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Market impacts of circuit breakers – Evidence from EU trading venues¹

Cyrille Guillaumie², Giuseppe Loiacono³, Christian Winkler⁴, Steffen Kern⁵ January 2020

Abstract

Sudden and drastic price swings in financial markets can be a source of market instability and are a concern for market participants, supervisors and regulators. Circuit breakers (CBs) are key instruments for trading venues to interrupt excessive price movements. Using a unique database of CBs, which were triggered between 1 April 2016 and 31 December 2016 on a sample of 10,000 financial instruments traded on EU trading venues, we analyse market impacts of CBs. We find that price volatility is significantly lower after the CB, while bid-ask spreads widen and the price discovery process is not negatively affected by the CB. We take advantage of the cross-venue character of our database to contribute to the discussion on cross-venue CB coordination. Cross-listed instruments traded in continuous trading on satellite markets during a CB on the reference market experience a "hidden CB". Despite being in continuous trading, trading activity on the satellite market decreases drastically and liquidity dries up as investors refrain from trading waiting for the reference market to set the CB auction price.

JEL Classifications: G10, G11, G14

Keywords: Circuit breaker, trading halt, flash crash, price discovery

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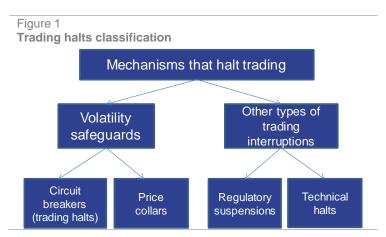
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I. Introduction

A number of events in recent years have highlighted the importance of ensuring orderly functioning of trading venues in situations of large and sudden market price movements. Examples of these events include the 6 May 2010 flash crash, out-of-control algorithms of Knight Capital Group in 2012, the Treasuries flash rally in October 2014, the market movements in US equity and ETF markets on 24 August 2015, or the large and sudden GBP/USD exchange rate moves in Asian FX markets on 7 October 2016⁶. Price movements not related to economic fundamentals can impact market quality by hindering the market from allocating capital efficiently in the short and long run, related uncertainty might lead investors or risk-absorbing market makers to retreat from the markets. This can be further influenced by significant market microstructure changes over the past decade, with concentrated marketplaces progressively being complemented by new market participants characterised by trading practices based on advanced technologies, such as high-frequency trading, that place market orders in a fast and automated way. An example are large institutional orders which are placed across markets and time by algorithms. Draus and van Achter (2015) have shown that this can under specific circumstances create the potential for short-term liquidity dry-ups⁷. In this context, mandated trading interruptions, so-called circuit breakers (CBs), can play a role as a tool for trading venues to manage extreme price swings.

Definitions

CBs are mechanisms that monitor the market continuously and trigger a trading halt as soon as the price (or its variation) of an individual security or an index falls below or rises above a predetermined level. In practice, practitioners and academics often use the terms "circuit breakers" and "trading halts" interchangeably. Conceptually, CBs – together with price collars – are a subcategory of volatility safeguards. Other types of trading interruptions include regulatory suspensions and technical halts.



Regulatory suspensions are temporary suspensions in the trading of a particular security enforced by the competent supervisory authority in cases of, for instance, insider trading, market manipulation, inaccuracy and non-availability of public information. Technical halts are initiated by a trading venue when outages occur on its IT infrastructures. In this article, we focus on CBs,

⁶ Here one needs to bear in mind that the dynamics in foreign exchange markets differ markedly from those in securities markets.

⁷ For more details on the relationships between algorithmic trading and circuit breakers see Draus and Van Achter (2015) "Circuit Breakers and Market Runs".

i.e. market-based halts applied and operated by trading venues. They can be triggered during either the auction phase or continuous trading.

Auction CBs are the result of order imbalances during the auction call phase, while continuous trading CBs are triggered during continuous trading because the execution price or potential execution price breaches predetermined price ranges. Both have the same aim: to interrupt a period of excessive volatility in order to calm the market and give investors the possibility to reassess their positions and strategies. The result of an auction CB is to extend the auction period, while continuous trading CBs either stop trading for a certain period to then resume it through an auction phase, or directly switch from continuous trading to an auction call.

CBs can be further differentiated by the reference price used to trigger the halt, which is usually calibrated in accordance with the nature of the financial instrument concerned and its liquidity profile. The reference price can be either static (e.g. the closing price of the previous trading session) or dynamic (e.g. the price of the last transaction). While a static threshold breach generally results from incremental changes over the trading day, e.g., due to company-related news, trading halts triggered based on dynamic thresholds generally reflect cases in which markets suddenly react to changed market conditions or technical issues/fat finger events.

CBs also differ as to whether they are calibrated at instrument level (single-stock CBs, for each individual security independently from other securities) or at market level (market-wide CBs; when the index breaches predetermined thresholds, continuous trading is halted for a wider set of securities), or a combination of both.

Price collars (or price limits) are another tool used by trading venues. Together with CBs they compose the set of safeguards that trading venues can adopt to manage periods of excess market volatility. Similar to price collars are fat-finger limits, these are limits on the size of the orders that can be sent into the system. As opposed to CBs, price collars/fat-finger limits do not halt continuous trading but rather constrain it; orders that would match a price above or below certain thresholds (collar) or orders above a size limit (fat-finger limit) are rejected while continuous trading is not stopped⁸.

Regulatory environment

In the EU regulatory framework⁹, the Directive on markets in financial instruments (MiFID II) addresses the topic of trading halts directly by imposing two different requirements for trading venues¹⁰:

⁸ According to Gomber et al. (2016) "Circuit breakers - A survey among international trading venues", the category "price collars" includes also the case in which continuous trading switches to auction due to an order that would match in a price outside predetermined price range. In this report this case is considered a trading halts, in the sense that continuous trading is halted due to a switch to auction trading.

⁹ In the United States, by comparison, CB mechanisms exist at single-stock and market-wide level. Market-wide CBs are designed for three levels of market declines: 7% (Level 1), 13% (Level 2), and 20% (Level 3). These triggers are set by the markets at point levels that are calculated daily based on the prior-day closing price of the S&P 500 Index. If a Level 1 or Level 2 halt is triggered before 3:25 p.m., trading can only be resumed after a 15-minute trading pause. After 3:25 p.m. trading does not stop unless there is a Level 3 market decline, in which case trading stops for the rest of the trading day (4.00 p.m.). At single-stock level, the "limit up-down mechanism" halts trading depending on the stock price and when declines occur. The mechanism is a combination of single-stock CB and order price collar. The price limit bands are set at percentage levels above and below the average price of the stock over the preceding 5-minute trading period. These price limit bands are 5%, 10%, 20%, or the lesser of USD 0.15 or 75%, depending on the price of the stock. The bands are double this size during the opening and closing periods of the trading day. If the national best bid and offer price for individual stock exceeds one of the upper or lower price limits for 15 seconds, trading is halted for 5 minutes. The limit up-down mechanism introduced on 31 May 2012 replaced a simpler single-stock CB mechanism which halted trading for five minutes if a stock price moved up or down by 10% in a five-minute window.

¹⁰ MiFID I did not specifically require trading venues to set in place mechanisms to halt or constrain trading, it provided for "fair and orderly trading" in Article 39(d). This concept was clarified in the ESMA Guidelines in 2012 specifying that this includes in particular trading halts, "arrangements (for example volatility interruptions or automatic rejections of orders which are

- Article 48(4) requires trading venues "to have in place effective systems, procedures and arrangements to reject orders that exceed predetermined volume and price thresholds or are clearly erroneous".
- Article 48(5) requires trading venues to have the ability to "temporarily halt or constrain trading if there is a significant price movement in a financial instrument on that market or a related market during a short period".

Finally, Article 48(13) mandates ESMA to develop guidelines on the appropriate calibration of trading halts, taking into account the liquidity of different asset classes and subclasses, the nature of the market model and the types of users. On 6 October 2016 ESMA issued a public consultation¹¹ regarding draft guidelines on trading halts under MiFID II, and on 6 April 2017 ESMA published the final guidelines¹².

<u>Analysis</u>

In this paper we focus on EU CBs and their relevance and contribution to price discovery and subsequent market conditions by analysing a database of CB trigger events for a sample of 10,000 financial instruments traded on EU trading venues. The database is built in-house based on a trade data feed provided by the commercial data vendor Morningstar Real Time. Our research is motivated by three distinct, although closely linked, research questions.

- First, we examine whether CBs, introduced to dampen volatility in financial markets, are in fact effective to set calmer trading conditions.
- Second, we test whether CBs contribute to the price discovery process, by giving time to investors to react to new information and reassess the price.
- Third, we take advantage of the cross-venue character of our database to contribute to the discussion on cross-venue CB coordination across reference and satellite markets. To the best of our knowledge, there are no previous empirical studies on CBs with a cross-EU trading venue perspective.

The paper is structured as follows. After providing the economic understanding of the CB mechanisms and a review of previous studies on this topic, we describe how these mechanisms are currently used by EU trading venues. Then we describe our data set and our empirical analysis. Finally, the last chapter concludes.

II. The economics of CBs

Liquidity in a market is determined mainly by two factors: first, the asymmetry of information between market participants supplying and demanding liquidity; second, the inventory risk taken by liquidity suppliers. The asymmetry of information exposes liquidity suppliers to potential losses arising from trading with better informed investors. Inventory risk arises because liquidity suppliers are exposed to variations in the value of their positions that cannot be unwound immediately. The bid-ask spread is the compensation required by liquidity suppliers to cover the adverse-selection cost and inventory-holding costs.

Market microstructure theories explain that market volatility has a strong negative relationship with market liquidity. In order to investigate this relationship, further examination of the components of market volatility is necessary. Market volatility can be separated into two components: the jump component and the diffusion component. The jump component refers to

outside of certain set volume and price thresholds) to constrain trading or halt trading in individual or multiple financial instruments when necessary, to maintain an orderly market".

¹¹ ESMA (2016); Consultation Paper: Guidelines on the calibration, publication and reporting of trading halts.

¹² ESMA (2017); Guidelines, Calibration of circuit breakers and publication of trading halts under MiFID II.

infrequent, large, isolated changes while the diffusion component arises from smooth and expected small price changes.

Amiram et al. (2016) have shown that the jump component has a more dominant effect on liquidity than the diffusion component. The jump component is associated with the inventoryrisk dimension of liquidity, in which market makers bear the risk of sudden, large price changes to their inventories. In contrast, the diffusion component, characterized by small (and more frequent) price changes, has a smaller effect on liquidity because market makers can adjust their portfolios in a more flexible and gradual manner.

The jump component also affects market liquidity through the information asymmetry channel, since the jump component is also driven by information events while the diffusion component is generally associated only with increased trading. The jump-component drives the negative relationship between volatility and liquidity through the channels of asymmetric information and inventory risk¹³.

CB mechanisms can be put in place to limit discontinuous price changes (the jump component) and to enhance liquidity. However, in order to assess the effectiveness of CB mechanisms we need to further differentiate volatility based on the nature of the trader: fundamental volatility and transitory volatility.

When traders discover new information about the fundamental value of a security, they push prices towards their estimated value, creating fundamental volatility. Literature refers to them as "informed" traders. "Uninformed" traders, in contrast, are considered to be those whose trades are not based on new information. Uninformed traders' trades are driven by market sentiment or private liquidity shocks and result in transitory volatility. When uninformed traders push prices away from their fundamentals, informed traders may step in and correct them. Transitory volatility is, therefore, the tendency of prices to fluctuate around their fundamental values. In other words, transitory volatility is the sudden price movement unexpected by market participants. For example, where the price of a share falls due to an income loss reported by the issuer, this constitutes fundamental and not transitory volatility, as public information would have been anticipated by some "informed" market participants.

CB mechanisms are considered particularly effective when they reduce transitory volatility caused by uninformed traders (Ackert et al., 2005). Such halts may also give informed traders an opportunity to enter the market and provide liquidity; without a market halt such traders may have been reluctant to post orders given the uncertainty about the price at which these orders will be executed. CBs are understood to be less effective if they try to address fundamental volatility (Ackert et al., 2005). In this case, CBs prevent prices adjusting quickly to new information; they are likely to generate substantial volatility when markets reopen. Therefore, when calibrating a CB framework, trading venues need to carefully assess which type of volatility they are targeting.

Another question in calibrating a CB framework is whether CB parameters should be disclosed. On the one hand, transparency about CB parameters can alter trading behaviour. Market events in China around early 2016 highlighted the complex dynamics and interaction between markets and trading rules full disclosure in stress situations¹⁴. In this case, a potential explanation for

¹³ See Pastor and Stambaugh (2003) for an empirical analysis on the negative relationship between volatility and liquidity.

¹⁴ A possible example are market events in China during the first weeks of January 2016. A new CB framework came into force where the parameters of the market-wide CBs were fully disclosed by the China Securities Regulatory Commission. Two CB levels were set. The first threshold was a market drop of 5%, triggering an automatic 15-minute pause in continuous trading. The second threshold was a 7% fall in market prices, triggering a trading halt for the entire trading day. The CB rules entered into force on 1 January 2016. On the first day of trading after implementation (4 January 2016) market-wide CBs were triggered: Trading on the Shanghai and Shenzhen exchanges was halted for 15 minutes when the CSI 300 index fell by 5%

issues in operating the CB framework may be that the introduction of a transparent CB regime under already stressed market conditions contributed to a downward spiral in market prices, as investors, fearing of being unable to sell financial instruments once the CB is triggered, rushed to sell before the CB threshold was reached.

On the other hand, higher transparency and predictability around the timing of a pause in the market following the trigger of a CB may be crucial to ensuring that market participants are prepared to provide the necessary market liquidity. In this context, the lack of disclosure regarding CB duration may lead to uncertainty and impair the willingness of participants to provide liquidity. Such a result could lead to liquidity dry-ups that may prolong the impact of the CBs and result in increased market volatility.

Between these two possible interpretations, there is no clear empirical evidence so far on whether CB parameter disclosure is beneficial for, or detrimental to, market stability.

III. Literature review

The literature on CBs dates to the period after the October 1987 market crash. In this context, e.g. Greenwald and Stein (1991) as well as Kodres and O'Brien (1994) analysed advantages and disadvantages of introducing a CB. The authors argued that CBs might lead to increased liquidity provision as they incentivise additional value-motivated traders to enter the market.

Since then, different aspects of CBs have been covered in the literature. We have identified four main strands of CB-related literature:

- empirical literature on market quality before, during and after a CB event,
- analysis of the "magnet effect" of CBs,
- coordination of CBs, and
- the relationship between CBs and the price discovery process.

Market quality before, during and after a CB event

Most of the empirical literature on the impact of CBs has analysed market quality before, during and after a CB event. Goldstein and Kavajecz (2004) analyse the CBs triggered on NYSE on October 27, 1997. They conclude that CBs did not calm the market and caused a reduction in liquidity on the following day as limit traders were not willing to resubmit previous days' expired orders, thus causing a lack of depth in the limit order book. Kim and Rhee (1997) and Bildik and Gulay (2006) find that price limits delay price discovery in their respective examination of Japanese and Turkish data. Kim and Yang (2004) found that CBs are effective to reduce volatility only when they are triggered consecutively, giving the time to investors to revaluate market information and from rational decisions. Clapham et al. (2017) demonstrate that volatility interruptions in general significantly decrease volatility in the post interruption phase. This decrease in volatility comes however at the cost of decreased liquidity. For the Indian market Chari et al. (2017) finds that the positive effect of market-wide circuit-breaker continues up to three post-event days.

Brugler and Linton (2014) evaluated the impact of LSE single-stock CBs on the subsequent market quality of the same security and other securities. The authors conclude that a breach of the lower limit of the CB reduces the market quality of the same security (greater degree of price inefficiency and market microstructure noise for a given volume and frequency of trading) but

from the previous closing price and then for the rest of the day as the index subsequently fell by 7%. On 7 January 2016, CBs were triggered again, and stock markets closed only 30 minutes after they had opened. In the evening of that day the CSRC suspended the CB rules, and the CSI 300 recovered 2% on the following day.

they do not find a significant effect for upper-limit breaches. Assessing the overall market quality, the authors conclude that CBs help to prevent contagion through poor market quality. Liu and Zeng (2019) demonstrate that - consistent with what happened in recent Chinese market events - in stressed times circuit breakers can cause crash contagion, volatility contagion, and high correlations among otherwise independent stocks.

Brogaard and Roshak (2016) proposed an alternative approach to analyse CB effectiveness. In their view, preceding studies did not take into account whether CBs may have elements of a self-fulfilling prophecy or magnet effect when prices approach the CB trigger. In other words, by studying the post-halt market quality compared to pre-halt market quality, researchers may have concluded that CBs prevent high volatility when it was in fact the presence of CBs themselves that fuelled ex-ante volatility. Brogaard and Roshak (2016) overcome this issue by analysing the effect of CBs on price paths that approach the limit, by comparing volatility in stocks where CBs are in place and for stocks for which there are no CBs. They take advantage of the SEC having introduced CB mechanisms for different parts of the equity market in a staggered manner.

The study does not find evidence that CBs have elements of a self-fulfilling prophecy when prices approach the CB trigger. They find that the existence of CBs causes informed traders to react strategically before the price of the security approaches the CB trigger. They will hold back some of their trading, as a trading halt would be detrimental for them (since they cannot take advantage of their information for a certain period of time). Overall this reduces the frequency and severity of extreme price movements, which in turn leads to increased provision of liquidity by market makers.

Draus and Van Achter (2015) evaluate the conditions under which CBs increase or decrease welfare. While CBs are set up to prevent short-term market runs, they cannot distinguish the underlying motivation for the excessive selling volume and might therefore restrain trading induced by actual liquidity needs. The authors analyse this trade-off and contribute to the literature by determining the characteristics of a socially-optimal CB which yield a maximum welfare improvement. According to the authors, the social usefulness of a CB is considerable when there is a low probability of traders having urgent liquidity needs. Similarly, they argue that high uncertainty about future liquidity needs implies that a restriction on trading can be more socially useful. To apply socially-optimal CBs in practice, the authors suggest that exchanges and regulators could use investor fear indices, market stress indicators or high-frequency market run predictors to capture the common uncertainty on future liquid shocks.

"Magnet effect" of CBs

Subrahmanyam (1994) introduces the "magnet effect" of CBs. The magnet effect in essence describes a situation where a CB can create a self-filling prophecy. Investors fearing that a CB could be triggered and not being able to trade in such a situation, could trade large volumes, thus triggering a CB. Such magnet effects could be reduced by randomising trading halts. Cho et al. (2003) use intraday data from the Taiwan Stock Exchange to test the magnet effect and find a statistically and economically significant tendency for stock prices to accelerate toward the upper CB threshold and weak evidence of acceleration toward the lower CB threshold. Nath (2005) finds that trading activity accelerates as stock prices approach their lower, but not upper, price limits on the National Stock Exchange of India. Du et al. (2005) find evidence of the magnet effect from their study of transaction data from the Korea Stock Exchange.

Coordination of CBs

The literature on the coordination of CBs is scarce, and most of it dates to the 1990s when the market structure was less fragmented. Subrahmanyam (1994) analyses a situation in which a

CB causes trading to be halted in both a "dominant" (more liquid) and a "satellite" market. As agents switch from the dominant market to the satellite, price variability and market liquidity decline on the former and increase on the latter. Morris et al. (1990) conclude that uncoordinated CBs will more likely harm the market than improve its quality due to higher volatility and a rising demand in liquidity on the non-halting markets. A recent study on the subject by Gomber et al. (2012) empirically found that CBs are effective in reducing volatility in the home market and in the satellite market, but at the cost of higher spreads. Moreover, the satellite market's quality and price discovery during the halt is weakened and only recovers as the other market resumes trading. Cui and Gozluklu (2016) analyse whether CBs create spill overs. In particular they find that the triggering of CBs is often linked to speculative strategies by arbitrageurs, such as momentum and pairs trading, thus CBs can transmit volume and volatility increases to other non-halted stocks.

Relationship between CBs and the price discovery process

The relationship between CBs and the price discovery process was analysed first by Chakrabarty *et al.* (2000) using a dataset on NYSE delayed openings between 2002 and 2005. During these halts, trading at other venues was allowed. Their results suggest that off-NYSE trades during NYSE halts provide significant price discovery that is incremental to that contained in the NYSE indicator quotes. Zimmermann (2013), building on the work of Chakrabarty *et al.* (2000) tested whether the CBs triggered on stocks traded on Xetra in the period from 01/2009 to 01/2012 contributed to price discovery process: the CB auction price reflects efficient learning. He demonstrated that CBs do not impede the price discovery process, and that the CB auction price contains incremental information for participants helping to return to orderly trading. Chan *et al.* (2005) examined the price discovery process of CBs using trade-to-trade transaction data and the limit order book from the Kuala Lumpur Stock Exchange. Their results suggest that CBs on individual securities do not improve price discovery processes but impose serious costs even when the limit band is as wide as 30%. Kwon et al. (2018) analysing CB on the Korean market demonstrate that the dynamic ones are improving price stabilisation discovery, while the effect of the static ones on price discovery is limited.

IV. Current volatility safeguard market practices

In this section, we map the current market practices by looking at the public documents on trading rules from a sample of EU trading venues. Results are shown in the table in Annex A.

Overall, there is strong heterogeneity in the volatility safeguard mechanisms applied by EU trading venues. A few trading venues do not have in place any type of volatility safeguards, the remaining venues under analysis have different types of volatility safeguards: price collars, CBs or both. The types, calibration and volatility safeguard mechanisms across EU trading venues are very different and not harmonised.

Typically, price collars applied on EU trading venues do not halt trading as such. CBs applied on EU trading venues halt trading whenever:

- The execution price or the potential execution price lies outside the "dynamic" price range around the reference price. The price range is generally defined individually for each security and specifies the maximum deviation (in either a positive or a negative direction) from the reference price. The reference price for the dynamic price range can be the last traded price of a security determined in an auction or during continuous trading;
- The execution price or the potential execution price lies outside the "static" price range, also
 around the reference price. The reference price for the static price range is generally the last

price determined in an auction on the current trading day or, if this price is not available, the last traded price determined on one of the previous trading days.

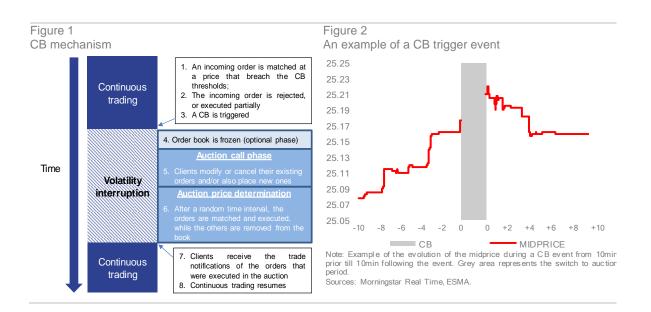
Two different cases of CBs on continuous trading occurs in practice:

- continuous trading is halted, and an auction is immediately triggered;
- continuous trading is halted, and the auction is triggered after some time; in this period the order book is frozen, no orders can be modified or cancelled;

The auction phase triggered by CBs can be divided into two sub-phases: call phase and price determination. During a call phase, market participants can react by modifying or deleting existing orders and quotes or by placing new ones. After a minimum duration which is not disclosed, the call phase ends randomly. However, if the potential trade price still remains outside the acceptable range the call phase will be extended until the volatility interruption is terminated manually. Continuous trading is resumed following the price determination phase, when the price is determined according to the principle of the highest executable volume.

Summarising, a typical pattern of a CB mechanism, as observed on EU trading venues (shown in Figure 1) is:

- 1. An incoming order is matched at a price that breach the CB thresholds;
- 2. The incoming order is rejected, or executed partially;
- 3. A CB is triggered, and continuous trading goes to pause mode or to auction trading;
- 4. *(optional phase)* Order book is frozen for a time interval, no orders can be inserted, modified, or cancelled;
- 5. Clients modify or cancel their existing orders and/or also place new ones;
- 6. After a random time-interval, the orders with matching prices are matched and executed, while the others are removed from the book;
- 7. Clients receive the trade notifications of the orders that were executed in the auction, if any;
- 8. Continuous trading resumes.



The duration of a trading halt is independently set by each trading venue and can be extended. In fact, if the potential execution price still remains outside the predetermined acceptable range the auction is extended until the potential price is within the acceptable range. In section VI, we provide descriptive statistics around CBs and show that the duration of trading halts differs substantially from one venue to the other.

As shown in the table in Annex A, the thresholds for CB triggers are disclosed only by around half of the EU trading venues under analysis.

The CBs and price collars have different thresholds according to the liquidity profile and the price of the security. Generally, less liquid products require the CBs and price collars to be proportionally larger than on highly liquid products, the reason being that information about fundamentals has a higher impact on the value of less liquid products. Similarly, very low priced (penny stocks) and very high-priced securities generally have *ad-hoc* thresholds. Generally speaking, the parametrisation of CBs on illiquid instruments, such as options, is much more difficult than liquid instruments, as price continuity and price ranges are also very dependent on time of trading activity.

Other factors that trading venues typically take into account when designing the CB framework are:

- Type of financial instrument;
- Expected (e.g. company figures, corporate actions or key macroeconomic figures) or unexpected relevant news;
- Correlation with the volatility (or pricing) of a corresponding index or instrument (e.g. if the S&P index suddenly moves 5%, then European equities and indices would also be expected to display increased volatility);
- The number of traders or liquidity providers active in a financial instrument or market;
- Statistical analysis on past CB trigger events in the affected instruments.

According to a survey¹⁵ conducted by the World Federation of Exchanges (WFE) in collaboration with the Goethe University Frankfurt in 2016 covering 44 trading venues, globally there are 56 distinct types of CB mechanisms, 47 of which are implemented on cash markets and 9 on derivatives markets. While in the EU CB mechanisms are only stock-specific, globally there are also market-wide CBs (i.e. when an index price falls above or below a pre-determined range, one or more market segments are halted).

CB mechanisms could be coordinated among different trading venues, and within the same exchange, between e.g. cash and derivatives markets. The literature on CB coordination is scarce; in principle, coordinated CBs should avoid sudden capital movement between exchanges and liquidity dry-ups; or in case of correlated instruments CB coordination could avoid pricing issues on the derivatives market when the cash market is absent. According to the above-mentioned survey, out of 15 trading venues which operate both cash and derivatives markets and that replied to the survey, six non-EU venues coordinate their CB mechanisms between the cash and the derivatives market¹⁶. This means that trading in a derivative is halted or suspended if the underlying on the cash market of the exchange is affected by a CB. In the EU, for example, according to the responses received to the ESMA consultation on the Guidelines on trading halts, in Euronext venues derivative instruments automatically halt if the underlying instrument is hit by a CB.

Proponents of CB coordination among different trading venues argue that a full CB coordination would ensure a level playing field for all trading venues when consistently applied and enforced by regulators; and in case of market-wide events can contribute to market stabilisation.

¹⁵ WFE, Goethe university; "Circuit Breakers – A Survey among International Trading Venues", 2016. <u>https://www.world-exchanges.org/home/index.php/files/18/Studies%20-20Reports/356/WFE%20Survey%20on%20Circuit%20Breakers.pdf</u>

¹⁶ The trading venues that, according to the WFE survey, coordinate CBs between cash and derivatives market are: BSE India, Intercontinental Exchange (NYSE), Nasdaq US, NSE India, Stock Exchange of Thailand, Tel-Aviv Stock Exchange.

Moreover, a lack of CB coordination could increase market volatility if traders move to other markets in a CB event. Critics of CB coordination, in contrast, claim that technical issues may arise in coordinating the reopening of markets after the trading halt between reference and satellite venues, while ensuring that each CB mechanism is tailored and parametrised to the market where the instrument is traded, in order to be adjusted in response to market events affecting particular sectors.

All in all, as of today, volatility safeguard mechanisms are developed in a discretionary way by EU trading venues, which results in a heterogeneous landscape of EU CBs and price collars, and their calibration parameters (trigger prices, thresholds, duration, extension mechanisms). This study analyses CBs effects only, as data on price collars are not available. Moreover, in the analysis all CBs are treated equally, under the assumption that all CBs have the same effects on market quality parameters. However, we acknowledge this as a limitation of this study, due to insufficient data on CB parameters, and that different calibration parameters may yield different results and may also affect competition between trading venues.

With the MiFID II requirements and the ESMA Guidelines, national authorities and trading venues now have an EU approach at their disposal to enhance existing and develop new CB landscapes, where necessary. The implementation of the new rules is set to bring new and instructive evidence on the performance of CBs in the coming years. However, trading venues will continue to have considerable latitude in calibrating CBs for the venue as a whole, for instrument classes, and for individual instruments. Our findings of current market practices suggest CB calibrations differ across the EU, between trading venues, across instrument classes per trading venue, and between individual instruments. At the same time, it is clear that the design of these instruments can have a profound effect on markets. The introduction of MiFID II facilitates the comparability of CB arrangements and their performance in critical situations. It will be important to gather and evaluate the market evidence that becomes available with the aim of learning from the experience under the new MiFID II environment.

In particular, we will need to understand any potential performance patterns, as well as the relevance of individual elements of the calibration, as e.g. addressed in the ESMA Guidelines, for the effectiveness of CBs. This particularly applies to critical situations of general financial instability across instruments and market segments, liquidity dry-ups in limited asset classes or wider market segments, as well as algorithms spinning out of control. As the technological changes related to infrastructure provision and access, as well as algorithmic routines, are set to continue, optimising the calibration of trading halt arrangements will be a key concern for trading venues and supervisors alike.

V. Dataset

Our dataset of CB trigger events and related market data has been built based on data feeds provided by Morningstar Real Time and covers the period from 1 April 2016 to 31 December 2016. It contains tick-by-tick order book and execution information on a selection of 10,000 financial instruments traded on European trading venues¹⁷. The sample of instruments includes:

- 7,921 stocks: All constituents of the STOXX Europe 200 Large/Mid/Small caps index;
- 1,287 futures: The underlying is one of the already selected stocks;

¹⁷ See Annex B for the detailed sample composition of type of financial instrument by trading venue. Some regional venues are specialist markets, where automatic volatility interruption mechanisms do not apply.

- 333 Exchange Traded Funds (ETFs): Selected ETFs track a European STOXX index or a subcategory (e.g. STOXX Europe 200 Large Banks);
- 446 Depository receipts: Random selection¹⁸;
- 13 foreign exchange rates derivatives: Exchange rates from EUR to other currencies.

Throughout the entire paper an "instrument" is defined as the combination of its security type and the trading venue on which it is traded. Since the sample contains a large number of crosslisted stocks, the absolute number of securities in the sample is less than 10,000. It is also worth noting that due to the sampling the analysis in the paper does cover a subset of available instruments.

Annex C describes in detail the methodological steps undertaken in order to build our dataset of CB trigger events and related market data used for the empirical study.

VI. Overview on CB trigger events – statistics and market practices

This section provides descriptive statistics with respect to our CB sample. In the period from 1 April 2016 to 31 December 2016 there were *8,896* CBs triggered on *3,360* financial instruments in our sample. We observed CBs for stocks and ETFs. For stocks we were able to cluster the CB trigger events according to the size of the stock (small, mid and large cap) and according to the sector of business.¹⁹

The descriptive statistics in Table 1 indicate that over the period of analysis an average of 44 CBs occurred per day on stocks and 2.5 per day on ETFs. Across all days, the minimum number of CBs trigger events on stocks and ETFs was 4 and 0, respectively; while the maximum number of CB events was 1,196 and 109 occurred on stocks and ETFs, respectively, on the day after the UK referendum. Financial sector stocks appear to be halted more frequently (on average 16 CB per day), compared to the other sectors where the average number of CBs per day ranges from four to 14. Regarding the market capitalisation of stocks, large cap stocks appear to be halted the most by CBs (on average 18 times per day, compared to 16 times per day for mid cap and eight for small cap. Low fragmented stocks are halted more frequently by CBs, 26 times per day compared to nine and seven CBs daily occurrences for medium and high fragmented stocks respectively. The higher incidences of CBs for low fragmented stocks holds across the three levels of market capitalisation (large, medium, small).

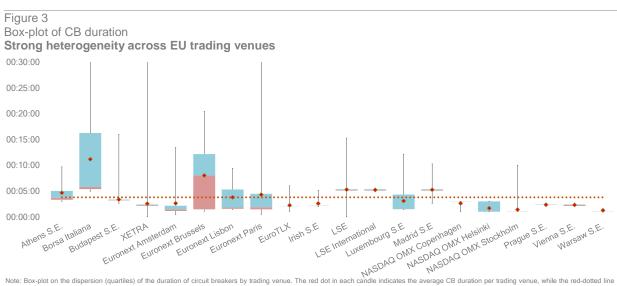
¹⁸ For the empirical study, depositary receipts are treated as stocks, because of their similarities in trading behaviour.

¹⁹ As our analysis is based on a sample of securities and as such does not cover the entire range of instruments available for trading, the actual number of CBs on trading venues will be higher than the number of CBs we have observed.

| Volatility Interruptions – 8,896 observations – 20 trading venues | Mean | Std dev | Min | Max | |
|---|---------------|-------------|-------|-----------|--|
| <u>Period 01/04/2016 - 31/1</u> | <u>2/2016</u> | | | | |
| Stocks | | | | | |
| Number of CBs per day (Number of stocks halted per day) | 44.0 (24.0) | 83.4 (34.3) | 4 (4) | 1087 (429 | |
| By sector: | | | | | |
| a) Sector Basic Materials | 6.5 (3.0) | 9.5 (3.4) | 0 (0) | 76 (36) | |
| b) Sector Consumer Cyclicals | 4.4 (2.6) | 14.4 (6.0) | 0 (0) | 190 (73) | |
| c) Sector Consumer Non-Cyclicals | 2.3 (1.5) | 5.8 (2.3) | 0 (0) | 76 (27) | |
| d) Sector Energy | 2.9 (1.8) | 4.6 (2.2) | 0 (0) | 51 (24) | |
| e) Sector Financials | 16.6 (8.7) | 30.5 (11.2) | 0 (0) | 367 (119 | |
| f) Sector Healthcare | 2.2 (1.1) | 5.4 (2.1) | 0 (0) | 51 (22) | |
| g) Sector Industrials | 3.7 (2.1) | 11.0 (4.5) | 0 (0) | 110 (54) | |
| h) Sector Technology | 2.2 (1.0) | 5.6 (2.0) | 0 (0) | 50 (25) | |
| i) Sector Telecommunications Services | 1.5 (0.9) | 4.7 (2.1) | 0 (0) | 49 (25) | |
| j) Sector Utilities | 1.9 (1.1) | 5.4 (2.2) | 0 (0) | 67 (24) | |
| By market capitalisation: | | | | | |
| a) Large caps | 18.1 (10.2) | 42.3 (19.2) | 0 (0) | 554 (239 | |
| b) Mid-caps | 16.0 (7.7) | 28.4 (9.3) | 0 (0) | 334 (113 | |
| c) Small caps | 8.0 (4.8) | 14.9 (6.1) | 0 (0) | 190 (71) | |
| By market fragmentation: | | | | | |
| a) High fragmented stocks | 6.5 (3.8) | 17.4 (8.1) | 0 (0) | 229 (105 | |
| b) Medium fragmented stocks | 8.9 (4.7) | 22.5 (10.8) | 0 (0) | 286 (139 | |
| c) Low fragmented stocks | 26.7 (14.2) | 45.3 (16.2) | 1 (1) | 563 (179 | |
| ETFs | | | | | |
| Number of CBs per day (Number of ETFs halted per day) | 2.5 (1.1) | 9.6 (3.0) | 0 (0) | 109 (33) | |

Note: Descriptive results for the CB sample of 8,896 observations in the period 01/04/2016 to 31/12/2016. Sources: Morningstar Real Time, ESMA.

The duration of CBs is very heterogeneous among EU trading venues. As shown in the box plot in Figure 3, Borsa Italiana and Euronext Brussels have the highest average CB duration, 10 minutes and 12 minutes respectively. Borsa Italiana has also the highest dispersion of CB duration, spanning from a minimum of 5 minutes to a maximum of 50 minutes. This means that in Borsa Italiana a CB is extended on average twice and its minimum duration is 5 minutes, the highest among the trading venues under analysis. The dispersion is low for the rest of the EU trading venues under analysis, which on average have a CB duration of 4 minutes.

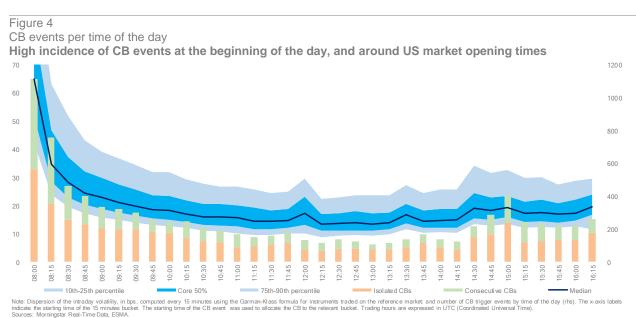


Note: Box-plot on the dispersion (quartiles) of the duration of circuit breakers by trading venue. The red dot in each candle indicates the average CB duration per trading venue, while the red-dotted line indicates the average CB duration across trading venues. Sources: Morningstar Real Time, ESMA.

The incidence of CB trigger events throughout the day is not uniform. As described in Figure 4, the incidence of CBs is very high at the beginning of the trading day before constantly decreasing during the first 2 hours. This pattern is in line with the pattern of intraday volatility, which is not surprising, as CBs are in place to reduce market volatility. From mid-morning to 14:15 UTC CB incidences remain broadly constant before starting to increase at 14:30, when US markets open.

The peak of CBs triggered in the first 30 minutes of the trading day is likely driven by a flow of new information which needs to be reflected in stock prices. Similarly, from 14.30 to 15.00 UTC investors in EU markets react to the information arising from the opening of the US market. A CB is flagged as "consecutive CB" if it follows or precedes another CB triggered on the same stock in the following or preceding 10 minutes; all the others are categorised as "isolated CBs". It emerges that among the CBs triggered on the CB peak hours, half of them were "consecutive CBs", meaning that CB events were concentrated on fewer stocks.

During the other trading hours, CB were triggered mostly in an isolated manner. Figure 5 shows that consecutive CBs in a ten-minute window includes prevalently cases in which one or two CBs are triggered after the initial one. The choice of a ten minutes window to qualify a CB as consecutive has been done on the basis of the distribution of CBs qualified as consecutive depending on the choice of time interval between CBs (Figure 6).





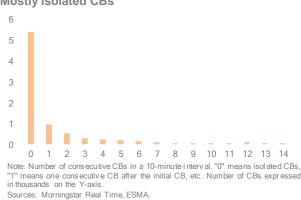
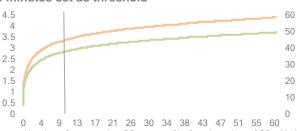


Figure 6 Distribution of consecutive CBs 10 minutes set as threshold

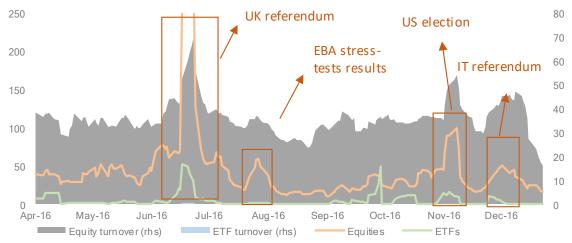


Number of consecutive CBs % of total number of CBs (rhs) Note: Number of CB trigger events qualified as consecutive depending on the choice of time interval between CBs.Number of CBs expressed in thousands on the primary Y-axis, and expressed as precentage of total number of CBs in the sample on the secodary axis. X-axis in minutes. Sources: Morningstar Real Time, ESMA. Figure 7 shows the evolution of the number of CB trigger events over our period of analysis. A clear spike can be observed in the days following the UK referendum vote on 23 June 2016. 320 and 130 CBs were on average triggered on stocks and ETFs respectively in the 4 trading days following the referendum. Thereafter CB activations decreased sharply in the following weeks reaching pre-UK referendum levels, which were about 50 CBs per day.

In July the indicators show financial markets reactiveness to the news on the EBA EU-wide stress tests, where about 58 CBs per day were triggered on average on 30 stocks in the first days of August 2016, comparing to an average of 24 CBs triggered on 15 stocks in the week preceding the news and in the 2 weeks after the news. The stocks halted pertain mainly to the banking sector. Additionally, following the outcome of the US Presidential elections in November 2016 and the Italian referendum in December of 2016, CB incidences increased to an average of 100 CBs per day in the week from 9 to 15 November 2016, and 51 CBs in the week going from 5 to 9 December 2016. These spikes of CB incidences are partly information-driven and partly due to noise trading, as trading activity intensified in these periods.

By analysing the CB occurrences on stocks by their market capitalisation (Annex D), it can be inferred that in normal market conditions there is no particular indication of a higher CB incidence stocks with high and low liquidity (large cap stocks being considered more liquid and small cap stocks less liquid). However, in stressed market situations (as on the days following the UK referendum, the EBA stress tests results, the US Presidential elections and the Italian referendum) CBs were triggered mostly on large cap stocks. In particular, in the week following the 24 June 2016 the CBs daily occurrences were on average 140 on large stocks, 103 on mid cap stocks and 45 on small cap stocks (on the days preceding the UK referendum result there were 30 on large stocks, 31 on mid cap stocks and 8 on small cap stocks).

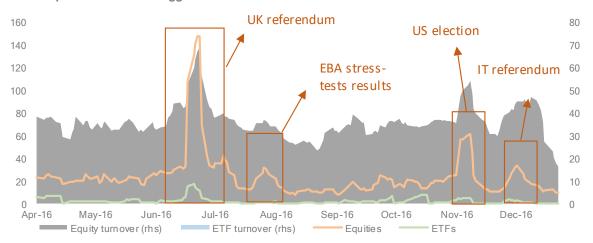




Note: Number of CBs trigger events by type of financial instrument in the period from 01/04/2016 to 31/12/2016, weekly average. Equity turnover of the EU trading venues under analysis on secondary axis, EUR bn. Sources: Monringstar Real Time, ESMA.

Figure 8

Number of financial instruments halted by CBs Similar pattern as for CB trigger events



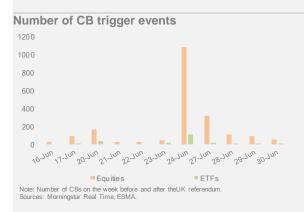
Note: Number of financial instruments affected by CBs in the period from 01/04/2016 to 31/12/2016, weekly average. Equity turnover of the EU trading venues under analysis on secondary axis, EUR bn. Sources: Monringstar Real Time, ESMA.

Box 1

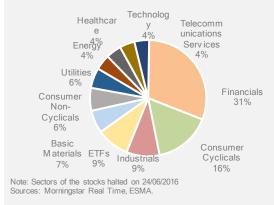
CBs in the context of significant market events

The result of the UK referendum on EU membership triggered very large trading activity on European stock markets on Friday 24 June 2016. The trading volume for the constituents of the STOXX Europe 200 high/medium/small cap indices was EUR 61bn on average in the four days following the UK referendum, compared to an average daily trading volume of EUR 35bn over the preceding three months. Additionally, volatility in financial markets increased rapidly during the UK referendum week, with the VSTOXX (the EURO STOXX 50 volatility index) 30% than its average daily level observed in the preceding six months. After the unexpected referendum result, the DAX, CAC, FTSE 100 and the EURO STOXX index opened down between 7% and 9% of the previous day close. Especially the stock market value of financial institutions declined significantly and triggered multiple CBs. However, the extreme volatility seen after the UK referendum, which varied to a certain degree across instruments and markets, was managed successfully with each venue applying its own CB mechanisms without any market-wide issue occurring.

An analysis of CB occurrences on the days around the UK referendum on the EU membership reveal a high number of CB trigger events. On the day after the referendum results (24 June) a total of 1250 CBs was triggered on 429 stocks and 427 CBs were triggered on 33 ETFs traded on EU trading venues. As shown in the graphs below, this number of CB trigger events is unusual and considerably higher in comparison with the average of 70 CBs triggered daily in the week preceding the referendum. After two days CBs trigger event went back to pre-referendum levels. The analysis by sector reveals that the stocks pertaining to the industrial sector were mostly affected (39%), followed by ETFs (27%) and banks (16%). Looking at CB occurrences by market capitalisation we observe that large cap stocks were most frequently halted by the trading interruptions mechanisms (52%) followed by mid cap stocks (31%).

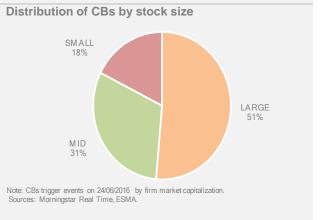








Number of Equities
Number of ETFs
Note: Number of financial instruments halted on the week before and after theUK referendum. Sources: Morningstar Real Time, ESMA.



19

VII. Effectiveness of CBs

In this section we perform an empirical analysis using our database on CB trigger events for the period from 1 April 2016 to 31 December 2016. The empirical study is focused on stocks and ETFs.²⁰

Our study follows the main strands of the CB literature.

- First, by analysing market quality parameters before and after a CB event, we determine whether market quality conditions improved in the post-CB period as a result of market price reassessments and a correction of overreactions.
- Second, we analyse whether the CB cooling-off effect has a positive effect on the price discovery process, as information dissemination and revelation during the CB are reflected in post-CB prices. For the analysis of the impact of CBs on the price discovery process we follow the two-stage regression methodology developed by Zimmermann (2015) based on Chakrabarty et al. (2011) and Corwin et Lipson (2000).
- Third, building on Gomber et al. (2012) we contribute to the literature on coordination of CBs and its implication for wider financial stability by analysing different impacts of CB depending on whether the CB is triggered on the reference or on a satellite market for a given security.

Our CB data set has a wide cross-venue coverage. We can thus extend findings from the existing literature, which mostly covers single venues. However, as shown in section IV and Annex A, CB mechanisms vary widely between trading venues and our aggregate analysis does not capture differing CB impacts for different CB calibrations. This caveat does however mostly also apply for single venue studies, as CB triggers on many trading venues vary depending e.g. on the liquidity of a stock or on general market conditions. Analysing differing CB impacts depending on CB trigger calibration and thus providing empirical evidence on how to effectively calibrate CBs would be a fruitful area for further research.

In order to correctly evaluate CB effectiveness on market quality conditions and price discovery process, the market data parameters used for the pre-CB and post-CB market status need to purely reflect normal trading conditions. In light of that, three database refinements were needed.

- First, CBs for which there is no continuous trading activity in the preceding and following 10 minutes are removed from the database. This means that the empirical study does not analyse the effect of consecutive CBs in a ten-minute interval, although they represent the clearest case of market stress periods where a trading halt may be needed to set calmer trading conditions. However, best bid and ask prices for the continuous trading in the 10-minute interval around a CB would be strongly biased if in this interval other CBs or scheduled auctions take place²¹. Nevertheless, we have provided an analysis of CB market effects in stressed market conditions in Box 2.
- Second, we removed the first and last 15 minutes of the trading day, in order to avoid having pre- and post-CB market data parameters outside continuous trading hours. Excluding the first 15 minutes of trading leads to the dismissal of a large number of events taking place following the opening auction as shown in Figure 4.

²⁰ Derivatives are not covered.

²¹ CBs market effect results tables for the subsample of consecutive CBs are presented in Annex G.

 Third, we removed the CB events for which market quality parameters around the CB event could not be computed due to insufficient data points.

This necessary database cleaning has reduced the number of CBs under analysis from 8,698 to 4,250 occurred on stocks and ETFs, and the number of cross-listed stocks from 23,226 to 12,958.

VII.a. CB impact on market quality

The first part of the analysis focuses on the market effects of CBs. For the period from 1 April 2016 to 31 December 2016 we analyse whether CBs improved post-CB market quality conditions. Market quality conditions are measured with two parameters: market volatility and bid-ask spread. Volatility is computed as the standard deviation of mid-prices divided by the average mid-price over the ten minutes preceding and following the trading halt²². The choice of using mid-price volatility rather than trade price volatility is motivated by the consideration that a reduced or non-existent trade activity does not mean nothing is happening in the orderbook. One can think of stocks that, by nature, exhibits a small trade activity, but not only. There might also be, for instance, a large flow of orders over a time frame that do not necessarily materialise in trades, but still are a reflection of a market event and the way market participants react to it.

When studying the impact of CBs, due to their inherent triggering mechanism and design that prevents the execution of trades for a certain period, the orderbook activity pre- and post-CB becomes particularly relevant and it is our opinion that it should be accounted for²³. Liquidity is measured by the relative bid-ask spread, i.e. the relative differences between the best bid and best ask quote, divided by the mid-price. The bid-ask spread so computed is then averaged throughout the ten minutes pre- and post-CB, weighted by the time duration of the bid ask spread. A weighted average bid-ask spread based on time duration better reflects the average spread throughout the time window by, for instance, reducing the impact of large spreads that could exist for a short time in the order book due to the execution of large orders²⁴.

For each halted instrument, market quality parameters computed for the ten minutes preceding the halt are compared with the same ones computed for the ten minutes following the halt. In this way, by benchmarking the volatility and liquidity levels after the CB with the immediate pre-CB market condition, we infer that possible changes are highly related to the CB effect assuming that trading intensity remains at the same level. In order to analyse whether the CB had a spill over effect on cross-listed instruments we used the same approach to compute, for every instrument affected by a CB, market quality parameters for the cross-listed instruments²⁵.

²² Standard deviation of mid-price is calculated taking into account the time duration of mid-prices.

²³ Statistics presented in this part based on mid-price volatility have also been computed using trade price volatility. They do not exhibit a different pattern and the general conclusions drawn in this part hold. See Annex E for more details.

For each measure computed we discarded the corresponded 5% outliers in order to avoid a fat tail distribution as shown in the graph of the distribution of the weighted average spread, where there are high number of observations at the opposite tails of the distribution (Figure E.1 in Annex E).

²⁵ It has to be noted that some endogenous effects might be at play, as described in Subrahmanyam (1994) or Brogaard and Roshak (2015), in particular for exchanges publicly disclosing the thresholds.

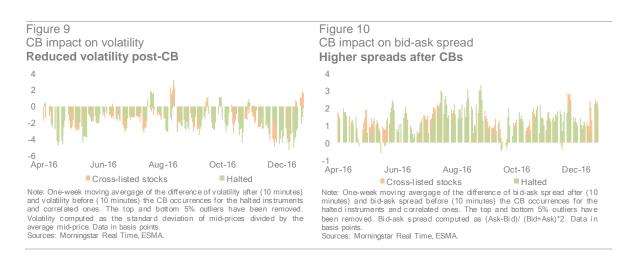


Figure 9 shows the difference between the mid-price normalised standard deviation observed during the 10 minutes after the CB and the mid-price normalised standard deviation observed during the 10 minutes before the CB for all instruments halted. The measure, computed for the halted instruments and for the cross-listed stocks, is negative for most of the trading days under analysis. Results show that during the period of analysis CBs were on average efficient in setting calmer trading conditions in the 10-minute window following the halt, although at the cost of higher spreads.

As shown in Figure 10, over the period of analysis CB activation generally had a negative effect on liquidity (in terms of increase of the bid-ask spread) of both the halted stocks and the crosslisted ones in the ten-minute following the CB trigger event. The results also hold when looking at subsamples of large, mid and small stocks (Annex E). Those three subsamples registered, for most of the days from1 April 2016 to 31 December 2016, lower levels of volatility and wider bid-ask spreads in the 10-minute window following the CB. As regards ETFs, the effect of CBs on volatility and spreads is mixed over time and firm conclusions cannot be drawn. The sample of ETFs halted is very small, containing only 131 observations throughout the period of analysis. However, it is important to note that, when looking at ETF CBs under stressed market conditions – around the June 2016 UK referendum and the US Presidential elections in early November 2016 – volatility for ETFs post-CB is lower than during the pre-halt period.

Different CB mechanism calibrations may, however, lead to different results. Given the availability of data related to CB parameters, this study assume that all CBs have the same market effect. However, in order to partially overcome this study limitation, the market effect analysis was run separately on subsamples of CBs triggered on some large EU trading venues, the results (Annex F) from a single venue perspective do not differ in substance from the analysis on the whole cross-EU trading venues sample, with lower volatility and wider bid-ask spreads after the CB event.

CBs may have very different market impacts depending on the type and timing of trading. As we focus our analysis on continuous trading, we have not included CB events in the first and last 15 minutes of trading and consecutive CBs. We have also removed outliers (see Annex G for detail on the data cleaning and the different market impacts):

- For consecutive circuit breakers, as well as circuit breakers during the opening and closing periods of the market, we observe reduced volatility, but also lower spreads. The same applies for outliers.

The case of consecutive circuit breakers warrants further analysis. Consecutive circuit breakers are likely to be an indication for comparatively large idiosyncratic or market-wide shocks, which cannot be resolved with a single circuit breaker. Therefore, our results for market impacts for consecutive CB events can either be driven by biases in the bid-ask spread (e.g. high bid-ask spreads during an CB period) or could be an indication that the impacts of CBs on bid-ask spreads are different for larger shocks compared to more normal market conditions.

In line with Kim and Yang (2008) and Gomber *et al.* (2012), we deepen our analysis on market quality parameters around a CB event by looking at the effects at different time intervals. Both measures, mid-price standard deviation and bid-ask spread, are calculated at a short term 2-minute interval, a medium term 5-minute interval and a long term 10-minutes interval. The differences between pre- and post-CB volatility and bid-ask spread parameters are tested for significance via the Wilcoxon sign rank test. The analysis is performed on stocks and ETFs halted as well as on cross-listed stocks. We also evaluate if the CBs trigger events impacts on market conditions varies by the market capitalisation and fragmentation of the stocks halted. The design of the samples of low and high fragmented stocks was done on the basis on the Herfindahl-Hirschman index (HHI) for each halted stock traded on EU venues using their total turnover in the period of trading 1 April 2016 – 31 December 2016. Halted stocks were divided into terciles according to their HHI.

Table 2

CBs market effects

| | | | Instrume | nts halted | | | Cross list | ed stocks |
|---------------------------------------|---------------------|---------------------|---------------------|---------------------------|----------------------------|------------------|---------------------|---------------------|
| | All stocks | Small cap | Large cap | Low fragmen- tation | High fragmen- tation | ETFs | Small cap | Large cap |
| 10min standard deviation | -1.70 (-1.00)*** | -1.98 (-0.92)*** | -2.01 (-0.91)*** | -1.15 (-0.56)*** | -3.46 (-2.35)*** | -0.90 (-0.96) | -1.51 (-0.86)*** | -2.08 (-0.95)*** |
| 5min standard deviation | -0.36 (0.15)** | -0.30 (-0.50) | -0.62 (-0.09)** | -0.05 (0.15) | -1.24 (-0.33)* | -0.69 (-0.05) | -0.45 (-0.14) | -0.84 (-0.44)*** |
| 2min standard deviation | 0.39 (0.13) | 0.89 (-0.42) | 0.11 (0.30) | 0.37 (0.02) | 0.58 (0.67) | -0.35 (0.09) | 0.32 (-0.33) | -0.21 (-0.16)*** |
| 10min relative spread | 0.79 (1.07)*** | 0.29 (1.28)*** | 0.39 (1.13)*** | 0.68 (0.92)*** | 0.81 (2.99)*** | -1.35 (-0.22) | 3.30 (2.55)*** | 0.86 (0.41)*** |
| 5min relative spread | 1.84 (1.76)*** | 1.48 (1.71)*** | 0.94 (0.84)*** | 1.56 (1.67)*** | 2.74 (3.24)*** | 0.28 (0.73) | 5.54 (4.51)*** | 1.61 (0.66)*** |
| 2min relative spread | 3.44 (2.61)*** | 2.98 (2.31)*** | 2.29 (2.24)*** | 2.99 (2.58)*** | 4.95 (4.91)*** | 0.39 (1.39)** | 7.75 (6.41)*** | 2.61 (1.34)*** |

Note: The table presents mean (median) parameters before and after CB activation on the financial instruments in our sample. Standard deviation computed as the standard deviation of mid-prices divided by the average mid-price. Relative spreads computed as (Ask - Bid) / (Ask + Bid) * 2. The top and bottom 5% outliers have been removed. Significance levels are 1%(***), 5%(**) and 10%(*) for the Wilcoxon sign rank testing for the null hypothesis that samples are drawn from the same population. Sources: Morningstar Real time, ESMA.

Results in Table 2 show, as expected from the previous graphs, that the average and the median mid-price normalised standard deviation for the halted stocks and cross-listed ones is significantly lower in the 10- and 5- minute interval after the CB activation. However, on the 2-minute interval the effect is not statistically significant. In the immediate post-CB trading phase investors may still be uncertain of stock price developments and as continuous trading normalises volatility decreases. When looking at the subsample of stocks halted, the significant 5-minute volatility reduction observed for the wider sample of all stock does not hold for the

small cap stocks. For the stocks cross-listed to the halted ones, instead, the median standard deviation is slightly lower than zero even in the immediate post-CB trading phase for large cap stocks, but not for small cap cross-listed stocks. In all samples under analysis, the reduction in standard deviation increases as the time interval increases. Results for the ETFs category do not reveal any significant results for volatility.

The increase in the bid-ask spread, already observed in Figure 10, both for halted and crosslisted stocks in the 10-minute interval around the CB is statistically significant. We also find statistically significant positive difference between post- and pre-CB bid-ask spread also in the 2-minute and in the 5-minute window, although at lower levels, revealing an adoption of the overall market premium after the CB²⁶. Particularly interesting is to observe that the spread increase is larger in the first minutes after the CB and decreases as long as the time interval increases. This could be explained by a decline in trading activity and large price uncertainty in the immediate post-CB trading. As regards ETFs, the only statistically significant result relates to increased spread in the 2-minute interval.

CB impacts also vary with the degree of trading fragmentation. Highly fragmented stocks registered a higher reduction of standard deviation compared to low fragmented stocks. In the same way, the CB widening effect on bid-ask spread is stronger for highly fragmented stocks.

Figures 10 to 13 in Annex E additionally show the entire developments of spread and volatility measures observed every 10 seconds between 10 minutes before and after the CB event, for all halted and cross-listed stocks.

Control group

A limiting issue in the analysis of CB impacts on market quality is the lack of a counterfactual, i.e. what would have happened if the trading halt had not been in place. The recent literature on CBs effectiveness proposes different methods to create a control group in this context.

Brugler and Linton (2016) use near-halt events as a control group for the effect of a CB on subsequent market quality. An event is assigned to the control group if the price movements of a stock are within 1% of the CB threshold (so, for example, a price change of +/-9% for a CB threshold of 10%). However, Brugler and Linton (2016) is based on CB events on stocks traded only on the LSE, which discloses their CB thresholds. Evidently, a control group on near-halt events can be created only if the actual CB thresholds are known; otherwise it is impossible to determine the threshold for the near-halt event. Our study has an EU-wide perspective, being based on CB events of stocks traded on 20 trading venues where only few of them disclose their CB thresholds (Annex A).

Cui and Gozluklu (2016) analyse the effect of the US single-stock circuit breaker system using a dataset of CBs triggered on stocks traded on US markets. The authors acknowledge the difficulty to have a proper counterfactual in order to evaluate CB impacts on market quality. Nevertheless, the authors provide statistics on market quality parameters registered on days when a CB was triggered compared to other days of full continuous trading, in order to verify if a CB led to extraordinary trading conditions on that day. Since we do not monitor the trading activity on the whole day of a CB event, we rather limit the CB effectiveness observation period from 10 minutes before the halt to 10 minutes after the halt. In addition, there might be other

²⁶ These results are in line with Gomber et al. (2012).

factors affecting trading conditions in a day without CB incidences, and as such, this exercise can provide only limited information on trading conditions in the absence of CBs.

Another approach to create a control group is to use non-halted highly correlated stocks from the same sector. The underlying assumption is that trading behaviour of these stocks is similar. However, the CB itself may alter trading conditions for correlated stocks, for example Cui and Gozluklu (2016) report spill over effect in volumes and volatility on correlated stocks during the trading halt. Preliminary evidence on trading patterns of correlated stocks during a trading halt is provided in Box 3, where we find indeed some spill over effect in volume of trading. In light of this, we do not develop a control group based on sectorial correlated stocks.

Finally, an alternative control group design could be a sample of midday auctions. However, midday auctions differ from circuit breaker auctions, as they are not volatility interruption mechanisms. As such, they do not halt continuous trading in periods of high volatility but rather during the trading day at pre-scheduled times. We use this control group later when we test price discovery during CB auctions, rather than in testing CB impacts on subsequent standard deviation and bid-ask spread.

Box 2

CB effects in stressed market conditions

As explained above, due to data cleaning the empirical study does not analyse the effect of consecutive CBs in a ten-minute interval. However, under stressed market conditions the number of CBs triggered consecutively in a 10-minute window is likely to be substantial. In order to partially overcome this study limitation, we performed the CB market effects analysis on a subsample of CBs for Friday 24 June, the first trading day after the UK referendum on the EU membership.

As mentioned in Box 1 above, the result of the UK referendum on the EU membership triggered large trading activity leading to a record on European stock-market trading volume on Friday 24 June 2016. Out of a total 1,250 CB incidences registered on that day, 658 were triggered consecutively in a 10-minute window (i.e. another CB was applied to a stock in the preceding or following 10 minutes).

In our main results, we excluded the consecutive CBs in order to compute market quality parameters post- and pre-CB while the market is in continuous trading. Without the removal of consecutive CBs, the market quality parameters would have been biased due to best bid and best ask taken in auction periods following CBs.

In this box, we also included CBs triggered on 24 June 2017. Since they all related to the same market event, we grouped the consecutive CBs. For each stock, if a CB is preceded or followed by another CB, it is flagged as "consecutive". In the case of consecutive CBs, market quality parameters computed after the last consecutive CB (for which there are no other CBs in the following 10 minutes) are compared with market quality parameters computed before the first consecutive CB (for which there are no other CBs in the following 10 minutes) are compared with market quality parameters computed before the first consecutive CB (for which there are no other CBs in the preceding 10 minutes). The table below shows the results for the isolated CBs and consecutive CBs.

The market impact under market-wide stress appear to be different compared to more normal market conditions – both for consecutive CBs and isolated CB events. Under stressed market conditions, CBs appear to have a positive effect on market liquidity and are followed by lower volatility, as opposed to the main results presented in *Section VII.a*, where we report that CBs are followed by lower volatility, but at the cost of higher spreads. Stocks affected by isolated CBs registered a reduction of mid-price standard deviation in the 10 minutes after the CB, while the bid-ask spread decreased considerably (-8bps in the 10-minute window); results are however not always statistically significant. In the case of consecutive CBs, the direction of the CB effects on bid-ask spread and mid-prices standard deviation is the same, yet on larger scale and statistically significant. Following a series of consecutive CBs, standard deviation decreased by 24 bps in a 10-minute window, while bid-ask spreads were reduced by 60 bps.

Table Box 2 CBs market effects

| | | Halted sto | cks | | Cross-listed | stocks |
|--------------------------|------------|--------------|-----------------|------------|--------------|-----------------|
| | All CBs | Isolated CBs | Consecutive CBs | All CBs | Isolated CBs | Consecutive CBs |
| 10min standard deviation | -15.61 | -8.70 | -24.28 | -12.02 | -5.28 | -18.70 |
| | (-6.64)*** | (-4.63)*** | (-10.96)*** | (-7.49)*** | (-3.92)*** | (-10.78)*** |
| 5min standard deviation | -5.93 | -2.17 | -10.19 | -6.37 | -3.65 | -8.65 |
| | (-2.98)*** | (-2.59) | (-3.15)*** | (-2.30)*** | (-2.36)*** | (-2.07)*** |
| 2min standard deviation | -2.61 | 1.10 | -9.59 | -3.15 | -0.84 | -5.22 |
| | (-0.80)** | (-0.46) | (0.36)*** | (-2.22)*** | (-1.07)*** | (-2.63)*** |
| 10min relative spread | -33.24 | -8.28 | -59.69 | -19.04 | -4.00 | -34.57 |
| | (-9.38)*** | (-1.20) | (-23.02)*** | (-5.89)*** | (0.11)*** | (-6.30)*** |
| 5min relative spread | -22.37 | -2.15 | -42.27 | -13.46 | -2.05 | -25.42 |
| | (-3.05)*** | (0.87)* | (-11.63)*** | (-2.94)*** | (1.01) | (-4.95)*** |
| 2min relative spread | -16.32 | 0.34 | -33.11 | -6.73 | 0.75 | -14.43 |
| | (-2.93)** | (4.23)*** | (-5.51)*** | (1.46)*** | (3.11)*** | (-1.77)*** |

VII.b. CB impact on the price discovery process

As explained in Section *II*, price volatility in itself is not necessarily negative, but a function of supply and demand, often in response to events that may significantly affect the value of an asset. CBs typically target transitory volatility, while information-driven volatility constitutes an essential part of the price formation process. Allowing prices to move up and down following news to fundamentals is essential to price discovery and for assessing risk management parameters by market participants, in particular by liquidity providers. In this regard, CBs may be detrimental to the price discovery process and to the whole market structure, as they artificially influence risk parameters based on volatility. This is particularly true in critical market conditions since it affects the opportunity for market participants to engage in risk transfer when they need the most. Under another point of view, CBs may give the time to informed traders to enter the market and provide liquidity; without the halt liquidity providers may not enter the market, because of significant price uncertainty in volatile market conditions.

In this section we test empirically whether CBs have a positive or negative impact on the price discovery process; we also contribute to the discussion on the informativeness brought by CB auction prices.

We employ the methodology developed by Chakrabarty et al. (2011) and Zimmermann (2015) built on the work of Corwin and Lipson (2000) and Madhavan and Panchapagesan (2000) in order to test the effect of a CB on the price discovery process in two stages. In the first stage, we evaluate the amount of uncertainty prevailing in the market around a CB event. Specifically, the total return from the 10-minute pre-CB mid-price to the mid-price 10 minutes after the CB (reference price) is regressed on the return from the 10-minute pre-CB mid-price to the last price before the CB. This regression takes this form:

Stage 1:
$$ln \frac{P_{ref,i}}{P_{pre,i}} = \alpha_1 + \beta_1 * ln \frac{P_{last,i}}{P_{pre,i}} + \epsilon_i$$

Where $P_{pre,i}$ is the pre-CB reference price, the weighted average order mid-price 10 minutes before the CB. $P_{ref,i}$ is the future post-CB auction reference price level, the average order midprice 10 minutes after the CB. $P_{last,i}$ is the last price before the CB was triggered. The underlying assumption is that prices prior to the CB are considered more uncertain the more they progress in incoherency to a future post-CB reference price level (Zimmermann, 2016). A pre-CB trend of falling prices is not considered distorted if it is consistent with price developments after the CB. If the pre-CB reference price is a perfect predictor for post-CB prices the intercept of the regression will be zero, the slope will be one and subsequently the R² will be one. On the contrary, should $P_{pre,i}$ provide no information about the future price, the slope and the Rsquared will equal zero and the intercept will equal the mean return from the pre-CB to post-CB reference mid-price return.

The slope of the regression can be interpreted as an estimate of the bias in the reference price. In line with the interpretation provided by Chakrabarty et al. (2011), a coefficient greater than one suggests that the pre-CB reference price tends to undershoot the future price, i.e. the returns exhibit continuations from before to after the reference price and a coefficient less than one means that the pre-CB reference price overshoots the future price. Particularly interesting is the error coefficient ϵ_i which represents the unsystematic dissonance between pre- and post-CB returns that cannot be explained by the average linear approximation.

In other words, the first stage of the regression measures to what extent price developments after the trading halt can be predicted from price developments before the halt takes place. New information that needs to be incorporated in the price cause the trading halt and introduce price dissonance measured by the error term.

The second stage regression focuses on the price dissonance, which may be solved entirely by the trading halt, in the sense the price set by the CB auction already fully incorporates the new information moving the pre-CB price to post-CB prices, or entirely by continuous trading after the CB, or the combination of both. A CB is supposed not to undermine the price discovery process; on the opposite, by providing a pause of trading, it should allow investors to reassess the price in light of the new information received. In this sense, we expect to see that price discovery mainly happens during the trading halt and not during post-CB continuous trading.

In the second stage of the regression we take the residual of the first stage to test to what extent the price dissonance is absorbed during the CB auction:

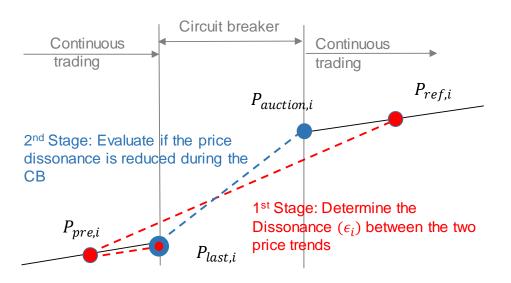
Stage 2 :
$$ln \frac{P_{auction, i}}{P_{last, i}} = \alpha_2 + \beta_2 * \epsilon_i + \gamma_i$$

The CB auction return, the natural logarithm of the ratio between the CB auction allocation price $P_{auction,i}$ and last trade price before the CB $P_{last,i}$, is regressed on the residual from the first stage regression ϵ_i . Following Zimmermann (2015), if the CB perfectly resolves price uncertainty, the intercept is equal to zero, the slope is equal to one and the R² is one. A coefficient higher than zero indicates the fraction of the resolved price uncertainty due to the CB; a negative slope indicates a systematic aggravation of the price uncertainty through the interruption, i.e. the CB worsens price discovery.

The results of the coefficients in step 2 need to be read in the context of step 1 results. More specifically, a step 2 coefficient significantly higher than zero implies that the CB resolves price uncertainty for any value of step 1 coefficients significantly different than one (i.e. price dissonances between post-CB and pre-CB price developments). For a step 1 coefficient equal to one, the step 2 coefficients do not provide any information relevant for economic interpretations.

The two-stage regressions are computed on all the stocks and ETFs affected by a CB and for the subsample of small, mid and large cap stocks halted. Furthermore, we investigate whether the CBs had a positive effect on price discovery on cross-listed instruments. In this specific case, while the first stage coefficient has the same meaning (the magnitude of price dissonance), the coefficient of the second stage regression can be interpreted as the amount of price dissonance explained by the CB triggered on the market of a cross-listed stock. The graph below provides a graphical explanation of the 2-stage regression where β is higher than 1 in the first stage and higher than zero in the second stage. Annex H provides graphical explanations of all other possible cases.

Graphical explanation of the 2-stage regression model²⁷



Note: Hypothesis tested : 1^{st} stage: $\beta < 1$, 2^{nd} stage: $\beta > 0$

Table 3 Price discovery process on halted instruments

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| | All s | tocks | Sma | ll cap | Mid | cap | Larg | e cap | Midday | auctions |
| VARIABLES | 1st stage | 2nd stage |
| | | | | | | | | | | |
| n(Plast/ | 1.02 | | 1.05 | | 1.09* | | 0.80*** | | 0.87*** | |
| Ppre) | (0.03) | | (0.07) | | (0.05) | | (0.03) | | (0.05) | |
| | | 0.34*** | | | | | | | | |
| res_all | | (0.03) | | | | | | | | |
| | | () | | 0.30*** | | | | | | |
| res_small | | | | (0.04) | | | | | | |
| | | | | (0.04) | | 0.37*** | | | | |
| res_mid | | | | | | | | | | |
| | | | | | | (0.04) | | 0.00*** | | |
| res_large | | | | | | | | 0.30*** | | |
| | | | | | | | | (0.07) | | |
| res_ETFs | | | | | | | | | | |
| res_mid- | | | | | | | | | | 0.12** |
| -dayauct | | | | | | | | | | (0.03) |
| Observations | 3,413 | 3,413 | 898 | 898 | 1,247 | 1,247 | 1,268 | 1,268 | 2,301 | 2,301 |
| R-squared | 0.75 | 0.30 | 0.77 | 0.24 | 0.77 | 0.37 | 0.73 | 0.26 | 0.45 | 0.01 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1 Regression coefficients in the first stages have been tested for being significantly different than one.

Regression coefficients in the second stages have been tested for being significantly different than zero.

Table 4

Price discovery process on instruments correlated to the halted ones

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| | All s | tocks | Sma | III cap | Mic | l cap | Larg | le cap |
| VARIABLES | 1st stage | 2nd stage |
| In(Plast/ | 0.96* | | 1.09*** | | 1.01 | | 0.89*** | |
| Ppre) | (0.02) | | (0.02) | | (0.04) | | (0.02) | |
| | | 0.39*** | | | | | | |
| res_corr_all | | (0.01) | | | | | | |
| | | | | 0.26*** | | | | |
| res_corr_small | | | | (0.03) | | | | |
| | | | | | | 0.38*** | | |
| res_corr_mid | | | | | | (0.02) | | |
| | | | | | | · · · · | | 0.46*** |
| res_corr_large | | | | | | | | (0.02) |
| | | | | | | | | |
| Observations | 12,957 | 12,957 | 2,447 | 2,447 | 4,115 | 4,115 | 6,395 | 6,395 |
| R-squared | 0.77 | 0.41 | 0.81 | 0.22 | 0.76 | 0.40 | 0.73 | 0.53 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Regression coefficients in the first stages have been tested for being significantly different than one.

Regression coefficients in the second stages have been tested for being significantly different than zero.

Results in Table 3 and 4 show the regression coefficients estimates for the halted instruments and for cross-listed stocks.

We find the coefficient for the first stage regression to be equal to 1.02 for the sample of all stocks, meaning that pre-CB prices are good predictors for post-CB prices. However, the magnitude of the coefficient is not uniform across stocks' subsamples: for large cap stock the coefficient is 0.8, indicating a much higher price dissonance than the one of mid cap (1.09) and small cap (1.05). This means that large cap stocks present a higher degree of price uncertainty prevailing in the market around a CB event. This was somehow expected: in the descriptive statistics part we saw already how, in periods of high market volatility, large cap stocks were the ones with the most CB occurrences. In particular, a coefficient lower than one indicates that pre-CB prices tend to overshoot post-CB prices; in other words, price returns exhibit a reversal from before to after the reference price. For mid and small cap stocks the coefficient is very close to one, meaning that pre-CB prices are on average good predictors for post-CB prices. As regards ETFs, the coefficient is equal to 0.75, but the sample of observations is rather small.

Having measured the price dissonances between post-CB and pre-CB prices, in the second stage regression we test to which magnitude this dissonance is explained by the CB auction return. The coefficients are significantly positive for all our samples of stocks analysed, indicating that the CB did not aggravate the price discovery process in the period going from 1 April 2016 to 31 December 2016. For the sample comprising all stocks, CB contributed to resolve 34% of price uncertainty. However, the informativeness brought by CB auction prices differ across the three subsamples. For small and large-cap stocks the portion of price dissonance resolved by the CB is 30%, while for mid-cap stocks that is 37%.

In order to validate the robustness of our analysis, we run the two-stage regression model on a sample of 3,010 scheduled midday auctions events²⁸. This robustness check tests whether price discovery during CB event is comparable to price discovery during scheduled midday auctions. We find that, although there is wide divergence between pre- and post-midday auction prices, the scheduled midday auctions contribute to price discovery only to a minor extent (12%), half the price informativeness contribution of CBs²⁹.

Finally, we are interested to test whether CBs improve price the discovery process also for the cross-listed stocks that are not halted. As shown in Table 4, price dissonances for cross-listed stocks are similar to the halted ones: large cap cross-listed stocks present larger price uncertainty around a CB event, and the majority of this dissonance is explained by the continuous trading time in correspondence of a CB on the related market³⁰.

However, it is important to take into account the nature of the halted market, being ether the reference market or a satellite one. We expect price dissonances to be low for the cross-listed stocks traded on a satellite market while the reference market is halted. On the opposite, if the halt happens on a satellite market, we expect the price dissonance to be larger (for the cross-listed stocks trade on the satellite market) because trading is not halted on the reference market. These intermarket cases will be analysed in the following section.

VII.c. Interplay between CBs across markets

In this section we aim contribute to the literature on CB coordination across markets, by analysing CB market effects taking into account whether the halt happens on the reference market or on a satellite one³¹. The intermarket analysis focuses on our sample of stocks halted and cross-listed³². The categorisation of the market as reference or satellite has been is based on information from Refinitiv EIKON/Datastream. Five different and mutually exclusive intermarket cases are identified. If a CB is triggered on a stock traded on the reference market, then the respective cross-listed stock is traded on a satellite market. If a CB is triggered on a stock traded either on the reference market or on another market satellite to the halted one. Table 5 below details the number of stocks for each category identified.

²⁸ The regression control group is composed of 3,010 scheduled midday auctions triggered on XETRA, London Stock Exchange and Vienna Stock Exchange in the period going from 1 April 2016 to 31 December 2016.

²⁹ As a further robustness check we analyse whether the extent to which CBs help resolving price uncertainty is different in cases where the last price before the halt overshot or undershot the post halt midpoint average. For example, for all stocks we find that CBs resolve 34% of price uncertainty. Distinguishing between cases of overshooting and undershooting, we find that CBs resolve 41% and 28% of price uncertainty respectively, at unchanged significance levels. Detailed results, also distinguishing between small, mid and large cap stocks as well as for midday auctions are reported in Annex I, Tables I.1 and I.2.

³⁰ Again, we analyse as robustness check whether the extent to which CBs help resolving price uncertainty is different in cases where the last price before the halt overshot or undershot the post halt midpoint average. We also find for correlated instruments that results are robust both in terms of the extent to which CBs resolve price uncertainty and levels of significance when distinguishing between cases of over- and undershooting. Detailed results, also distinguishing between small, mid and large cap stocks as well as for midday auctions are reported in Annex I, Tables I.3 and I.4.

³¹ It has to be noted that different CB interaction effects may also be observed between cash and futures markets, other than the interplay between the reference and satellite markets. We leave this CBs interaction to future research.

³² ETFs have not been taken into account, due to lack of correlated instruments.

| I able 5 | Т | ab | le | 5 |
|----------|---|----|----|---|
|----------|---|----|----|---|

Number of stocks for each intermarket case identified

| Halted on: | Halted | <u>Cross-li</u> Reference market | <u>sted on</u> Satellite markets | Total |
|---------------------|--------|-------------------------------------|-------------------------------------|--------|
| Reference market | 2,181 | - | 5,708 | 7,889 |
| Satellite markets | 1,328 | 1,193 | 6,013 | 8,534 |
| Total | 3,509 | 1,193 | 11,721 | 16,423 |

Having added this market categorisation, we compute the price discovery two-stage regressions for each intermarket case identified and try to qualify the CB effects based on the nature of the market where the halt takes place. In parallel, we assess the implications for investors in terms of changes in mid-price standard deviation and bid-ask spread; taking into account also eventual unusual messaging activity and cancellation orders. Table 6 shows the price discovery results, Table 7 presents the difference in volatility and spread parameters for cross-listed instruments around a CB happening on a related (reference or satellite) market, and Annex J contains the graphs on messaging activity and cancellation orders and the table on CB market effects. In this analysis, we do not differentiate between small, mid and large cap stocks.

The two-stage regression model used is Zimmermann (2013), which is explained in the section above.

The CB effects are analysed separately for each intermarket case identified³³:

• *First case*: The CB is triggered on the reference market; we analyse the effects on the stocks traded on the reference market

Table 6 shows that, despite the CB trigger event, price uncertainty prevailing in the market around the CB is rather small and the coefficient is close to one and not significant. Yet price swings activated a CB that contributed positively to price discovery (23%). On the 2-minute and 5-minute intervals, the CB did not have clear effects on market volatility, while the standard deviation registered 10 minutes after the CB is significantly lower than the one prevailing in the 10 minutes prior to the halt. The bid-ask spread post-CB is higher at all time intervals considered, however it increases at a slower pace as long as we look further in the future (+2.5 bps at 10 minutes interval, +1.65 bps at 5 minutes interval and +0.96 bps at 10 minutes interval) (Table J.7 in Annex J).

 Second case: The CB is triggered on the reference market; we analyse the effects on the cross-listed stocks traded on a satellite market

The cross-listed stocks under analysis are traded, in continuous trading, on a satellite market while the main reference market is halted. However, the price discovery process on the satellite market replicates the price discovery on the reference market which is on halt – this could be described as a "hidden CB" on the satellite market as liquidity evaporates on the satellite market. In terms of regression results, first and second stage coefficients are very close to the first case described above. While the reference market is on halt, we observe more than twice order

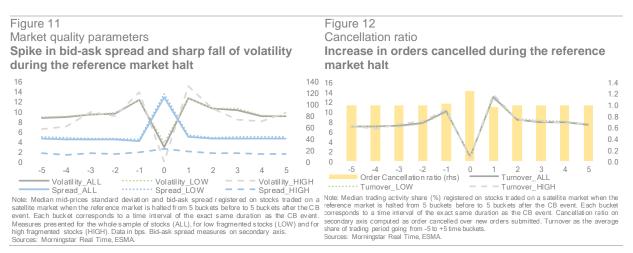
³³ Again, we analyse as robustness check whether the extent to which CBs contribute to price discovery is different in cases where the last price before the halt overshot or undershot the post halt midpoint average. We find for all five intermarket case presented below that results are robust both in terms of the extent to which CBs contribute to price discovery and levels of significance when distinguishing between cases of over- and undershooting. Detailed results, also distinguishing between small, mid and large cap stocks as well as for midday auctions are reported in Annex I, Tables I.5 and I.6.

cancellations compared to new orders on the satellite market (Figure 12), combined with lower messaging activity on the satellite market (Figures J.1 and J.2 in Annex J). As a result of low trading activity, the bid-ask spread widens sharply, from 40 bps in the immediate pre-CB period to 110 bps during the reference market halt (Figure 11). As soon as continuous trading resumes on the reference market, the order book gets quickly refilled and the bid-ask spread for the post-CB trading phase registers higher levels than pre-CB trading phase: +7.4 bps in the 2-minute window, +5 bps on the 5-minute window, and +3.1 in the 10-minute window (Table J.7 in Annex J).

Volatility on the satellite market slightly increases ahead of the reference market halt, before falling sharply by 70% throughout all the duration of the reference market CB (Figure 11). After trading resumes on the reference market, trading activity also picks up again on the satellite market as a consequence volatility increases reaching higher levels in the 2-minutes (+1.21 bps) and 5-minutes (+0.28) post-CB trading compared to the same intervals pre-CB.

These developments can be summarised as follows. Although satellite markets offer the possibility to trade in continuous trading while the reference market is on halt, investors largely refrain to trade (low trading activity and high order cancellation rates, Figure 12) waiting for the reference market to end the halting period and set the new price. In this sense, price uncertainty in satellite markets closely follows the reference market, and the additional contribution to the price discovery process brought by the satellite markets' continuous trading is very low (second stage coefficient equal to 0.68 for the cross-listed stocks traded on satellite markets, compared to a coefficient of 0.53 for the cross-listed stocks traded and halted on the reference market).

The "hidden CB" effects (fall in standard deviation and trading activity) hold for the sample of low and high fragmented stocks. However, the low fragmented stocks bid-ask spreads on the satellite market vary only to a minor extent during the reference market halt despite the marked decrease in trading activity.



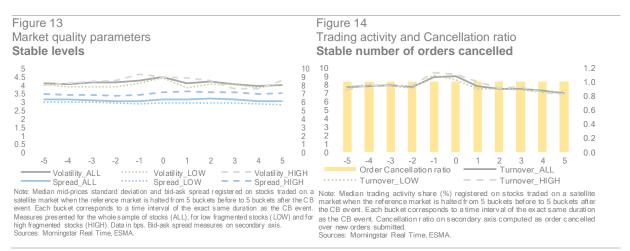
• *Third case*: The CB is triggered on a satellite market, we analyse the effects on those cross-listed stocks, while the reference market operates in continuous trading.

The price uncertainty prevailing on a cross-listed stock traded on a satellite market around a CB event, while the reference market operates in continuous trading, is large as price discovery happens in the reference market. The CB auction returns absorb 59% of the price dissonance. However, one can question that the presence of CB itself created the price dissonance between post- and pre-CB prices. Despite having a positive effect on the 10-minute standard deviation,

the CB widened significantly the bid-ask spreads in the immediate post-CB trading phases (Table J.7 in Annex J).

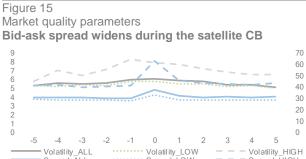
• *Fourth case*: The CB is triggered on a satellite market; we analyse the effects on the cross-listed stocks traded on the reference market.

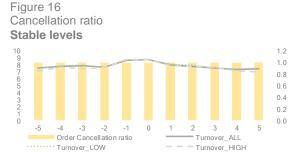
In this case, as expected, we do not observe any reaction in terms of orders cancelled on the reference market during a satellite market CB (Figure 14), while order submissions to the reference market increase by 28% during a satellite market CB (Figures G.3 and G.4 in Annex G) as investors move from the halted market to the reference market. As soon as continuous trading resumes on the satellite market, order submissions on the reference market decrease by 50% on average. Reference market price dissonance around the satellite's CB is, as expected rather low comparing to the one prevailing on the satellite market (Table 6). Bid-ask spreads on the reference markets are not affected by the satellite halt, while market volatility increase marginally during the satellite market halt before decreasing in the post-CB phase, reaching levels slightly below pre-CB ones (Tables 7 and J.7 in Annex J). This decrease in volatility can be interpreted as a positive spill over effect caused by the satellite market halt, which sets calmer trading conditions without any additional costs paid by investors in terms of higher bid-ask spreads.



 Fifth case: The CB is triggered on a satellite market; we analyse the effects on the crosslisted stocks traded on another satellite market.

The last case is the effect of a satellite market's CB on the cross-listed stocks traded on another satellite market that operates in continuous trading. Here price uncertainty is similar to the other satellite market (coefficient equal to 0.91) around the other satellite's CB despite the fact the satellite market under analysis and the reference market are operating in continuous trading. 55% of the price dissonance is explained by price development happening during the other satellite's CB. The positive volatility spill over effect of the CB is manifested also for other satellite markets that operate in continuous trading: All time windows' mid-price standard deviations are lower after the CB. However, satellite markets are generally less liquid than a reference market and, for this reason, are less able to absorb the shock that caused a CB on a parallel market. Bid-ask spreads widen clearly during the parallel satellite market CB (Figure 15), and post-CB spreads remain at levels higher than pre-CB trading (Tables 7 and J.7 in Annex J).





Note: Median trading activity share (%) registered on stocks traded on a satellite market when the reference market is halted from 5 buckets before to 5 buckets after the CB event. Each bucket corresponds to a time interval of the exact same duration as the CB event. Cancellation ratio on secondary axis computed as order cancelled over new orders submitted. Sources: Morningstar Real Time, ESMA.

Table 6

Price discovery process on intermarket cases

| | (1) | (2) | (5) | (6) | (3) | (4) | (7) | (8) | (9) | (10) |
|--|--------------|------------------------------------|--------------|---|--|---------------------|--|---------------|--|---------------------|
| | | Reference r | narket is h | alted | | | Satellite ma | rket is halte | ed | |
| | traded | on stocks I on the ce market | listed st | s on cross- ocks traded llite markets | Effect or traded satellite n ha | on the narket on | Effect on t listed stoo on the re mar | cks traded | Effect on t listed stoc on other mark | ks traded satellite |
| VARIABLES | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| In(Plast/ | 1.06* | | 1.04 | | 0.84*** | | 1.03 | | 0.91*** | |
| Ppre) | (0.03) | | (0.03) | | (0.04) | | (0.05) | | (0.02) | |
| | | 0.23*** | | | | | | | | |
| res_halt_ref | | (0.03) | | | | | | | | |
| | | | | | | 0.59*** | | | | |
| res_halt_sat res_corr_halt onREF | | | | 0.24*** | | (0.06) | | | | |
| res_corr_halt | | | | ~ / | | | | 0.54*** | | |
| SAT_trade REF | | | | | | | | (0.03) | | |
| res_corr_halt SAT_trade SAT | | | | | | | | | | 0.55*** (0.02) |
| Observations | 2,225 | 2,225 | 6,044 | 6,044 | 1,188 | 1,188 | 1,106 | 1,106 | 5,807 | 5,807 |
| R-squared | 0.77 | 0.22 | 0.76 | 0.20 | 0.71 | 0.45 | 0.68 | 0.68 | 0.71 | 0.65 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Regression coefficients in the first stages have been tested for being significantly different than one.

Regression coefficients in the second stages have been tested for being significantly different than zero.

Focus on cross listed instruments

Table 7

| | | | Reference is ha | | | Satellite mai | rket is halted | |
|-------------------|----------------------------------|------------------|---------------------------------------|-----------------------|-----------------|--|-----------------|---|
| | | | Effects or trad on the s mar | ed atellite ket | lis stocks f | the cross- sted traded on ence market | lis stocks t | the cross- ted raded on lite markets |
| | | | Median | P value | Median | P value | Median | P value |
| | | Time window 1 | -5.49 | *** | 0.00 | | -0.09 | *** |
| | DURING | Time window 2 | -3.08 | *** | 0.15 | *** | 0.26 | *** |
| | CB | Time window 3 | -3.09 | *** | 0.22 | *** | 0.17 | *** |
| | PRE CB | Time window 4 | -3.09 | *** | 0.32 | *** | 0.31 | *** |
| | | Time window 5 | -3.12 | *** | 0.24 | *** | 0.26 | *** |
| VOLATILITY | | Time | 4.42 | *** | -0.24 | *** | -0.36 | *** |
| | | window 1 Time | 3.38 | *** | -0.37 | *** | -0.34 | *** |
| | POST CB minus | window 2 Time | 3.03 | *** | -0.42 | *** | -0.51 | *** |
| | DURING CB | window 3 Time | 2.77 | *** | -0.40 | *** | -0.40 | *** |
| | | window 4 Time | 3.00 | *** | -0.54 | *** | -0.75 | *** |
| | | window 5 Time | 13.81 | *** | 0.01 | *** | 0.34 | *** |
| | | window 1 Time | | *** | | ** | | *** |
| | DURING CB minus PRE CB | window 2 Time | 14.37 | *** | 0.00 | | 0.39 | *** |
| | | window 3 Time | 13.08 | | 0.00 | | 0.30 | |
| | | window 4 Time | 12.71 | *** | 0.00 | | 0.30 | *** |
| BID-ASK | | window 5 | 11.37 | *** | -0.01 | * | 0.29 | *** |
| SPREAD | POST CB minus DURING CB | Time window 1 | -30.59 | *** | 0.00 | | -0.25 | *** |
| | | Time window 2 | -26.69 | *** | -0.01 | * | -0.33 | *** |
| | | Time window 3 | -23.38 | *** | 0.00 | * | -0.43 | *** |
| | | Time window 4 | -20.38 | *** | -0.07 | *** | -0.50 | *** |
| | | Time window 5 | -20.76 | *** | -0.04 | *** | -0.58 | *** |
| | | Time window 1 | -9% | *** | -0.2% | | 0.1% | |
| | DURING | Time window 2 | -6% | *** | 1.0% | *** | 0.9% | *** |
| | CB | Time window 3 | -6% | *** | 0.8% | *** | 0.7% | *** |
| | PRE CB | Time window 4 | -6% | *** | 0.9% | *** | 0.9% | *** |
| | | Time | -6% | *** | 0.9% | *** | 1.0% | *** |
| TURNOVER SHARE | | window 5 Time | 11% | *** | -1.2% | *** | -0.6% | *** |
| | | window 1 Time | 7% | *** | -1.2% | *** | -0.9% | *** |
| | POST CB minus | window 2 Time | 7% | *** | -1.6% | *** | -1.2% | *** |
| | DURING CB | window 3 Time | | *** | | *** | | *** |
| | | window 4 | 7% | | -1.6% | | -1.2% | |

Note: Trading conditions parameters are compared during the CB period with 1,2,3,4,5 equivalent CB periods before and after the CB occurrence. Turnover share is computed per time window as share of the sum of turnover from 5-time windows before the CB to 5-time windows after the CB. A time window is equal to the respective CB duration. Source: Morningstar Real Time, ESMA.

6%

-1.8%

-1.2%

window 4 Time

window 5

Box 3

CB interplay for correlated assets – an example

CBs may also have cross-sectional spill over effects on correlated, but not cross-listed, non-halted stocks. The focus so far has been on the interplay of CBs between halted stocks and non-halted cross-listed stocks. However, a CB may also have an impact on non-halted stocks in the same sector of the halted one.

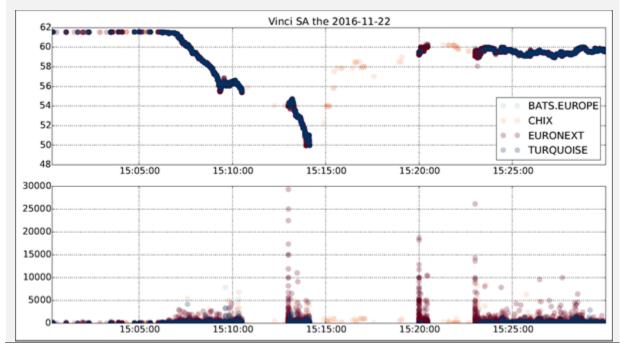
On 22 November 2016 Vinci S.A., a large French construction company, was victim of a fake-news event related to its earnings that led the share price to fall by 19% in 7 minutes, before recovering quickly its losses in the subsequent 6 minutes. As shown in the table below, three CBs were triggered on Euronext: the first one from 15:10 to 15:13 pertains to the share price fall, while the second one (from 15:14 to 15:20) and the third one (from 15:20 to 15:23) were triggered during the share price recovery. Those CBs are likely to be entirely information-driven, and not related to transitory volatility induced by increased trading activity.

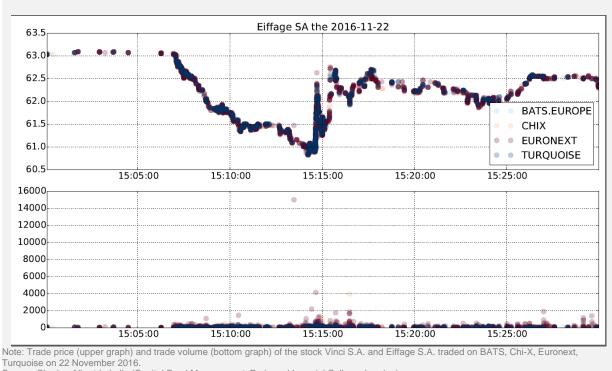
Eiffage S.A. is operating in the same sector as Vinci S.A. The fake-news was related only to Vinci earnings, not to Eiffage. However, the Eiffage share price reacted to Vinci's fake-news, yet to a lesser extent losing about 3% without triggering any CBs. According to market efficiency theories, the Eiffage share price should have not reacted at all to Vinci fake-news, as the share price already incorporated all public information. The right-hand charts below provide a graphical evidence of price and volume dynamics of the non-halted Eiffage share during Vinci share halts: trading volumes of Eiffage share increased while the share price registered swings. These results, probably due to speculative trading strategies which traded Eiffage shares during Vinci share halts, betting on the Vinci reopening price.

This case offers a preliminary analysis of CB repercussions on other non-halted correlated assets, which constitute an important aspect of CBs to be further investigated.

| DATE | ID | EXCHANGE | MARKET_CAP | SECTOR | CB - START | CB - END |
|------------|-------|----------------|------------|-------------|--------------|--------------|
| 22/11/2016 | VINCI | Euronext Paris | LARGE | Industrials | 15:10:46:421 | 15:13:00:031 |
| 22/11/2016 | VINCI | Euronext Paris | LARGE | Industrials | 15:14:17:240 | 15:20:00:058 |
| 22/11/2016 | VINCI | Euronext Paris | LARGE | Industrials | 15:20:32:093 | 15:23:00:009 |







Source: Charles-Albert Lehalle (Capital Fund Management, Paris and Imperial College, London).

VIII. Conclusion

Sudden and drastic price swings in financial markets can be a source of market instability and are a concern for market participants, supervisors and regulators. Safeguard mechanisms such as circuit breakers (CBs) are key instruments for trading venues to interrupt excessive price movements. Over the past years, and in many cases prior to MiFID I implementation, European trading venues have successfully implemented safeguard mechanisms. These mechanisms have been developed in a discretionary way which resulted in a heterogeneous landscape of volatility safeguard mechanisms and their calibration parameters. The volatility safeguard mechanisms used by EU trading venues can be divided into two types: CBs and price collars. CBs halt trading if the price of individual securities falls outside a predetermined range while price collars do not halt trading, but rather constrain it by rejecting an order if the potential execution price is outside predetermined price ranges. However, CBs are not the only cases in which trading is halted. The wider category of trading halts also comprises regulatory and technical halts.

In the EU regulatory framework, MiFID II requires trading venues to have the ability to temporarily halt trading, and ESMA has issued guidelines on their appropriate calibration. We provide an overview of volatility safeguards implemented on EU trading venues and observe these safeguards are implemented heterogeneously across EU trading venues. They differ in the type of volatility interruption (price collars, CBs or both), in reference price specification, thresholds, duration and their disclosure to market participants.

The theoretical literature on CBs states that CBs are effective if they address transitory volatility, defined as the tendency for prices to fluctuate around their fundamental values. However, the literature also finds that CBs are not effective if they address fundamental volatility. In this case a trading halt prevents prices from reflecting the new information on fundamental values. The recent empirical literature on CB efficacy in increasing market quality provides mixed evidence.

There is some evidence that CBs did not calm the market and caused a reduction in liquidity. By analysing the effect of CBs on price paths approaching the limit, there is evidence that the presence of CBs reduces extreme price movements and increases market liquidity.

Our CB data set has a wide EU cross-venue coverage. We can, thus, extend findings from the existing literature, which mostly covers single venues. However, as CB mechanisms vary widely between trading venues, our aggregate analysis does not capture differing CB impacts for different CB calibrations. This caveat does however mostly also apply for single venue studies, as CB triggers on many trading venues vary depending e.g. on the liquidity of a stock or on general market conditions. Analysing differing CB impacts depending on CB trigger calibration and thus providing empirical evidence on how to effectively calibrate CBs would be a fruitful area for further research.

Using a unique database of CBs, which were triggered between 1 April 2016 and 31 December 2016 on a sample of 10,000 financial instruments traded on EU trading venues, we analyse market impacts of CBs. First, we provide descriptive statistics on CBs and investigate whether CBs helped to improve market quality conditions such as volatility and bid-ask spreads. Secondly, we study the impact of CBs on the price discovery process for the instruments concerned. Finally, we analyse cross-venue impacts of CBs and thus contribute to the discussion on cross-venue CB coordination.

Our statistics look at CB occurrences, when they happen during a trading day and duration of CBs. We find that CB occurrences vary widely depending on market conditions. On average we find that in our sample CBs have been triggered 44 times per day. However, we observe a multiple of this during times of market stress. In our sample period, this was observed around four events: the UK referendum, the publication of banking stress test results, the US Presidential election, and the Italian constitutional referendum. In all of these cases, large cap stocks were relatively more affected by CBs compared to mid- and small-cap stocks. Heterogeneity of CB calibration across trading venues is reflected in wide variations of the average duration of trading halts across venues, from less than a minute to 50 minutes. Throughout a trading day, CB incidents are mostly concentrated in the first 15 minutes of the trading and around the opening of US markets, when new information flows need to be incorporated quickly in the prices.

We find that price volatility, measured by the normalised standard deviation of mid-prices, declines significantly in both halted and cross-listed stocks at different time intervals (10, 5 and 2 minutes after the CB). However, calmer trading conditions come at the cost of higher spreads; the relative bid-ask spreads significantly increase after the halt, and the increase is even more pronounced for stocks cross-listed compared to the halted instruments.

Our analysis of the price discovery process shows that it is not negatively affected by the CB; on the contrary, we find that CB auction prices provide incremental information for participants helping to return to orderly trading. In particular for large cap stocks, where price dissonances are found to be larger, CB auction prices contributed to reducing about 78 percent of price uncertainty.

Finally, we take advantage of the cross-venue character of our database and analyse the impact of CBs on cross-listed instruments, differentiating by reference and satellite markets. This analysis can contribute to any future analysis on co-ordination of CBs across venues. Crosslisted instruments traded in continuous trading on satellite markets during a CB on the reference market experience a sort of "hidden CB". Despite being in continuous trading, trading activity decreases drastically (high cancellation orders) and liquidity dries up (spike in the bid ask spread) as investors refrain from trading waiting for the reference market to set the CB auction price. When continuous trading resumes bid-ask spreads increase to a higher extent than in the sample of halted instruments on the reference market (three to five bps compared to one bps for the halted instruments) and volatility levels for the two- and five-minute window around a CB increase compared to the reference market halted.

Satellite markets are generally characterised by lower liquidity levels compared to the reference market. CBs on a satellite market lead to large price distortions and markedly wider bid-ask spreads on the halted instruments and on the cross-listed ones traded on another satellite venue, whereas we observe no impact on spreads on the reference market. Volatility decreases on all other satellite markets as well as on the reference market.

However, a better understanding of the complexity of potential dynamic interactions between CBs and market events is needed. Of particular future interest for market participants and supervisors are three dimensions of interaction.

First, the incidence of flash crashes and any potential feedback loops between high-frequency traders and algorithms. As algorithms become more complex, and through machine learning, more reactive to market developments, the effects one algorithm that causes severe price movements may have on others needs to be empirically investigated.

Second, the interaction between any cascading price movements that may result and the changing regulatory landscape of CBs in extreme market conditions. This is particularly relevant given that the composition of traders around a CB event may influence the effectiveness of the CB. The composition can be heterogeneous and vary over time, as HFTs typically do not participate to auction trading, and may enter after a CB auction is over.

Finally, trading venues and supervisors will need to be aware of any potential feedback loops between the different CBs. As we found out for the EU, there is no systematic diversion of liquidity from reference to satellite markets, when a CB is triggered on the reference market. The satellite market experiences a "hidden CB", which can be interpreted as de facto coordination of CBs by market participants and may prevent feedback loops between trading venues. In the context of changes in market structure and market fragmentation this empirical result may not be robust in cases where a reference market loses its lead status related to price discovery. This could create the potential for liquidity spill overs between trading venues around CB events; in other words, cascading effects triggering sequences of CBs on one instrument between trading venues may result. Similarly, such cascades could not be excluded for price movements between correlated instruments.

To conclude, trading practices and volatility safeguards are moving into a new phase of their development. On the one hand, high-frequency infrastructure and algorithmic trading practices coupled with machine learning capacities are becoming more sophisticated, rendering securities trading increasingly complex. On the other hand, the regulatory environment has evolved as well, with MiFID II including the requirement for a more harmonised approach to CBs. While the new regulatory framework provides greater market transparency and promote orderly markets and financial stability, structural market developments as well as critical market incidences, such as flash crashes, will need to be analysed and fully understood to ensure a robust market functioning going forward.

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Annex A. Volatility safeguard mapping

Mapping of current volatility safeguard practices by EU trading venues³⁴

| Trading venue | Volatility safeguard | Dynamic price | Static price | Threshold disclosed |
|---------------------------|----------------------|---------------|--------------|---------------------|
| Athens Stock Exchange | CBs/price collars | Y | Y | Ν |
| BATS Chi-X Europe BXE | Price collars | Ν | Y | Y |
| BATS Chi-X Europe CXE | Price collars | Ν | Y | Y |
| Borsa Italiana | CBs | Y | Y | Ν |
| Bucharest Stock Exchange | Price collars | Y | Y | Y |
| Budapest Stock Exchange | CBs | Y | Y | Ν |
| Cyprus Stock Exchange | CBs/price collars | Y | Y | Ν |
| Deutsche Boerse Xetra | CBs | Y | Y | Ν |
| Equiduct | None | | | |
| Euronext Amsterdam | CBs/price collars | Y | Y | Ν |
| Euronext Brussels | CBs/price collars | Y | Y | Ν |
| Euronext Lisbon | CBs/price collars | Y | Y | Ν |
| Euronext Paris | CBs/price collars | Y | Y | Ν |
| EuroTLX | CBs | Y | Y | Y |
| Irish Stock Exchange | CBs | Y | Y | Ν |
| London Stock Exchange | CBs | Y | Y | Y |
| Luxembourg Stock Exchange | CBs | Y | Y | Ν |
| Madrid Stock Exchange | CBs | Y | Y | Ν |
| Malta Stock Exchange | CBs | Y | Y | Ν |
| NASDAQ OMX Copenhagen | CBs | Y | Y | Y |
| NASDAQ OMX Helsinki | CBs | Y | Y | Y |
| NASDAQ OMX Stockholm | CBs | Y | Y | Y |
| Prague Stock Exchange | CBs | Y | Y | Ν |
| TOM MTF | CBs | Ν | Y | Y |
| Tradegate | None | | | |
| Turquoise | price collars | Y | Y | Ν |
| Vienna Stock Exchange | CBs | Y | Y | Ν |
| Warsaw Stock Exchange | CBs/price collars | Y | Y | Y |

Note: According to ESMA registers, as of May 2016 there were 98 regulated markets (RMs) and 146 multilateral trading facilities (MTFs) in the EU. The table includes only the main national RMs and MTFs on which CBs were triggered. BATS Chi-X Europe, Europext and Nasdaq OMX operate with different trading platforms and each trading platform is analysed independently. Y denotes yes; N denotes no; blank fields denote not available. Sources: Trading rulebooks published on their websites, ESMA.

³⁴ Going forward, ESMA will provide a regular overview of volatility safeguard practices based on MiFID II information in its Securities Markets Annual Statistical Report. The first edition of ESMA's Securities Markets Annual Statistics Report is scheduled for 2020.

Annex B. Sample of financial instruments under analysis

| Sample of CBs initial database | | | | | | |
|---|------------|------------------------|------|---------|--------|--------|
| Trading venue | Currencies | Depository receipts | ETFs | Futures | Stocks | Total |
| Athens Stock Exchange | | 1 | | | 3 | 4 |
| BATS Chi-X Europe BXE | | | | | 644 | 644 |
| BATS Chi-X Europe CXE | | 6 | 37 | | 644 | 687 |
| Boerse Berlin | | 73 | 19 | | 521 | 613 |
| Boerse Düsseldorf | | 16 | 24 | | 484 | 524 |
| Boerse Frankfurt | | 92 | 25 | | 544 | 661 |
| Boerse Hamburg | | 6 | 22 | | 204 | 232 |
| Boerse Hannover | | 2 | | | 165 | 167 |
| Boerse München | | 34 | 17 | | 407 | 458 |
| Boerse Stuttgart | | 82 | | | 510 | 592 |
| Borsa Italiana | | | 42 | | 132 | 174 |
| Bucharest Stock Exchange | | | | | 31 | 31 |
| Budapest Stock Exchange | | | | | 22 | 22 |
| Deutsche Boerse Xetra | | 16 | 25 | | 222 | 263 |
| Equiduct | | | | | 580 | 580 |
| Euronext Amsterdam | | 1 | 6 | | 39 | 46 |
| Euronext Brussels | | | | | 15 | 15 |
| Euronext Lisbon | | | 1 | | 5 | 6 |
| Euronext Paris | | 1 | 20 | | 85 | 106 |
| EuroTLX | | | | | 73 | 73 |
| Financial Industry Regulatory Authority | | 35 | 7 | | 5 | 47 |
| FX LITE | 13 | | | | | 13 |
| ICE Futures Europe | | | | 1,287 | | 1,287 |
| Irish Stock Exchange | | | | | 17 | 17 |
| London Stock Exchange | | 17 | | | 597 | 614 |
| London Stock Exchange International | | 35 | | | 2 | 37 |
| Luxembourg Stock Exchange | | 27 | | | 6 | 33 |
| Madrid Stock Exchange | | | | | 35 | 35 |
| NASDAQ OMX Copenhagen | | | | | 22 | 22 |
| NASDAQ OMX Helsinki | | 1 | | | 17 | 18 |
| NASDAQ OMX Stockholm | | 1 | 1 | | 57 | 59 |
| Oslo Stock Exchange | | | | | 24 | 24 |
| Prague Stock Exchange | | | | | 4 | 4 |
| SIX Swiss Exchange | | | 84 | | 657 | 741 |
| SIX Swiss Exchange - Blue Chip Segment | | | | | 29 | 29 |
| TOM MTF | | | | | 77 | 77 |
| Tradegate | | | | | 403 | 403 |
| Turquoise | | | | | 625 | 625 |
| Vienna Stock Exchange | | | 3 | | 6 | 9 |
| Warsaw Stock Exchange | | | | | 8 | 8 |
| Total | 13 | 446 | 333 | 1,287 | 7,921 | 10,000 |

Annex C. Technical description of the dataset

The dataset of CB trigger events used for this study has been created according the following methodology:

1. Structure of the raw data

ESMA receives daily data in very large text files (~50 GB of unzipped data per day) with no headers and in an unconventional format.

The field separator within each file is a pipe, and each record is composed of a fixed-length and a variable-length part. The fixed-length part corresponds to the first seven fields (date, timestamp, message type, symbol, exchange code, security type and sequence number). Taken together, the symbol (instrument name), exchange code and security type uniquely identify an instrument. The sequence number uniquely identifies each record.

The variable-length part corresponds to the concatenation of all the reported fields available in the Morningstar documentation. Those fields are always reported under the following format: fXXX=YYY, where XXX is the field number as defined in the Morningstar documentation and YYY its value. Furthermore, depending on the message type in the fixed-length part, the meaning of a field (*fXXX*) can differ. For example, *f25=3.2* could refer either to a bid price or to an opening auction price depending on the message type). The timestamps are all reported under the GMT time zone and are sensitive to the change to summer or winter time.

2. Identification and extraction of the circuit breakers events

The second step involves, based on the technical documentation provided by Morningstar, the identification of the combination of fields and values fXXX=YYY (referred as "CB flags" hereinafter) that indicate the triggering of a CB. However, the CB flag was not reported in a harmonised manner by the trading venues, and the documentation was not always sufficient if not purely missing.

For instance, according to the documentation provided by the data vendor, in the case of a venue XYZ there existed different flags corresponding to trading halts, but not necessarily to a volatility interruption CB³⁵ (for example, labels such as "suspension", "technical halt", "market halt" or just simply "halt"). On top of that, the CB flags did not always correspond to the actual trading halt mechanisms currently put in place by the trading venue concerned.

In light of that, all the CB flags explicitly referred to as regulatory suspensions and technical halts were discarded. For the ambiguous cases (e.g. halt or market halt), on the best-effort basis, a crosschecking was performed between the CB flags reported in the Morningstar database with the trading rulebooks of the trading venues concerned. In this latter case, flags referring to halts that did not exist according to the trading venues' rulebooks were discarded.

Moreover, there were cases where trading venues reported the CB activation fields multiple times during the halting period, even if those pertained to only a single CB trigger event. In this case, our data extraction script was refined in order to select only the first CB event where it is reported consecutively in a given timeframe, decided on the basis of the average observed duration of a CB per trading venue³⁶. For example, if the venue XYZ reported that a CB lasted

³⁵ Refer to Figure 1 for the categorisation of trading halts.

³⁶ Refer to bullet point 6. For the methodology to calculate the exact duration

on average 2 minutes, only the first CB field was selected whenever it is reported consecutively for at least 2 minutes.

On the basis of the above script refinements, all CB events triggered over the period of analysis were extracted from the database of raw trade feeds.

3. Identification of instruments cross-listed and correlated to the halted ones.

In the third step, for all the CB events, correlated instruments to the halted ones were identified. The identification of the correlated instruments (cross-listed stocks and futures derivatives whose underlying is the halted stock) for each individual CB event was achieved based on the ISIN code of the stocks.

4. Extraction of the relevant market data

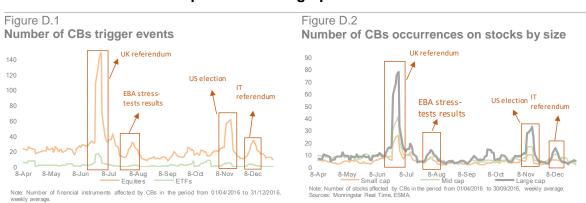
For every instrument hit by a CB event and for all the correlated instruments ones, the following market data needed for the empirical study were extracted:

- Price data: extraction of the best bid and best ask price;
- Order book data: extraction of the orders sent;
- Trade data: extraction of information on trades execution.
- *Trading period data*: extraction of the fields that categorise the trading phase (auction trading, continuous trading, pre-trading, etc...)

At the end of the extraction, it emerged that there were no relevant market data for the derivatives whose underlying stock was halted. Therefore, our final dataset comprises only market data for the instruments halted and for the cross-listed stocks.

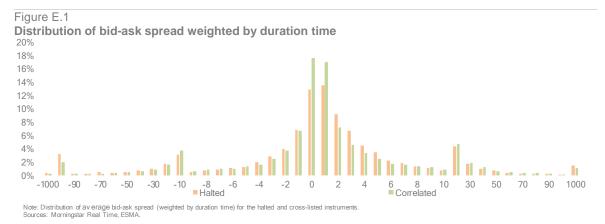
5. Calculation of the exact duration of circuit breakers

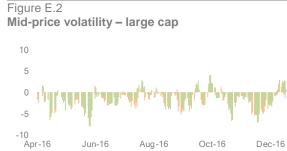
In step 5 CB duration time was estimated. For each trading venue and security type, the mechanisms at play to switch from the CB phase to a normal trading phase on the basis of the *trading period data* were analysed. On this basis, the appearance of any trading phase flag different from a CB flag defined the exact end of the CB.



Annex D. Additional descriptive statistics graphs

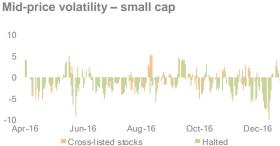






Cross-listed stocks Halted Note: One-week moving average of the difference of volatility after (10 minutes) and volatility before (10 minutes) the CB occurrences for the halted instruments (large caps) and correlated ones. The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of mid-prices divided by the average mid-price. Data in basis points. Sources: Morningstar Real Time, ESMA.

Figure E.4



Note: One-week moving average of the difference of volatility after (10 minutes) and volatility before (10 minutes) the CB occurrences for the halted instruments (small caps) and correlated ones. The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of mid-prices divided by the average mid-price. Data in basis points. Sources: Morningstar Real Time, ESMA.

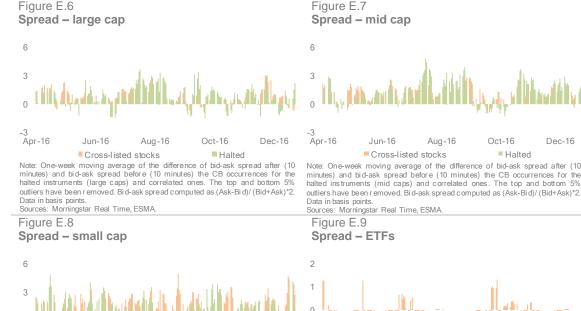


Note: O ne-week moving average of the difference of volatility after (10 minutes) and volatility before (10 minutes) the CB occurrences for the halted instruments (mid caps) and correlated ones. The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of mid-prices divided by the average mid-price. Data in basis points. Sources: Morningstar Real Time, ESMA.



lote: One-week moving average of the difference of volatility after (10 minutes) nd volatility before (10 minutes) the CB occurrences for the halted instruments ETFs). The top and bottom 5% outliers have been removed. Volatility computed s the standard deviation of mid-prices divided by the average mid-price. Data in asis points. ources: Morningstar Real Time, ESMA.

Figure E.5



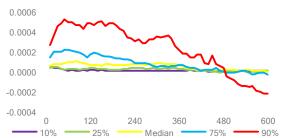


outliers have been removed. Bid-ask spread computed as (Ask-Bid)/ (Bid+Ask)*2. Data in basis points. Sources: Morningstar Real Time, ESMA.

Figure E.10

0

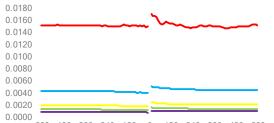
Std dev difference around a CB – halted stocks



Note: Distribution of the difference of the volatility after the CB minus the one observed before the CB, observed every 10 seconds between 10 minutes after and before the CB event (at 0 on the X-axis). Only halted instruments considered. Sources: Morningstar Real Time, ESMA.

Figure E.12

Spread developments in the 10 min interval around the CB - halted stocks



-600 -480 -360 -240 -120 0 120 240 360 480 600 10% 25% Median 75% 90% Note: Distribution of the average spread observed every 10s between 10 minutes before and after the CB event (at 0 on the X-axis) occuring on both the reference and the satellite markets. Only halted instruments considered. Sources: Morningstar Real Time, ESMA.



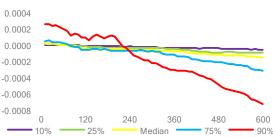
Halted Note: One-week moving average of the difference of bid-ask spread after (10 minutes) and bid-ask spread before (10 minutes) the CB occurrences for the halted instruments (mid caps) and correlated ones. The top and bottom 5%



Note: One-week moving average of the difference of bid-ask spread after (10 minutes) and bid-ask spread before (10 minutes) the CB occurrences for the halted instruments (ETFs). The top and bottom 5% outliers have been removed. Bid-ask spread computed as (Ask-Bid)/ (Bid+Ask)*2. Data in basis points. Sources: Morningstar Real Time, ESMA.

Figure E.11

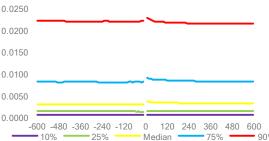
Std dev difference around a CB - cross-listed



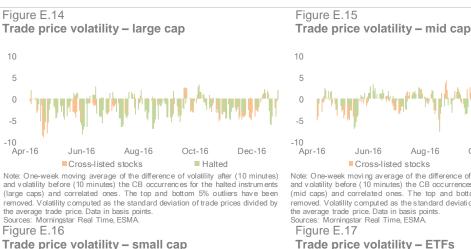
Note: Distribution of the difference of the volatility after the CB minus the one observed before the CB, observed every 10 seconds between 10 minutes after and before the CB event (at 0 on the X-axis). Only correlated instruments considered.

Sources: Morningstar Real Time, ESMA. Figure E.13

Spread developments in the 10 min interval around the CB - cross-listed



10% 25% Median 75% 90% Note: Distribution of the average spread observed every 10s between 10 minutes before and after the CB event (at 0 on the X-axis) occuring on both the reference and the satellite markets. Only correlated instruments considered. Sources: Morningstar Real Time, ESMA



10

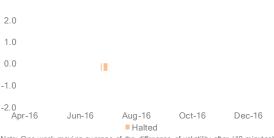


removed. Volatility computed as the standard deviation of trade prices divided by the average trade price. Data in basis points. Sources: Morningstar Real Time, ESMA.

Aug-16 Oct-16 Dec-16 Cross-listed stocks Halted

Note: One-week moving average of the difference of volatility after (10 minutes) and volatility before (10 minutes) the CB occurrences for the halted instruments (mid caps) and correlated ones. The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of trade prices divided by the average trade price. Data in basis points. Sources: Morningstar Real Time, ESMA.

Trade price volatility – ETFs



Note: One-week moving average of the difference of volatility after (10 minutes) and volatility before (10 minutes) the CB occurrences for the halted instruments (ETFs). The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of trade prices divided by the average trade price. Data in basis points. Sources: Morningstar Real Time, ESMA.

Table E.18 **CBs market effects**

| | | | Instrume | nts halted | | | Cross list | ed stocks |
|---------------------------------------|---------------------|-------------------|---------------------|---------------------------|----------------------------|--------------------|-------------------|---------------------|
| | All stocks | Small cap | Large cap | Low fragmen- tation | High fragmen- tation | ETFs | Small cap | Large cap |
| 10min standard deviation | -1.47 (-0.93)*** | -1.14 (-0.63)* | -3.51 (-2.99)*** | -0.67 (-0.39)** | -5.11 (-5.84)*** | -1.83 (-1.83) | -0.71 (1.45) | -2.38 (-1.75)*** |
| 5min standard deviation | -1.02 (1.19)*** | 1.48 (1.44)*** | -0.19 (-0.25) | 1.36 (1.29)*** | -0.61 (-1.69)* | -24.15 (-24.15) | 2.09 (2.39)*** | -0.68 (-0.4)*** |
| 2min standard deviation | 2.42 (2.01)*** | 3.70 (2.13)*** | 1.17 (0.83)* | 2.25 (2.06)*** | 4.70 (2.19)*** | 37.48 (37.48) | 3.87 (3.11)*** | 0.01 (0.02)** |

Note: The table presents mean (median) parameters before and after CB activation on the financial instruments in our sample. Standard deviation computed as the standard deviation of trade prices divided by the average trade price. The top and bottom 5% outliers have been removed. Significance levels are 1%(***), 5%(**) and 10%(*) for the Wilcoxon sign rank testing for the null hypothesis that samples are drawn from the same population.

Sources: Morningstar Real time, ESMA



Annex F. Additional graphs on CBs effects for selected trading venues

and volatility before (10 minutes) the CB occurrences for the halted instruments and correlated ones. The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of mid-prices divided by the average mid-price. Data in basis points. Sources: Morningstar Real Time, ESMA.

Figure F.3



Note: One-week moving average of the difference of volatility after (10 minutes) Note: One-week intoving average of the unreferice of volating after (10 minutes) to and volatility before (10 minutes) the CB occurrences for the halted instruments and correlated ones. The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of mid-prices divided by the average mid-price. Data in basis points. Sources: Morningstar Real Time, ESMA.

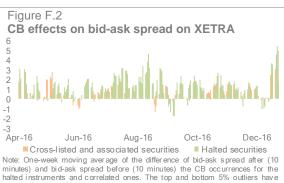
Figure F.5



Note: One-week moving average of the difference of volatility after (10 minutes) and volatility before (10 minutes) the CB occurrences for the halted instruments and correlated ones. The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of mid-prices divided by the average mid-price. Data in basis points. Sources: Morningstar Real Time, ESMA.



Cross-listed and associated securities Halted securities Note: One-week moving average of the difference of volatility after (10 minutes) and volatility before (10 minutes) the CB occurrences for the halted instruments and correlated ones. The top and bottom 5% outliers have been removed. Volatility computed as the standard deviation of mid-prices divided by the average mid-price. Data in basis points. Sources: Morningstar Real Time, ESMA



been removed. Bid-ask spread computed as (Ask-Bid)/ (Bid+Ask)*2. Data in

basis points

Sources: Morningstar Real Time, ESMA





Cross-listed and associated securities Halted securities Note: One-week moving average of the difference of bid-ask spread after (10 minutes) and bid-ask spread before (10 minutes) the CB occurrences for the halted instruments and correlated ones. The top and bottom 5% outliers have been removed. Bid-ask spread computed as (Ask-Bid)/ (Bid+Ask)*2. Data in basis points. Sources: Morningstar Real Time, ESMA.

Figure F.6



Note: One-week moving average of the difference of bid-ask spread after (10 minutes) and bid-ask spread before (10 minutes) the CB occurrences for the halted instruments and correlated ones. The top and bottom 5% outliers have been removed. Bid-ask spread computed as (Ask-Bid)/ (Bid+Ask)*2. Data in basis points

Sources: Morningstar Real Time, ESMA.



been removed. Bid-ask spread computed as (Ask-Bid)/ (Bid+Ask)*2. Data in basis points. Sources: Morningstar Real Time, ESMA.

Annex G. Robustness checks

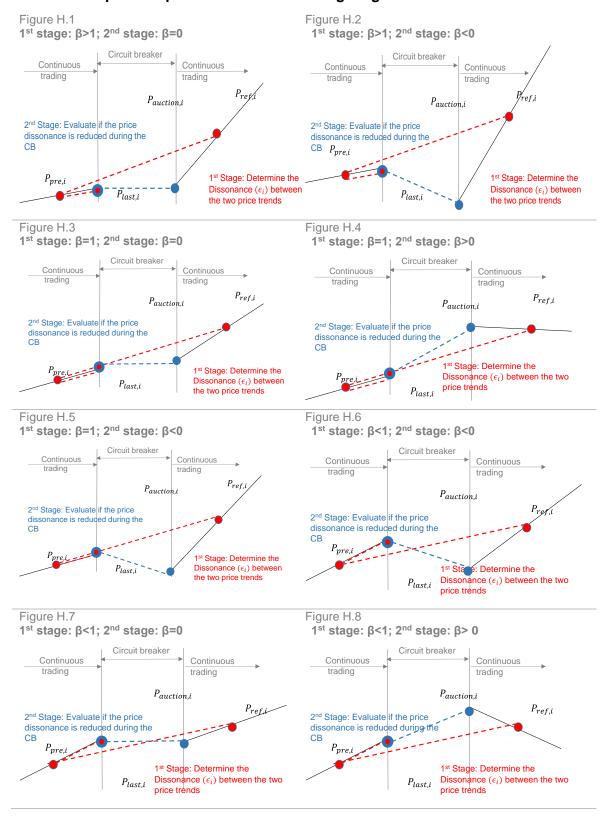
| Table G.1 - Robustne | ss checl | ks for s | stocks | | | | | | | | | |
|------------------------------------|----------|----------|--------|-----------------------------|-----|------|--------|---------|-------|-----------------------------|------|------|
| | | Bi | d-ask | spread | | | | | Vola | tility | | |
| | Halted | Instrur | nents | Cross-listed instruments | | | Halted | Instrun | nents | Cross-listed instruments | | |
| Trading venue | Count | Avg | Med. | Count | Avg | Med | Count | Avg | Med | Count | Avg | Med |
| Initial database of CB observation | 5737 | -19 | 0.2 | 23,226 | -10 | 0.0 | 5,737 | -7.5 | -1.6 | 23,226 | -6 | -1.5 |
| minus | | | | | | | | | | | | |
| first/last 15min of trading day: | 810 | -112 | -8.4 | 3,155 | -75 | -7.2 | 810 | -24 | -10.4 | 3,155 | -25 | -6.5 |
| Consecutive CBs within 10 minutes | 1,317 | -10.7 | -0.3 | 7,113 | -1 | 0.1 | 1,317 | -10.3 | -1.3 | 7,113 | -6 | -1.0 |
| Outliers - Top/Bottom 5% | 362 | -29.5 | -0.8 | 1,296 | -2 | 4.7 | 362 | -10.2 | -5.7 | 1,296 | -7 | -4.3 |
| Final database of CB observation | 3,248 | 0.8 | 1.0 | 11,662 | 1.7 | 1.5 | 3,248 | -1.7 | -1.0 | 11,662 | -1.7 | -0.9 |

Note: The table presents mean (median) parameters before and after CB activation on the ETFs in our sample. Standard deviation computed as the standard deviation of mid-prices divided by the average mid-price. Relative spreads computed as (Ask - Bid) / (Ask + Bid) * 2, then averaged weighting by the duration time. The top and bottom 5% outliers have been removed. Significance levels are 1%(***), 5%(**) and 10%(*) for the Wilcoxon sign rank testing for the null hypothesis that samples are drawn from the same population.

Sources: Morningstar Real time, ESMA.

| Table G.2 -Robustness checks for E | TFs | | | | | |
|------------------------------------|-------|-----------|------------|----------|------------|-------|
| | Bid | ask sprea | d. | | Volatility | |
| | | | Halted Ins | truments | | |
| Trading venue | Count | Avg | Med. | Count | Avg | Med |
| Initial database of CB observation | 342 | -1.48 | -0.08 | 342 | -2.47 | -0.41 |
| minus | | | | | | |
| first/last 15min of trading day: | 57 | -9.34 | -0.94 | 57 | -5.48 | -2.03 |
| Consecutive CBs within 10 minutes | 138 | 1.00 | 0.27 | 138 | -0.41 | -0.05 |
| Outliers - Top/Bottom 5% | 16 | -0.12 | -4.19 | 16 | -23.6 | -3.44 |
| Final database of CB observation | 131 | -1.35 | -0.22 | 131 | -0.90 | -1.00 |

Note: The table presents mean (median) parameters before and after CB activation on the ETFs in our sample. Standard deviation computed as the standard deviation of mid-prices divided by the average mid-price. Relative spreads computed as (Ask - Bid) / (Ask + Bid) * 2, then averaged weighting by the duration time. The top and bottom 5% outliers have been removed. Significance levels are 1%(***), 5%(**) and 10%(*) for the Wilcoxon sign rank testing for the null hypothesis that samples are drawn from the same population. Sources: Morningstar Real time, ESMA.



Annex H. Graphical representation of the 2-stage regression model

Annex I. Robustness checks for the 2nd stage regression

Table I.1

Price discovery process on halted instruments with positive error sign after 1st stage regression

| | J 1 | | | | | | | | | |
|----------------------|--------------|-------------------|--------------|------------------|--------------|-------------------|--------------|-------------------|--------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | All s | tocks | Sma | ll cap | Mid | l cap | Larg | e cap | Midday | auctions |
| VARIABLES | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| ln(Plast/ Ppre) | 1.02 | | 1.05 | | 1.09* | | 0.80*** | | 0.87*** | |
| res_all | (0.03) | 0.41*** (0.06) | (0.07) | | (0.05) | | (0.03) | | (0.05) | |
| res_small | | | | 0.26** (0.12) | | | | | | |
| res_mid | | | | | | 0.45*** (0.05) | | | | |
| res_large | | | | | | | | 0.18*** (0.05) | | |
| res_ETFs | | | | | | | | | | |
| res_mid- -dayauct | | | | | | | | | | 0.13*** (0.05) |
| Observations | 3,413 | 1,711 | 898 | 451 | 1,247 | 609 | 1,268 | 626 | 2,301 | 1,166 |
| R-squared | 0.75 | 0.33 | 0.77 | 0.13 | 0.77 | 0.45 | 0.73 | 0.11 | 0.45 | 0.01 |

Table I.2

Price discovery process on halted instruments with negative error sign after 1st stage regression

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|----------------------|--------------|-------------------|--------------|-------------------|--------------|-------------------|--------------|------------------|--------------|------------------|
| | All s | tocks | Sma | ll cap | Mid | сар | Large | e cap | Midday a | auctions |
| VARIABLES | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| ln(Plast/ Ppre) | 1.02 | | 1.05 | | 1.09* | | 0.80*** | | 0.87*** | |
| res_all | (0.03) | 0.28*** (0.04) | (0.07) | | (0.05) | | (0.03) | | (0.05) | |
| res_small | | (0.0.1) | | 0.28*** (0.05) | | | | | | |
| res_mid | | | | | | 0.37*** (0.06) | | | | |
| res_large | | | | | | | | 0.13** (0.06) | | |
| res_ETFs | | | | | | | | | | |
| res_mid- -dayauct | | | | | | | | | | 0.09** (0.03) |
| Observations | 3,413 | 1,702 | 898 | 447 | 1,247 | 638 | 1,268 | 642 | 2,301 | 1,135 |
| R-squared | 0.75 | 0.13 | 0.77 | 0.13 | 0.77 | 0.17 | 0.73 | 0.04 | 0.45 | 0.01 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1 Regression coefficients in the first stages have been tested for being significantly different than one. Regression coefficients in the second stages have been tested for being significantly different than zero.

Table I.3

Price discovery process on instruments correlated to the halted ones with positive error sign after 1st stage regression

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|----------------|-----------|-------------------|-----------|-------------------|-----------|-------------------|-----------|-------------------|
| | All s | tocks | Sma | ll cap | Mid | сар | Larg | le cap |
| VARIABLES | 1st stage | 2nd stage |
| In(Plast/ | 0.96* | | 1.09*** | | 1.01 | | 0.89*** | |
| Ppre) | (0.02) | | (0.02) | | (0.04) | | (0.02) | |
| res_corr_all | | 0.46*** (0.03) | | | | | | |
| res_corr_small | | | | 0.24*** (0.06) | | | | |
| res_corr_mid | | | | | | 0.49*** (0.07) | | |
| res_corr_large | | | | | | | | 0.50*** (0.03) |
| Observations | 12,957 | 6,438 | 2,447 | 1,217 | 4,115 | 1,986 | 6,395 | 3,186 |
| R-squared | 0.77 | 0.39 | 0.81 | 0.12 | 0.76 | 0.37 | 0.73 | 0.51 |

Table I.4

Price discovery process on instruments correlated to the halted ones with negative error sign after 1st stage regression

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| | All s | tocks | Sma | II cap | Mic | I сар | Larg | e cap |
| VARIABLES | 1st stage | 2nd stage |
| n(Plast/ | 0.96* | | 1.09*** | | 1.01 | | 0.89*** | |
| Ppre) | (0.02) | | (0.02) | | (0.04) | | (0.02) | |
| | | 0.32*** | | | | | | |
| res_corr_all | | (0.02) | | | | | | |
| | | | | 0.20*** | | | | |
| res_corr_small | | | | (0.05) | | | | |
| | | | | | | 0.36*** | | |
| res_corr_mid | | | | | | (0.03) | | |
| | | | | | | | | 0.37*** |
| res_corr_large | | | | | | | | (0.06) |
| Observations | 12,957 | 6,519 | 2,447 | 1,230 | 4,115 | 2,219 | 6,395 | 3,209 |
| R-squared | 0.77 | 0.21 | 0.81 | 0.08 | 0.76 | 0.28 | 0.73 | 0.25 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Regression coefficients in the first stages have been tested for being significantly different than one. Regression coefficients in the second stages have been tested for being significantly different than zero.

| Та | bl | е | 1.5 |
|----|----|---|-----|
|----|----|---|-----|

Price discovery process on intermarket cases with positive error sign after 1st stage regression

| | | | | - | | 0 | | 0 0 | | |
|-------------------------------|--------------------|--|-------------------|--|--|---------------------|--|-------------------|-------------------------------|---|
| | (1) | (2) | (5) | (6) | (3) | (4) | (7) | (8) | (9) | (10) |
| | Re | ference ma | arket is ha | lted | | s | atellite mar | ket is halte | d | |
| | stocks t the re | cts on raded on ference irket | cross stocks t | cts on -listed raded on markets | Effect or traded satellite n ha | on the narket on | Effect cross-list traded referenc | ed stocks | cross stocks to other s | on the -listed raded on atellite kets |
| VARIABLES | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| In(Plast/ Ppre) | 1.06* (0.03) | | 1.04 (0.03) | | 0.84*** (0.04) | <u> </u> | 1.03 | 0 | 0.91*** (0.02) | |
| res_halt_ref | | 0.20*** (0.05) | | | | 0.53*** | | | | |
| res_halt_sat | | | | | | (0.07) | | | | |
| res_corr_haltonREF | | | | 0.29*** (0.05) | | | | | | |
| res_corr_haltSAT_trade REF | | | | | | | | 0.59*** (0.04) | | |
| res_corr_haltSAT_trade SAT | | | | | | | | | | 0.60*** (0.04) |
| Observations R-squared | 2,225 0.77 | 1,114 0.14 | 6,044 0.76 | 2,956 0.17 | 1,188 0.71 | 585 0.39 | 1,106 0.68 | 542 0.69 | 5,807 0.71 | 2,912 0.63 |

Table I.6

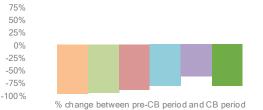
Price discovery process on intermarket cases with negative error sign after 1st stage regression

| | (1) Re | (2) ference ma | (5) arket is ha | (6) Ited | (3) | (4) S | (7) atellite marl | (8) ket is halte | (9) d | (10) |
|-------------------------------|--|-------------------|--|-------------------|---|--------------|---|---------------------|---------------|-------------------|
| | Effects on Effects on stocks traded on cross-listed the reference stocks traded on market satellite markets | | Effect on stocks traded on the satellite market on halt | | Effect on the cross-listed stocks traded on the reference market | | Effect on the cross-listed stocks traded on other satellite markets | | | |
| VARIABLES | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| ln(Plast/ Ppre) | 1.06* | | 1.04 | | 0.84*** | | 1.03 | | 0.91*** | |
| | (0.03) | | (0.03) | | (0.04) | | (0.05) | | (0.02) | |
| | | 0.22*** | | | | | | | | |
| res_halt_ref | | (0.04) | | | | | | | | |
| | | | | | | 0.76*** | | | | |
| res_halt_sat | | | | 0 0 4 * * * | | (0.18) | | | | |
| res_corr_haltonREF | | | | 0.21*** (0.03) | | | | | | |
| res_corr_haltSAT_trade REF | | | | | | | | 0.56*** | | |
| | | | | | | | | (0.04) | | |
| res_corr_haltSAT_trade SAT | | | | | | | | | | 0.55*** (0.05) |
| Observations R-squared | 2,225 0.77 | 1,111 0.11 | 6,044 0.76 | 3,088 0.09 | 1,188 0.71 | 603 0.38 | 1,106 0.68 | 564 0.53 | 5,807 0.71 | 2,895 0.43 |

Regression coefficients in the first stages have been tested for being significantly different than one Regression coefficients in the second stages have been tested for being significantly different than zero.

Annex J. Additional graphs and table on the intermarket cases

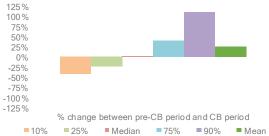




10% 25% Median 75% 90% Mean Note: Selection of centiles describing the % of change in the number of orders submitted between the pre- and actual CB period for cross-listed stocks traded on a satellite market while the reference market is halted. Sources: Morningstar Real Time, ESMA.

Figure J.3

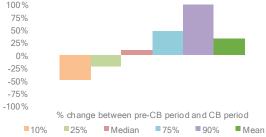
Order submission pre-CB - Cross-listed traded on reference market - halted on satellite



Note: Selection of centiles describing the % of change in the number of orders submitted between the pre- and actual CB period for cross-listed stocks traded on the reference market while a satellite market is halted. Sources: Morningstar Real Time, ESMA.

Figure J.5

Order submission pre-CB – Cross-listed traded on satellite markets - halted on satellite



Note: Selection of centiles describing the % of change in the number of orders submitted between the pre- and actual CB period for cross-listed stocks traded on a satellitemarket while a satellite market is halted. Sources: Morningstar Real Time, ESMA.

Figure J.2

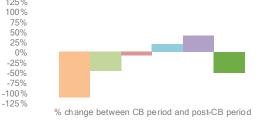
Order submission post-CB – Cross-listed traded on satellite - halted on the reference market



Note: Selection of centiles describing the % of change in the number of orders submitted between the actual and post-CB period for cross-listed stocks traded on a satellite market while the reference market is halted. Sources: Morningstar Real Time, ESMA.

Figure J.4

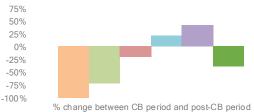




10% 25% Median ■75% ■90% Mean Note: Selection of centiles describing the % of change in the number of orders submitted between the actual and post-CB period for cross-listed stocks traded on the reference market while a satellite market is halted. Sources: Morningstar Real Time, ESMA.

Figure J.6

Order submission post-CB – Cross-listed traded on satellite markets - halted on satellite 100%



■ 25% ■ Median ■ 75% ■ 90% Mean

10% Note: Selection of centiles describing the % of change in the number of orders submitted between the actual and post-CB period for cross-listed stocks traded on a satellitemarket while a satellite market is halted. Sources: Morningstar Real Time, ESMA.

Table J.7

Market effects around CB on intermarket cases

| | Reference m | arket is halted | Satellite market is halted | | | |
|--------------------------------|--|--|--|--|---|--|
| | Effects on stocks traded on the reference market | Effect on cross- listed stocks traded on satellite markets | Effect on stocks traded on the satellite market on halt | Effect on the cross-listed stocks traded on the reference market | Effect on the cross-listed stocks traded on other satellite markets | |
| 10min standard deviation | -1.81 (-0.94)*** | -1.28 (-0.66)*** | -1.57 (-0.70)*** | -1.69 (-0.84)*** | -1.99 (-0.89)*** | |
| 5min standard deviation | 0.09 | 0.82 | -0.98 | -0.91 | -1.39 | |
| | (0.16) | (0.62)*** | (0.14)*** | (-0.50)*** | (-0.39)*** | |
| 2min standard deviation | 0.60 | 1.21 | 0.13 | -0.16 | -0.58 | |
| | (0.26) | (0.25)*** | (0.45) | (-0.15)*** | (-0.01)*** | |
| 10min relative spread | 0.96 | 3.14 | -0.54 | -0.06 | 0.73 | |
| | (1.03)*** | (3.38)*** | (2.8)*** | (0.02)** | (0.73)*** | |
| 5min relative spread | 1.65 | 5.09 | 1.24 | 0.09 | 1.48 | |
| | (1.63)*** | (5.06)*** | (3.23)*** | (0.12)** | (0.79)*** | |
| 2min relative spread | 2.5 | 7.47 | 4.42 | 0.15 | 2.13 | |
| | (2.40)*** | (7.19)*** | (5.36)*** | (0.16)*** | (1.61)*** | |

Note: The table presents mean (median) parameters before and after CB activation on the financial instruments in our sample. Standard deviation computed as the standard deviation of mid-prices divided by the average mid-price. Relative spreads computed as (Ask - Bid) / (Ask + Bid) * 2. The top and bottom 5% outliers have been removed. Significance levels are 1%(***), 5%(**) and 10%(*) for the Wilcoxon sign rank testing for the null hypothesis that samples are drawn from the same population. Data expressed in basis points.

Table J.8

Market effects around CB on intermarket cases

| | Reference m | arket is halted | Satellite market is halted | | | |
|--------------------------------|--|--|--|--|---|--|
| | Effects on stocks traded on the reference market | Effect on cross- listed stocks traded on satellite markets | Effect on stocks traded on the satellite market on halt | Effect on the cross-listed stocks traded on the reference market | Effect on the cross-listed stocks traded on other satellite markets | |
| 10min standard deviation | -1.36 (-1.01)*** | -1.45 (-0.77)*** | -3.54 (-2.08)*** | -1.83 (-0.90)*** | -2.33 (-1.17)*** | |
| 5min standard deviation | 1.12 (1.14)*** | 1.57 (1.65)*** | -2.34 (1.50)*** | -0.97 (-0.45)*** | -1.30 (-0.30)*** | |
| 2min standard deviation | 2.3 (1.86)*** | 3.38 (2.24)*** | 9.47 (5.93)*** | -0.43 (-0.10)*** | -0.15 (-0.12)*** | |

Note: The table presents mean (median) parameters before and after CB activation on the financial instruments in our sample. Standard deviation computed as the standard deviation of trade prices divided by the average trade price. The top and bottom 5% outliers have been removed. Significance levels are 1%(***), 5%(**) and 10%(*) for the Wilcoxon sign rank testing for the null hypothesis that samples are drawn from the same population. Data expressed in basis points.

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