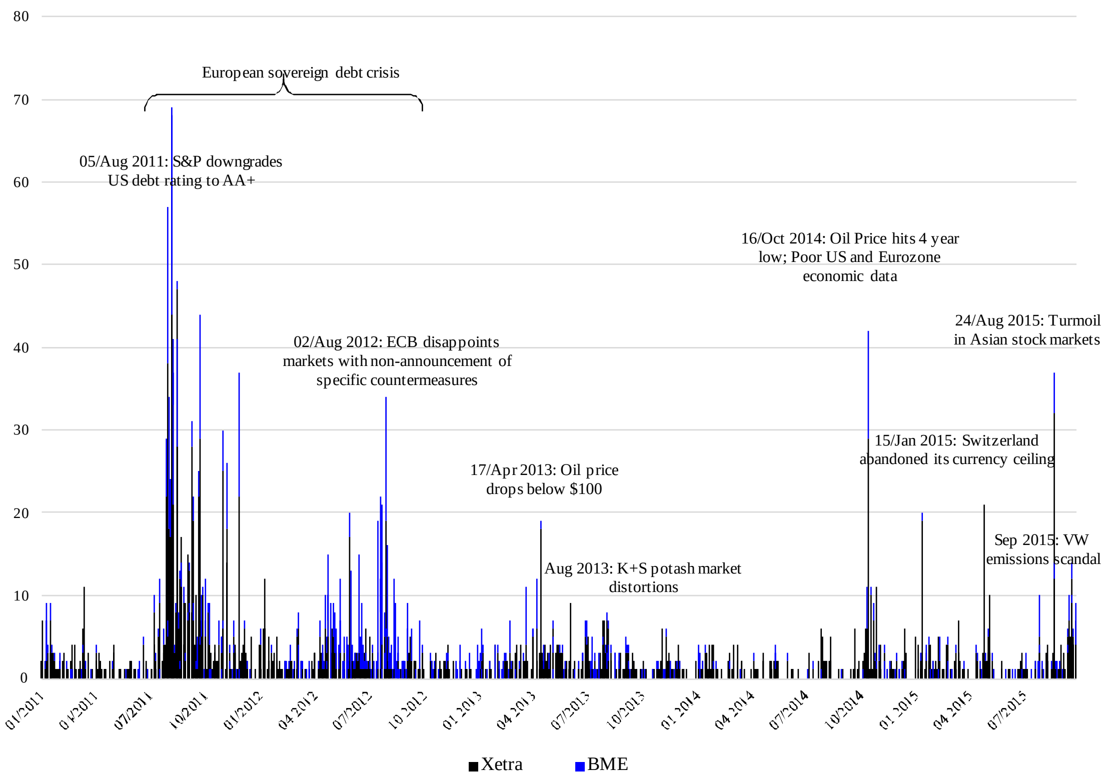



Figure 1: Triggering Events and Frequency of Volatility Interruptions

While BME makes the stock-specific triggering thresholds transparent to all market participants, they are not disclosed on Xetra. Therefore, we reverse engineer the static thresholds for Xetra and validate our approximation procedure with the Spanish sample where the thresholds are known. We calculate the static thresholds by determining the highest possible deviation from the last auction price within the 15 minutes before the start of each volatility interruption. The validation of our procedure based on the actual thresholds provided by BME shows, that we are able to correctly approximate more than 81% of the thresholds with a smaller deviation than 0.25 percentage points. Since we observe that 65% of the approximated thresholds for Xetra are in the range from 2.9% to 3.0% and feature a much lower variation than the thresholds for BME, the percentage of correctly approximated thresholds should be even higher.

The mean and maximum of approximated thresholds for each stock are reported in Tables 8 - 9 in the appendix. For Xetra, these vary between 2.9% and 4.0% on average. The mean deviation from the reference price on BME is between 4.0% and 8.9% while the actual thresholds range from 4.0% to 10%. By investigating the highest possible deviation, we observe a maximum deviation of 6.5% (Lanxess AG) on Xetra, which is considerably lower compared to BME where the thresholds for Bankia were widened to 30% (based on both actual and approximated thresholds).

To determine which category of threshold works best, we divide all thresholds in three separated categories as depicted in Table 4. We choose these categories to achieve a fairly balanced allocation along the categories. Due to the small range of 2.9% and 3.0%, a further separation of this category would not be reasonable although the majority of thresholds on Xetra are within this medium category. When allocating the volatility interruptions into the derived categories, we observe that the volatility interruption mechanism on BME allows more price deviations than the mechanism on Xetra. Therefore, it is not surprising that Xetra has 2.5 times more volatility interruptions than BME. However, the number of volatility interruption could also be influenced by the duration of the interruption and the disclosure of thresholds.

**Triggering Threshold Categories**

This table reports the allocation of the volatility interruptions (volas) into three threshold categories (low/medium/high). For Xetra, the volatility interruptions are categorized based on the approximated thresholds. For interruptions on BME, we use the actually disclosed thresholds, which are also used for the subsequent analysis.

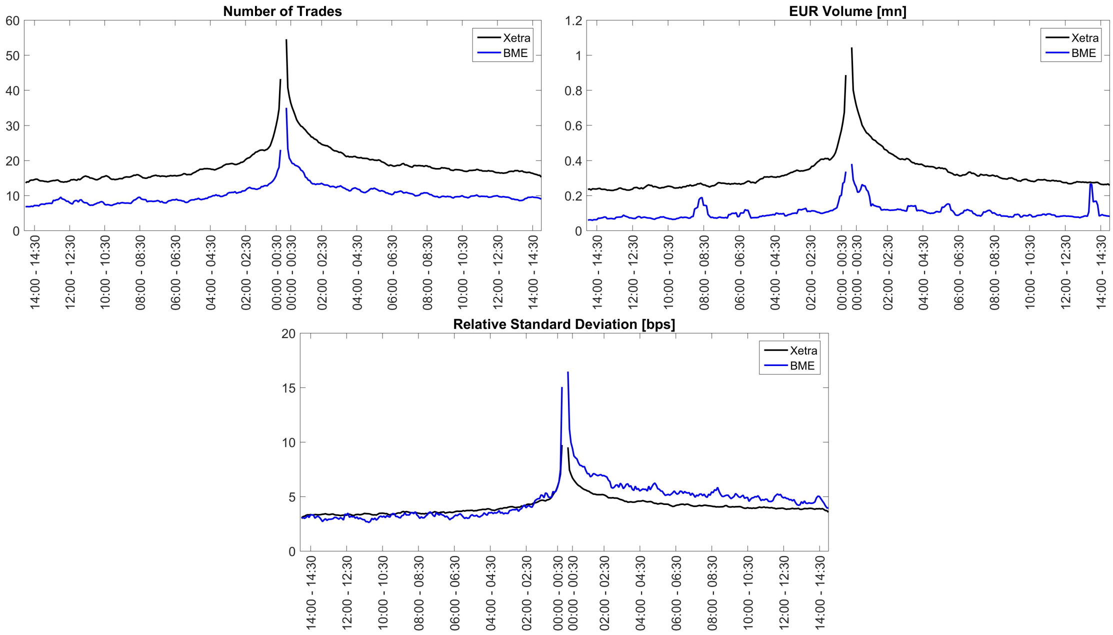
| | **Xetra** | | | | **BME** | | |
|---|---|---|---|---|---|---|---|
| Category | Low | Medium | High | Category | Low | Medium | High |
| From > | 0.0% | 2.9% | 3.0% | From > | 4.0% | 5.0% | 6.0% |
| To ≤ | 2.9% | 3.0% | 6.5% | To ≤ | 5.0% | 6.0% | 30.0% |
| No. of Volas | 54 | 1,519 | 764 | No. of Volas | 300 | 368 | 266 |

Table 4: Threshold Categories and Number of Volatility Interruptions

## 3.4 Market Quality around Volatility Interruptions

This section presents descriptive statistics regarding trading activity and market quality around volatility interruptions. For the analysis, we rely both on a longer observation window of 15 minutes around the interruption and a window of five minutes to examine short-term effects. In order to analyze the effectiveness of differently configured volatility interruptions, price variation before and after the interruption is of special relevance since volatility interruptions are meant to calm markets down. Different from other empirical studies, we normalize the standard deviation by the price level to measure price variation, i.e., we apply the relative standard deviation (also called variation coefficient) that eases cross-sectional comparability. This procedure is meaningful because the standard deviation always depends on the mean of the data. Therefore, stocks with a higher price level exhibit higher levels of absolute variation, most commonly measured as the standard deviation.

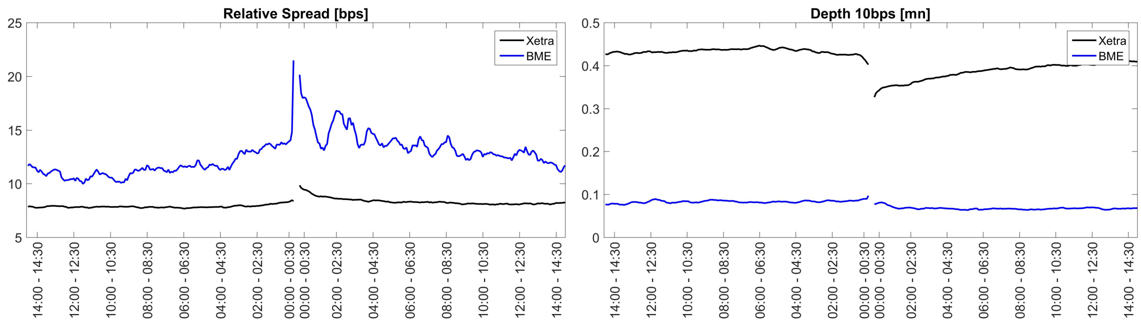
Figure 2 shows the number of trades, the executed volume, and the relative standard deviation 15 minutes before and after the volatility interruptions. To plot these different measures over time, we use a rolling window of 30 seconds and compute them every five seconds for each volatility interruption separately and aggregate the average for each venue. The number of trades spikes sharply just before the volatility interruption. This observation holds for both markets. The executed volume shows a similar trend as the number of trades. Shortly before the volatility interruption, more volume is executed, but it is even higher briefly after the end of the auction. After the volatility interruption, it takes up to two minutes until the depicted market variables revert to a normal level. Consequently, trading activity in the seconds before and after an interruption is significantly higher than during the remaining observation window. Price variation in terms of relative standard deviation also spikes before the volatility interruption, is even higher shortly after the volatility interruption and takes again some time to revert to normal levels. While the number of trades and the executed volume is higher on the German market, the relative standard deviation is higher on the Spanish market. Although the relative standard deviation reverts to normal levels after the volatility interruption, the figures give no precise answer whether volatility interruptions help to decrease price variation in the post-interruption phase.




A window of 30 seconds is used to compute the moving average of the number of trades, the executed volume, and the relative standard deviation every five seconds for each volatility interruption of individual stocks separately. Next, the average for all volatility interruptions on the respective venue is calculated and reported.

Figure 2: Moving Average of the Number of Trades, Executed Volume, and Relative Standard Deviation around Volatility Interruptions

The development of important liquidity parameters such as the relative spread and order book depth is shown in Figure 3. Again, the volatility interruption exhibits a clear pattern since the liquidity parameters change shortly before and after the interruption. Before the volatility interruption, the relative spread spikes and reflects increased uncertainty in the market. This is most prominent for BME where the relative spread is higher and more volatile than on Xetra. After the volatility interruption, the relative spread on Xetra is higher than before and it takes several minutes until it reverts to a normal level which is in line with Abad and Pascual (2010). On BME, the relative spread is on average higher in the post-interruption as well. However, it is slightly lower immediately after the interruption compared to the seconds before. Due to the high spread, order book depth measured 10bps around the midpoint (Depth(10) as proposed by Degryse et al. (2015)) of IBEX35 constituents is far lower than the order book depth on Xetra. For both markets, however, the order book depth is lower after a volatility interruption than before and reverts slowly to the pre-period level.




A window of 30 seconds is used to compute every five seconds the moving average of the relative bid-ask spread and the order book depth (Depth(10)) for each volatility interruption separately. Next, the average for all volatility interruption on the respective venue is calculated.

Figure 3: Moving Average of Spread and Depth(10) around Volatility Interruptions

These findings are also shown in Table 5 which descriptively reports relevant market quality parameters around volatility interruptions and their relative changes for two different aggregation periods of 15 and five minutes before and after the interruption. As already indicated in Figures 2 and 3, the total number of trades and the executed volume are considerably higher after the volatility interruption compared to the time period before. Considering a period of 15 minutes, we observe that executed volumes (number of trades) increase by 17% (16%) on the German market and by 15% (11%) on the Spanish market. The reported percentage change in the relative standard deviation highlights that volatility after the volatility interruption is reduced on both markets in the post-period, which shows that the dampening effect on price volatility - its main purpose - is successful. However, this reduction in volatility after the volatility interruption is accompanied by associated costs. Liquidity after the volatility interruption, measured by relative spread and order book depth, is significantly reduced. The increase in the relative spread after the volatility interruption varies between 10% and 23%. Order book depth (Depth(10)) decreases between 10% and 43%. Based on our discussions with market operators and market participants, two reasons may explain this behavior: First, all non-persistent orders will be deleted with the start of the volatility interruption and might not be re-entered during the volatility interruption. Second, liquidity providers might decrease their market making activities or demand higher risk premia, i.e., higher relative spreads, due to increased uncertainty. This is in line with a recent study by the German Federal Bank showing that HFT firms acting as market makers refrain from trading in cases of high uncertainty (Deutsche Bundesbank, 2016).

**Market Quality around Volatility Interruptions**

This table provides market quality parameters 15min and 5min before and after the volatility interruptions. The parameters are calculated as the average over all observations separately for each market. Executed volume and Depth(10) are reported in millions of euro. Relative standard deviation (RSD) and relative spreads are reported in basis points. The percentage change is computed as the relative difference of the mean before and after the volatility interruption.

| | **Xetra** | | | | | **BME** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | % Change | Med | Min | Max | Mean | % Change | Med | Min | Max |
| **15min Before** | | | | | | | | | | |
| Number of Trades | 541 | | 416 | 4 | 4573 | 322 | | 171 | 2 | 4540 |
| Exec. Volume [mn] | 9.40 | | 6.48 | 0.02 | 146.02 | 3.22 | | 0.88 | 0.00 | 92.30 |
| Depth(10) [mn] | 0.42 | | 0.32 | 0.00 | 3.08 | 0.08 | | 0.03 | 0.00 | 0.97 |
| Rel. Spread [bps] | 8.12 | | 6.91 | 2.14 | 81.64 | 25.08 | | 18.18 | 2.74 | 162.11 |
| Std. Dev. | 0.16 | | 0.09 | 0.00 | 2.00 | 0.04 | | 0.02 | 0.00 | 0.98 |
| RSD [bps] | 36.23 | | 30.31 | 3.11 | 176.46 | 48.88 | | 33.14 | 0.00 | 381.11 |
| **15min After** | | | | | | | | | | |
| Number of Trades | 629 | 16% | 476 | 1 | 4474 | 359 | 11% | 192 | 10 | 4765 |
| Exec. Volume [mn] | 11.04 | 17% | 7.18 | 0.01 | 155.14 | 3.69 | 15% | 0.98 | 0.03 | 95.80 |
| Depth(10) [mn] | 0.37 | -10% | 0.28 | 0.00 | 2.71 | 0.06 | -19% | 0.02 | 0.00 | 0.80 |
| Rel. Spread [bps] | 8.63 | 6% | 7.23 | 2.32 | 146.32 | 28.04 | 12% | 20.95 | 2.24 | 172.65 |
| Std. Dev. | 0.12 | -25% | 0.07 | 0.00 | 1.59 | 0.04 | -17% | 0.02 | 0.00 | 0.45 |
| RSD [bps] | 27.81 | -23% | 22.77 | 0.00 | 134.34 | 39.19 | -20% | 30.01 | 3.53 | 368.55 |
| **5min Before** | | | | | | | | | | |
| Number of Trades | 228 | | 169 | 0 | 1513 | 134 | | 71 | 0 | 2402 |
| Exec. Volume [mn] | 4.17 | | 2.60 | 0.00 | 44.95 | 1.34 | | 0.36 | 0.00 | 64.49 |
| Depth(10) [mn] | 0.41 | | 0.31 | 0.00 | 3.95 | 0.08 | | 0.03 | 0.00 | 1.23 |
| Rel. Spread [bps] | 8.21 | | 6.89 | 2.21 | 96.45 | 25.22 | | 17.67 | 2.36 | 192.10 |
| Std. Dev. | 0.10 | | 0.05 | 0.00 | 1.85 | 0.03 | | 0.01 | 0.00 | 0.87 |
| RSD [bps] | 23.30 | | 18.55 | 0.00 | 156.17 | 34.33 | | 19.65 | 0.00 | 449.13 |
| **5min After** | | | | | | | | | | |
| Number of Trades | 277 | 21% | 199 | 0 | 2019 | 157 | 17% | 88 | 2 | 1564 |
| Exec. Volume [mn] | 5.12 | 23% | 3.19 | 0.00 | 80.62 | 1.65 | 24% | 0.46 | 0.00 | 44.50 |
| Depth(10) [mn] | 0.35 | -16% | 0.26 | 0.00 | 2.08 | 0.06 | -18% | 0.02 | 0.00 | 1.39 |
| Rel. Spread [bps] | 9.03 | 10% | 7.46 | 2.00 | 165.59 | 29.50 | 17% | 21.16 | 2.23 | 189.04 |
| Std. Dev. | 0.08 | -21% | 0.05 | 0.00 | 1.67 | 0.03 | -14% | 0.01 | 0.00 | 0.36 |
| RSD [bps] | 19.11 | -18% | 15.04 | 0.00 | 120.49 | 28.77 | -16% | 20.97 | 0.92 | 344.51 |

Table 5: Average Market Quality Parameters 15min and 5min around Volatility Interruptions

# 4 Empirical Analysis

The descriptive analysis indicates that volatility interruptions are on average able to decrease volatility and thus fulfill their purpose. However, this comes at costs in terms of decreased liquidity. This chapter examines in detail how design parameters and market quality variables influence the effect of volatility interruptions on volatility and liquidity. We first introduce the regression approach as well as relevant parameters and variables and then apply different regression models to investigate which design parameters and market quality variables influence the effectiveness of volatility interruptions.

## 4.1 Research Approach and Regression Variables

In the following two subsections, we analyze the effectiveness of volatility interruptions regarding their ability to decrease volatility and to preserve liquidity, i.e., dampening the costs of this volatility reduction. In this regard, we investigate factors influencing the effect of volatility interruptions on liquidity. We propose that the drop in liquidity shown in the descriptive statistics can be interpreted as the costs of the volatility interruption. We analyze each market separately as well as both markets together to draw conclusions on design parameters which can only be analyzed in the full model (such as the disclosure of thresholds or the duration of the interruption). Next, we describe important variables relating to volatility interruptions as well as their intuition and interpretation.

- Duration: This variable represents the actual duration of the volatility interruption and takes values between 120 and 150 seconds for Xetra (up to 253 seconds in case of an extension) and 300 to 330 seconds for BME.
- Thresholds: This variable captures the actual thresholds for BME and the approximated thresholds for Xetra categorized in three different groups (low, medium, and high).
- Up or Down: If the price of the last trade before the volatility interruption is below (above) the reference price, we determine this volatility interruption to be triggered in a downward (upward) price movement. We do so, in order to examine whether volatility interruptions are equally effective both in upward and downward price movements. This variable is set to 1 in case of upward triggered volatility interruptions (0 otherwise).
- Number of Stocks in Volatility Interruption: This variable reflects the number of stocks where at least one volatility interruption was triggered on a given day on the respective market. Therefore, it indicates whether the reason for the volatility interruption is likely to be a single-stock event (few stocks with

volatility interruptions) or a market-wide event (many stocks with volatility interruptions).

- Disclosure of Thresholds: This variable is set to 1 (0 otherwise) for each volatility interruption on BME and indicates whether the venue operator discloses the width of the triggering thresholds.
- Auction Variables of the Volatility Interruptions:
  - Absolute Auction Yield: This yield is computed as the relative difference between the last trade price and the auction price of the volatility interruption. The return of the auction reflects the incorporation of new information and possible reassessments during the volatility interruption into stock prices.
  - Auction Trend Change: If the volatility interruption is flagged as a downward (upward) volatility interruption and the auction yield has a positive (negative) sign, this variable is set to 1 (0 otherwise) indicating that price changes before the auction were exaggerated and were corrected by the volatility interruption.
  - Auction Volume: Total sum of executed volume in euro that is executed at the end of the (volatility) auction since a high auction volume provides a valid price signal due to the high amount of information incorporated in the auction price (Madhavan, 1992).
- Market Quality Variables before the Volatility Interruptions:
  - Executed Volume: Total sum of executed volume in euro.
  - Depth(10): Total euro volume of all orders 10 bps around the midpoint (see Degryse et al., 2015).
  - Order Imbalance: Similar to Chordia et al. (2002), we compute the order book imbalance as $\frac{|Depth(10)_{Ask} - Depth(10)_{Bid}|}{Depth(10)}$.
  - Relative Standard Deviation (RSD): Represents the relative standard deviation of trade prices calculated as the standard deviation divided by the average trade price for the same period.
  - Relative Spread: Difference between the best bid and best ask price divided by the midpoint.
  - OTR: The order-to-trade ratio (OTR) is the total number of submitted orders to the order book divided by the number of trades. This measure can be used to analyze effects resulting from HFT activity (Brogaard et al., 2015).

## 4.2 Effect on Volatility

### 4.2.1 Regression Setup and Results

In this section, we present how different design and market quality parameters influence the effectiveness of volatility interruptions to reduce volatility. Instead of analyzing the effectiveness of volatility interruptions to reduce overall volatility in the post-interruption phase, we account for the reduction of volatility relative to the pre-period. It could be the case that a volatility interruption significantly reduces volatility but the market still exhibits high volatility. On the other hand, situations are possible in which volatility interruptions do not reduce volatility but overall volatility is already on a comparable low level. By only considering the post-period volatility level, an analysis would lead to considerably wrong results. To avoid this potential bias, we follow the argumentation of Brugler and Linton (2016) and focus on the following variable:

$$\Delta RSD = RSD_{pre} - RSD_{post}.$$

Volatility interruptions featuring a positive and high $\Delta RSD$ have obviously fulfilled their purpose. Therefore, we analyze parameters which increase $\Delta RSD$. To investigate the effect of different design parameters and market situations, we run the following regression model:

$$\begin{aligned}
\Delta RSD_{i,j} \quad = \quad & \alpha + \beta_1 \cdot Duration_{i,j} + \beta_2 \cdot ThresholdCategories_{i,j} \\
& + \beta_3 \cdot ThresholdDisclosed_{i,j} + \beta_4 \cdot StocksInVola_{i,j} + \beta_5 \cdot UpOrDown_{i,j} \\
& + \sum_{k=6}^{10} \beta_k \cdot MarketVariables_{i,j} + \sum_{k=11}^{13} \beta_k \cdot AuctionVariables_{i,j} \\
& + \sum_{k=14}^{n} \beta_k \cdot Controls_{i,j} \cdot I_j + \varepsilon_{i,j}
\end{aligned}$$

where $i$ represents the volatility interruption and $j$ either Xetra or BME. Normal distributed residuals are denoted as $\varepsilon_{i,j}$. As $MarketVariables$, we use $ExecutedVolume$, $OrderImbalance$, $RelativeSpread$, $Depth(10)$, and $OTR$, all of them capturing the respective period before the interruption. Therefore, these variables account for differences in the market environment in which the volatility interruption was triggered. As $AuctionVariables$, we use $AuctionTrendChange$, $abs(AuctionYield)$ and $AuctionVolume$ to capture auction specific characteristics. Additionally, we control for stock and year specific effects. We run the regression for a 15 minutes (five minutes) window separately for each market as well as for a full model considering both markets at the same time. This procedure results in six regression models in total. The estimation results of these models are depicted in Table 6. Heteroscedasticity-robust standard errors are computed in the pooled OLS regressions.

| Regression Results: Volatility | | | | | | |
|---|---|---|---|---|---|---|
| This table reports the regression results for our volatility interruption sample for each market separately as well as for a full model. The endogenous variable is $\Delta RSD$. Exogenous variables are design parameters, market variables and volatility interruption variables. We apply robust standard error estimations (Newey West respectively White) to correct for potential heteroscedasticity and autocorrelation biases. Please note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. | | | | | | |
| Dependent Variable: | $\Delta RSD$ $15min$ | | | $\Delta RSD$ $5min$ | | |
| | Xetra | BME | Both | Xetra | BME | Both |
| Constant | 0.001 | 0.003 | 0.001 | 0.001 | 0.002 | 0.001 |
| | t = 1.460 | t = 0.811 | t = 1.436 | t = 1.467 | t = 0.419 | t = 0.979 |
| Duration | −0.00000 | −0.00001 | −0.00001 | −0.00000 | −0.00001 | −0.00001 |
| | t = −0.901 | t = −1.089 | t = −2.031** | t = −0.940 | t = −1.245 | t = −1.954* |
| Threshold_low | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.001 |
| | t = 3.307*** | t = 1.696* | t = 2.080** | t = 2.336** | t = 3.877*** | t = 3.260*** |
| Threshold_med | 0.0004 | 0.001 | 0.0003 | 0.0001 | 0.001 | 0.0002 |
| | t = 3.867*** | t = 1.562 | t = 3.068*** | t = 1.419 | t = 2.883*** | t = 1.736* |
| Thresholds disclosed | | | 0.001 | | | 0.0001 |
| | | | t = 1.058 | | | t = 0.066 |
| Stocks in Vola | −0.00001 | −0.0001 | −0.00002 | −0.00000 | −0.00004 | −0.00001 |
| | t = −1.992** | t = −2.675*** | t = −3.803*** | t = −0.611 | t = −2.400** | t = −2.456** |
| UpOrDown | −0.0001 | −0.001 | −0.0002 | −0.0001 | −0.0004 | −0.0002 |
| | t = −1.047 | t = −2.546** | t = −2.589*** | t = −1.774* | t = −2.078** | t = −2.715*** |
| Exec. Volume | 0.00004 | 0.00000 | 0.00003 | 0.0001 | 0.0001 | 0.0001 |
| | t = 5.812*** | t = 0.069 | t = 6.028*** | t = 4.714*** | t = 3.269*** | t = 5.545*** |
| OrderImbalance | −0.001 | −0.001 | −0.001 | −0.0004 | −0.001 | −0.001 |
| | t = −2.630*** | t = −2.186** | t = −3.529*** | t = −1.709* | t = −1.596 | t = −3.018*** |
| Relative Spread | 0.357 | 0.662 | 0.636 | 0.197 | 0.662 | 0.615 |
| | t = 3.931*** | t = 6.048*** | t = 7.113*** | t = 2.179** | t = 5.291*** | t = 5.800*** |
| Depth10 | −0.001 | −0.002 | −0.001 | −0.0002 | −0.001 | −0.0001 |
| | t = −4.647*** | t = −2.255** | t = −4.333*** | t = −2.181** | t = −1.189 | t = −0.932 |
| OTR | −0.00001 | −0.00000 | −0.00001 | −0.00001 | −0.00002 | −0.00002 |
| | t = −1.860* | t = −1.530 | t = −1.785* | t = −1.594 | t = −2.964*** | t = −3.650*** |
| AucTrendChange | 0.001 | 0.001 | 0.001 | 0.0004 | 0.001 | 0.0004 |
| | t = 6.569*** | t = 2.973*** | t = 6.502*** | t = 5.531*** | t = 2.506** | t = 5.108*** |
| AucEuroVolume | 0.0002 | 0.002 | 0.0002 | 0.0001 | 0.001 | 0.0001 |
| | t = 2.780*** | t = 4.516*** | t = 3.458*** | t = 1.636 | t = 1.962** | t = 1.798* |
| abs(AucYield) | 0.044 | 0.087 | 0.085 | 0.054 | 0.055 | 0.066 |
| | t = 1.587 | t = 2.725*** | t = 3.540*** | t = 1.751* | t = 1.401 | t = 2.346** |
| Controls (Year) | yes | yes | yes | yes | yes | yes |
| Controls (RIC) | yes | yes | yes | yes | yes | yes |
| Observations | 2,337 | 934 | 3,271 | 2,327 | 895 | 3,222 |
| $R^2$ | 0.134 | 0.280 | 0.201 | 0.127 | 0.291 | 0.212 |
| Adjusted $R^2$ | 0.117 | 0.240 | 0.181 | 0.109 | 0.250 | 0.192 |
| Residual Std. Error | 0.002 | 0.003 | 0.002 | 0.001 | 0.003 | 0.002 |
| | (df = 2290) | (df = 884) | (df = 3191) | (df = 2280) | (df = 845) | (df = 3142) |
| F Statistic | 7.699*** | 7.002*** | 10.151*** | 7.191*** | 7.086*** | 10.687*** |
| | (df = 46; 2290) | (df = 49; 884) | (df = 79; 3191) | (df = 46; 2280) | (df = 49; 845) | (df = 79; 3142) |

Table 6: Regression Results: Volatility

### 4.2.2 Interpretation of the Results

Next, we interpret the regression results and discuss the most important variables.

*Duration.* For the single market regression, this variable has no effect on a volatility reduction since it captures only differences in duration due to the random end. The few observed extensions on Xetra do not seem to influence the results significantly. Regarding the full model including both the short interruptions on Xetra and the longer interruptions on BME, we can conclude that a shorter duration of the volatility interruption leads to a significantly higher reduction of volatility.

*Width of Thresholds.* By analyzing the different categories of thresholds, we observe that not all thresholds have the same effect on volatility reduction. Considering the highest possible beta coefficient (highest decline in volatility) we observe that volatility interruptions work best when they are triggered close to the reference price, i.e., within the narrowest thresholds (0%-2.9% for DAX30 constituents and 4%-5% for IBEX35 constituents).

*Disclosure of Thresholds.* Due to missing variation within the single markets, this variable can only be analyzed in the full model including both volatility interruptions on Xetra and BME. As there is no significant effect, we cannot observe any difference for the (non-)disclosure of thresholds. This may be traced back to the possibility of market participants to approximate the thresholds based on trading experience or trading data. Since this variable represents a dummy for Xetra and BME at the same time, it may also capture other market specific characteristics. However, all observable differences in the volatility mechanisms and the general market environment are already included in the regression model.

*Stocks in Vola.* This variable represents whether the event is a single-stock or market-wide event. The more stocks are affected by a volatility interruption on the same day, the more market-wide is the event. From the regression analysis, we can infer that the more stocks are affected, the less volatility is reduced. This effect is consistent for all models and both aggregation periods. Consequently, volatility interruptions are less effective in case of market-wide events.

*Up or Down.* Our estimations suggest that volatility interruptions triggered in a downward (*UpOrDown* equals zero) price movement are able to reduce volatility more than volatility interruptions triggered in an upward (*UpOrDown* equals one) movement. This result shows that volatility interruptions are more helpful in situations where the price of a stock is negatively affected, e.g., by negative news. In these situations, market participants seem to overreact at first but calm down due to the volatility interruption as they have time to reassess the information.

*Market Variables.* While a higher trading activity (*executed volume*) before the volatility interruption enables the auction to reduce volatility, a higher HFT activity (*OTR*) does not. We also find that a greater order book imbalance and depth before the volatility interruption have a negative effect on the effectiveness regarding a volatility reduction. The higher the *relative spread* before the volatility interruption, which can also be understood as a measure of uncertainty, the more volatility can be reduced by the volatility interruption. These effects are consistent and mostly significant for all models and both aggregation periods.

*Auction Variables.* The higher the *executed volume*, the better the volatility reduction. This is due to the fact that auction prices with a high executed volume serve as a stronger reference and signal for the market which is in line with Madhavan (1992). If the *price trend* during the auction changes, volatility interruptions reduce volatility stronger as the auction price indicates that price changes before the auction are the result of market overreactions. The same argument holds for the *auction yield*. A high *auction yield* signals that prices before the volatility interruption do not reflect all available information. The higher the deviation of the resulting auction price from the last traded price, the higher the variance reduction. Consequently, all variables capturing participation in the volatility interruption are associated with a reduction of volatility. Furthermore, these auction variables feature consistent beta coefficients for all models and both periods.

## 4.3 Effect on Liquidity

### 4.3.1 Regression Setup and Results

As shown before, volatility interruptions are able to lower volatility which comes at a price of reduced liquidity. Therefore, we analyze factors affecting the liquidity change from the period before the volatility interruption to the period after volatility interruption and use

$$\Delta Depth(10) = Depth(10)_{pre} - Depth(10)_{post}$$

as the dependent variable. To identify not only influential factors which decrease volatility, we aim to identify those factors which are able to keep the liquidity situation as stable as possible. Therefore, we run a similar regression as before to identify factors that reduce the costs of a triggered volatility interruption, i.e., which lower $\Delta Depth(10)$ as the the dependent variable. The endogenous variables of the next regression models are to a large extent identical to the regression analysis regarding the reduction of volatility described in section 4.2.1 apart from the $MarketVariables$ where we use $Depth(10)$ and $RelativeSpread$ opposed to $RSD$.

| **Regression Results: Liquidity** | | | | | | |
|---|---|---|---|---|---|---|
| This table reports the regression results for our volatility interruption sample for each market separately as well as for a full model. The endogenous variable is $\Delta Depth(10)$. Exogenous variables are design parameters, market variables and volatility interruption variables. We apply robust standard error estimations (Newey West respectively White) to correct for potential heteroscedasticity and autocorrelation biases. Please note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. | | | | | | |
| Dependent Variable: | $\Delta Depth(10)$ $15min$ | | | $\Delta Depth(10)$ $5min$ | | |
| | Xetra | BME | Both | Xetra | BME | Both |
| Constant | 0.057 | 0.024 | 0.064 | 0.163 | −0.061 | 0.112 |
| | t = 1.183 | t = 0.300 | t = 1.559 | t = 2.978*** | t = −0.410 | t = 2.350** |
| Duration | −0.001 | −0.0001 | −0.0004 | −0.001 | 0.0002 | −0.001 |
| | t = −2.332** | t = −0.317 | t = −1.799* | t = −3.384*** | t = 0.432 | t = −2.493** |
| Threshold_low | 0.031 | 0.006 | 0.023 | 0.012 | 0.012 | 0.031 |
| | t = 1.053 | t = 0.911 | t = 2.131** | t = 0.449 | t = 1.055 | t = 2.942*** |
| Threshold_med | 0.020 | 0.010 | 0.017 | 0.023 | 0.008 | 0.024 |
| | t = 3.101*** | t = 1.280 | t = 3.254*** | t = 3.134*** | t = 0.586 | t = 3.872*** |
| Thresholds disclosed | | | 0.024 | | | 0.044 |
| | | | t = 0.502 | | | t = 0.766 |
| Stocks in Vola | 0.001 | −0.0003 | 0.0005 | −0.001 | −0.002 | −0.001 |
| | t = 1.267 | t = −0.724 | t = 1.355 | t = −1.232 | t = −2.718*** | t = −2.129** |
| UpOrDown | −0.022 | −0.0001 | −0.017 | −0.004 | 0.002 | −0.003 |
| | t = −3.637*** | t = −0.015 | t = −3.620*** | t = −0.552 | t = 0.264 | t = −0.623 |
| Exec. Volume | −0.001 | 0.0002 | −0.0003 | −0.002 | 0.001 | −0.001 |
| | t = −1.186 | t = 0.269 | t = −0.698 | t = −1.295 | t = 0.623 | t = −0.545 |
| OrderImbalance | 0.345 | 0.061 | 0.188 | 0.387 | 0.078 | 0.224 |
| | t = 4.806*** | t = 4.899*** | t = 5.316*** | t = 6.226*** | t = 4.678*** | t = 6.912*** |
| RSD | 2.117 | −1.259 | −0.716 | 0.634 | −2.156 | −1.504 |
| | t = 1.286 | t = −2.816*** | t = −1.025 | t = 0.208 | t = −2.573** | t = −1.362 |
| OTR | 0.0001 | 0.0001 | −0.00004 | −0.001 | 0.0001 | −0.001 |
| | t = 0.128 | t = 2.567** | t = −0.485 | t = −3.021*** | t = 0.482 | t = −2.251** |
| AucTrendChange | −0.015 | 0.003 | −0.007 | −0.013 | −0.0002 | −0.008 |
| | t = −2.317** | t = 0.749 | t = −1.420 | t = −1.874* | t = −0.033 | t = −1.396 |
| AucEuroVolume | 0.023 | 0.016 | 0.026 | 0.028 | 0.012 | 0.026 |
| | t = 3.591*** | t = 1.448 | t = 4.155*** | t = 3.268*** | t = 0.676 | t = 3.395*** |
| abs(AucYield) | 4.226 | 0.105 | 1.359 | 2.563 | 0.347 | 0.983 |
| | t = 3.514*** | t = 0.402 | t = 3.174*** | t = 2.190** | t = 0.920 | t = 2.077** |
| Controls (Year) | yes | yes | yes | yes | yes | yes |
| Controls (RIC) | yes | yes | yes | yes | yes | yes |
| Observations | 2,337 | 934 | 3,271 | 2,327 | 895 | 3,222 |
| $R^2$ | 0.145 | 0.159 | 0.125 | 0.162 | 0.131 | 0.147 |
| Adjusted $R^2$ | 0.128 | 0.113 | 0.104 | 0.145 | 0.082 | 0.126 |
| Residual Std. Error | 0.149 | 0.068 | 0.133 | 0.169 | 0.101 | 0.156 |
| | (df = 2291) | (df = 885) | (df = 3192) | (df = 2281) | (df = 846) | (df = 3143) |
| F Statistic | 8.646*** | 3.477*** | 5.841*** | 9.788*** | 2.664*** | 6.935*** |
| | (df = 45; 2291) | (df = 48; 885) | (df = 78; 3192) | (df = 45; 2281) | (df = 48; 846) | (df = 78; 3143) |

Table 7: Regression Results: Liquidity

### 4.3.2 Interpretation of the Results

While positive signs of the coefficients in the regression of $\Delta RSD$ are associated with a positive impact on the reduction in volatility and the same holds for $\Delta Depth(10)$, where positive signs indicate a reduction in liquidity, the interpretation of $\Delta Depth(10)$ switches: A positive coefficient indicates a worse liquidity situation after the interruption than before and hints at circumstances where the interruption comes at particular high costs.

*Duration.* The longer the duration of the interruption, the lower the reduction of liquidity in terms of order book depth. Thus, longer interruptions seem to build up trading pressure, which is transformed into liquidity after the interruption.

*Width of Thresholds.* Apart from the fact that the results are not significant for the single regression of BME, the other coefficients support the conclusion that the category of medium-wide thresholds is most effective and leads to a lower reduction of liquidity. Volatility interruptions which are triggered within these ranges seem to be those volatility interruptions which are less expensive.

*Stocks in Vola.* Although there is some evidence for a lower liquidity reduction in case of market-wide events, our results are mixed regarding this effect and do not lead to clear conclusions.

*Disclosure of Thresholds.* As for the regression on volatility and due to the aforementioned reasoning, we do not observe a specific effect due to the (non-)disclosure of thresholds regarding their effect on liquidity.

*Up or Down.* Upward triggered volatility interruptions seem to work better in terms of a lower liquidity reduction than downward triggered volatility interruptions. Consequently and as analyzed before, downward triggered volatility interruptions are more effective in terms of volatility reduction but are also associated with higher costs in terms of worse liquidity. However, this effect does not hold for the shorter aggregation period at BME and is not significant in all models.

*Market Variables.* For the effect on liquidity, we observe no significant effects for trading activity (*executed volume*) and only partial significance of volatility (*RSD*). The mixed effects of the *OTR* also do not allow to draw any clear conclusions. However, the effects of the order book imbalance before the interruption are consistent and significant for all models: The higher the order book imbalance before the volatility interruption, the lower the liquidity buildup and the more expensive the volatility reduction. As we measure order book depth based on the whole order book regardless of the direction of a volatility interruption, a positive sign of the order book imbalance indicates that an unbalanced order book is associated with high costs. This might be the result of a high asymmetry of expectations.

*Auction Variables.* The *executed volume* of the auction has a negative effect on liquidity (i.e., a positive effect on $\Delta Depth(10)$). Market participants have to decide whether they participate in the auction or delay their orders to the time after the volatility interruption. If they decide to participate in the auction, the auction volume increases but they are less likely to submit orders and the liquidity situation decreases after the volatility interruption. This effect is consistent and mostly significant for all models. While the effects of a changing price trend are mixed, the effect of the *auction yield* is consistent and significant apart from the model for BME. Opposed to the effect on volatility, a high *auction yield* seems to discourage market participants to provide liquidity after the interruption.

# 5 Discussion

The goal of this paper is to investigate the impact of specific design parameters on the effectiveness of circuit breakers in the form of volatility interruptions. Therefore, we analyze the volatility interruption mechanisms on Xetra and BME that differ in important design parameters such as the duration of the interruption and the width as well as disclosure of the thresholds. Additionally, we derive results on upward and downward triggered volatility interruptions and whether single-stock interruptions are also capable to reduce volatility in case of market-wide events.

Our results indicate that the shorter volatility interruptions on Xetra are more effective in reducing volatility and preserving liquidity than the longer interruptions on BME. In today's HFT environment, where algorithms react to new information within short periods of time, short interruptions might be sufficient for market participants to reassess their orders and inventories as proposed by the cooling-off hypothesis by Ma et al. (1989). Consequently, longer interruptions do not provide any additional advantages but unnecessarily interfere with continuous trading (Lauterbach and Ben-Zion, 1993) and defer price discovery (Lehmann, 1989).

Moreover, narrower triggering thresholds lead to more effective volatility interruptions in terms of volatility reduction. Our results show that tighter thresholds, which trigger interruptions earlier, seem to prevent the spread of uncertainty better than wide thresholds. Therefore, they lead to a larger decrease in volatility measured by the relative standard deviation. This observation is also confirmed by Berkman and Lee (2002). But tighter thresholds come at the cost of more "unnecessary" volatility interruptions which are associated with a drop of liquidity. This is also discussed by Subrahmanyam (1997) who examines the functioning of the market with respect to price ranges of thresholds.

Regarding the disclosure of triggering thresholds, our regression analysis shows no significant effect on volatility and liquidity. Exchange operators who do not publish the triggering thresholds of their volatility interruption mechanism regularly state that this is necessary to avoid manipulation and to prevent the triggering of an interruption on purpose (Gomber et al., 2017). However, we do not observe any significant effect which might result from threshold approximation by professional market participants. Since retail investors typically do not have the data or experience to approximate thresholds, disclosing them might provide a level playing field for all market participants in this regard.

For market-wide events approximated by the number of stocks that are affected by volatility interruptions on a specific day, volatility interruptions are not as effective in reducing volatility as in case of events that have an effect on few stocks. Therefore, volatility interruptions are more effective in handling high volatility in case of unexpected, single-stock events than in case of far-reaching market-wide events, where the consequences might be harder to predict. Regarding the effect on liquidity, our analysis shows mixed results.

Finally, our results indicate that on average, downward triggered volatility interruptions are more effective in reducing volatility, but are also associated with higher costs in terms of liquidity. Nevertheless, in today's highly automated trading environment, volatility interruptions should be triggered both upwards and downwards since out-of-control algorithms or fat finger trades might lead to large price movements in both directions. Moreover, long and short positions should be protected equally. This corresponds with current implementations since the vast majority of circuit breakers on trading venues worldwide are triggered in both directions (see Gomber et al., 2017).

The results of our empirical study confirm results of previous research and extend the insights to volatility interruptions manifold. By analyzing two venues, we are able to compare the effectiveness of differently configured volatility interruptions with regard to volatility and liquidity. We show that design parameters significantly influence the effectiveness of volatility interruptions and highlight that a shorter duration and tighter price ranges support interruptions in achieving their goals. Moreover, our findings are in line with previous literature, i.e., circuit breakers in the form of volatility interruptions are able to reduce volatility (Lee and Kim, 1995; Zimmermann, 2014) but decrease liquidity at the same time (Corwin and Lipson, 2000; Kim et al., 2008).

Our analysis is also of high interest for practitioners. First, we conduct a profound analysis for exchange operators to better understand circuit breakers in the form of volatility interruptions and their impact on volatility and liquidity. Second, our results on design parameters enable exchange operators to review their current circuit breaker configurations or to shape its initial implementation. Moreover, our results are also relevant for regulators who are responsible for the regulatory framework regarding market safeguards that trading venues have to comply with. In this respect, regulators might use our insights in order to discuss and provide meaningful regulatory standards for the application of circuit breakers.

Our study also has some limitations. As Deutsche Boerse does not disclose the triggering thresholds of the volatility interruptions, we reverse engineered them. Nevertheless, we validate our procedure based on the data for BME and show that we can approximate the thresholds reliably. Moreover, the results and conclusions of this study could be generalized further by considering more than two markets and markets with completely different circuit breakers than volatility interruptions.

To avoid confounding effects, we exclude those volatility interruptions where our observation window of 15 minutes overlapped with another volatility interruption. Therefore, we exclude those volatility interruptions which were triggered shortly after each other in very volatile phases. This procedure is unavoidable but may lead to biased results. The same holds for volatility interruptions that take place close to an auction. Furthermore, a lot of volatility interruptions appear during the opening auction which is extended in case a volatility interruption is triggered. However, the effectiveness of a volatility interruption in an opening auction is hard to assess since no comparison of pre- and post-interruption phases is possible.

# 6 Conclusion

In this paper, we provide insights on circuit breakers and contribute to the ongoing debate about their design, benefits, and drawbacks. With our empirical analysis, we show that circuit breakers in the form of volatility interruptions are able to reduce volatility but are also associated with a drop in liquidity. In particular, our results reveal how design parameters such as duration, width of triggering thresholds, and the publication of these thresholds influence the effectiveness of volatility interruptions in reducing volatility and preserving liquidity.

We compare volatility interruption mechanisms on two European venues and show that a shorter duration and narrower price ranges support their effectiveness. The disclosure respectively non-disclosure of triggering thresholds, however, has no effect on the interruption's effectiveness, which might result from the possibility to approximate the thresholds based on tick-by-tick trade data. Furthermore, there is empirical evidence that volatility interruptions triggered by market-wide events are not as effective as interruptions triggered by single-stock events. These results may serve as a starting point for exchange operators and regulators to review existing circuit breaker designs or to start implementing them. Although we analyze a specific type of circuit breakers and focus on its occurrence in continuous trading, the results provide relevant insights regarding the configuration of circuit breakers. Future research could extend our analysis based on other types of differently configured circuit breakers such as trading halts and investigate the effect of different design parameters on the information asymmetry around circuit breakers (Easley et al., 1996; Johnson and So, 2016). Considering the increasing fragmentation of investors' order flow in Europe, the question whether a coordination of circuit breakers among venues is necessary to ensure their effectiveness is another highly relevant topic for future research.

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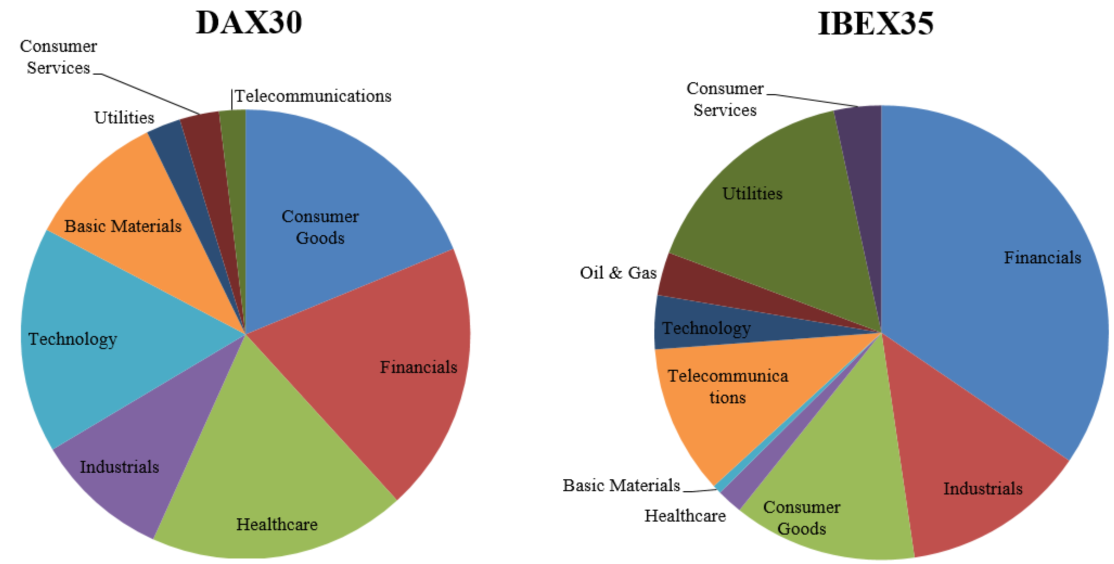
# Appendix




Source: Own compilation based on Bloomberg data.

Figure 4: Index Composition of DAX30 and IBEX35 according to Industries

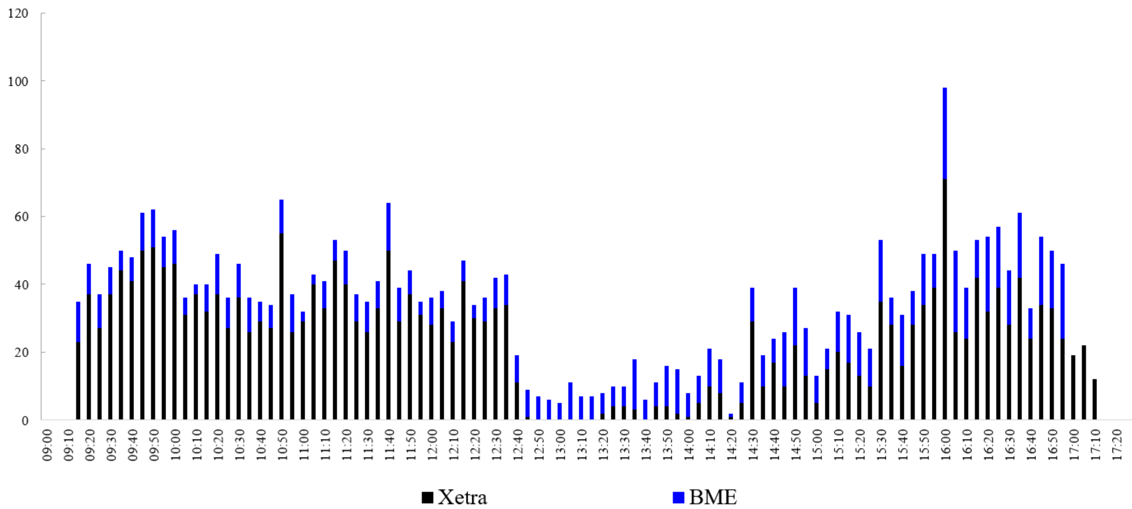



Figure 5: Frequency of Volatility Interruptions during the Trading Day

**Index Constituents, Number of Volatility Interruptions, and Approximated Thresholds**

This table provides all considered DAX30 constituents, the number of considered volatility interruptions during our observation period, and an approximation of the undisclosed thresholds per stock.

| | | Up | | Down | |
|---|---|---|---|---|---|
| Instrument | # of CBs | Mean | Max | Mean | Min |
| ADSGn.DE | 48 | 3.1% | 3.82% | -3.1% | -3.87% |
| ALVG.DE | 54 | 3.6% | 4.49% | -3.1% | -4.49% |
| BASFn.DE | 52 | 3.5% | 4.50% | -3.1% | -4.10% |
| BAYGn.DE | 57 | 3.3% | 4.66% | -3.3% | -4.64% |
| BEIG.DE | 29 | 2.9% | 3.00% | -3.1% | -3.90% |
| BMWG.DE | 94 | 3.2% | 4.50% | -3.3% | -4.49% |
| CBKG.DE | 281 | 3.5% | 4.50% | -3.4% | -5.87% |
| CONG.DE | 65 | 4.0% | 6.47% | -3.8% | -6.43% |
| DAIGn.DE | 90 | 3.3% | 4.50% | -3.2% | -4.50% |
| DB1Gn.DE | 52 | 3.0% | 4.07% | -2.9% | -4.38% |
| DBKGn.DE | 149 | 3.4% | 4.50% | -3.4% | -4.50% |
| DPWGn.DE | 38 | 3.1% | 3.89% | -3.0% | -3.90% |
| DTEGn.DE | 39 | 3.0% | 3.87% | -3.1% | -3.90% |
| EONGn.DE | 86 | 3.1% | 3.89% | -3.2% | -3.90% |
| FMEG.DE | 32 | 3.1% | 3.86% | -3.2% | -3.90% |
| FREG.DE | 41 | 3.2% | 3.90% | -3.1% | -3.90% |
| HEIG.DE | 107 | 3.4% | 4.50% | -3.2% | -4.50% |
| HNKG_p.DE | 27 | 2.9% | 3.88% | -3.1% | -3.87% |
| IFXGn.DE | 114 | 3.4% | 4.50% | -3.2% | -4.84% |
| LHAG.DE | 137 | 3.1% | 3.86% | -3.1% | -4.10% |
| LING.DE | 37 | 3.1% | 3.84% | -3.0% | -3.89% |
| LXSG.DE | 87 | 3.9% | 6.50% | -3.7% | -6.50% |
| MRCG.DE | 36 | 3.1% | 3.90% | -3.1% | -3.89% |
| MUVGn.DE | 32 | 3.1% | 3.58% | -3.1% | -3.90% |
| RWEG.DE | 108 | 3.1% | 3.90% | -3.2% | -3.90% |
| SAPG.DE | 28 | 3.1% | 3.89% | -3.2% | -4.09% |
| SDFGn.DE | 139 | 3.2% | 4.48% | -3.2% | -4.06% |
| SIEGn.DE | 37 | 3.2% | 4.31% | -3.2% | -3.90% |
| TKAG.DE | 128 | 3.2% | 4.34% | -3.2% | -4.35% |
| VOWG_p.DE | 113 | 3.2% | 4.50% | -3.2% | -4.50% |
| Sum | 2,337 | | | | |

Table 8: DAX30 Constituents, Number of Volatility Interruptions, and Approximated Thresholds

| **Index Constituents, Number of Volatility Interruptions, and Approximated Thresholds** | | | | | |
|---|---|---|---|---|---|
| This table provides all considered IBEX35 constituents, the number of considered volatility interruptions during our observation period, and the approximated thresholds per stock. | | | | | |
| | | Up | | Down | |
| Instrument | # of CBs | Mean | Max | Mean | Min |
| ABE.MC | 11 | 4.4% | 4.9% | -4.9% | -4.9% |
| ACS.MC | 36 | 5.2% | 7.0% | -5.3% | -7.0% |
| ACX.MC | 30 | 4.8% | 5.0% | -4.8% | -5.0% |
| AMA.MC | 5 | 5.9% | 5.9% | -5.0% | -6.0% |
| ANA.MC | 38 | 5.1% | 7.0% | -5.3% | -7.0% |
| BBVA.MC | 28 | 6.0% | 6.0% | -5.7% | -6.0% |
| BKIA.MC | 71 | 8.9% | 20.7% | -8.6% | -29.9% |
| BKT.MC | 30 | 6.1% | 6.9% | -6.2% | -7.0% |
| CABK.MC | 30 | 5.5% | 6.0% | -5.2% | -6.0% |
| DIDA.MC | 7 | 7.8% | 8.0% | -6.2% | -7.0% |
| ELE.MC | 19 | 4.0% | 4.9% | -4.7% | -5.0% |
| ENAG.MC | 7 | n.a. | n.a. | -4.4% | -5.0% |
| FCC.MC | 75 | 5.4% | 7.0% | -5.2% | -7.0% |
| FER.MC | 2 | n.a. | n.a. | -6.0% | -6.0% |
| GAM.MC | 56 | 6.4% | 8.0% | -6.5% | -8.0% |
| GAS.MC | 24 | 4.9% | 5.0% | -4.4% | -5.0% |
| GRLS.MC | 21 | 4.9% | 5.0% | -4.6% | -5.0% |
| IBE.MC | 22 | 5.4% | 6.0% | -5.2% | -6.0% |
| ICAG.MC | 10 | 6.9% | 7.0% | -6.9% | -7.0% |
| IDR.MC | 33 | 5.9% | 12.0% | -4.5% | -6.0% |
| ITX.MC | 10 | 5.6% | 6.0% | -5.5% | -6.0% |
| MAP.MC | 40 | 5.3% | 6.0% | -5.3% | -5.9% |
| MTS.MC | 35 | 5.3% | 6.0% | -5.1% | -6.0% |
| OHL.MC | 33 | 5.9% | 6.0% | -5.7% | -6.0% |
| POP.MC | 44 | 6.0% | 7.8% | -5.6% | -7.0% |
| REE.MC | 11 | 4.4% | 5.0% | -5.0% | -5.0% |
| REP.MC | 29 | 4.7% | 5.9% | -4.9% | -5.0% |
| SABE.MC | 38 | 5.8% | 5.9% | -5.9% | -6.0% |
| SAN.MC | 24 | 5.3% | 6.0% | -6.0% | -6.0% |
| SCYR.MC | 57 | 7.5% | 7.9% | -6.9% | -8.0% |
| TEF.MC | 12 | 5.1% | 10.0% | -5.0% | -5.0% |
| TL5.MC | 26 | 5.9% | 7.0% | -5.8% | -6.9% |
| TRE.MC | 20 | 5.7% | 7.0% | -5.5% | -7.0% |
| Sum | 934 | | | | |

Table 9: IBEX35 Constituents, Number of Volatility Interruptions, and Approximated Thresholds