Price Discovery in European Volatility Interruptions

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Abstract

We study a special form of securities market circuit breaker, i.e., European volatility interruptions. Instead of halt trading like traditional circuit breaker, these short-living call auctions allow for continual price discovery after price limit hits. Based upon approximately 1,800 Xetra volatility interruption events from 01/2009 to 01/2012, we empirically assess whether such auctions contribute to price uncertainty resolution and how they influence post-auction continuous trading. We find that volatility interruptions dissolve on average 36 percent of the pre-interruption price uncertainty. In addition, our results provide strong indications that this level of price discovery is a major determinant in shaping post-interruption market quality as subsequent continuous trading benefits conditionally on the price discovery contribution of the interruption. By analyzing drivers of volatility interruption price discovery, our results give indications that in contrast to a prolongation of the call phase, foremost traders' participation does promote the auction's ability to display a price relevant for future trading.

Keywords: Circuit Breaker, Volatility Interruptions, Price Discovery, Europe

JEL Classification: G14, G15, G18, G28

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Introduction

Current discussions on stricter regulation of securities trading mainly reflect fears of market crash scenarios initiated by malfunctioning algorithm systems or investors' price overreactions. Otcchere and Chan (2003) have found short-term investors to be especially prone to price overreactions in times of market distress. Price overreactions may create undesired excessive volatility further catalyzing price uncertainty and asymmetric information (Madhavan, 1995). Similar, malfunctioning trading algorithms are found to create order imbalances and sudden price drops if adjusted improperly like in the 2010 U.S. Flash Crash (Kirilenko, Kyle, Samadi, & Tuzun, 2011). One common approach that attained endorsement in the eyes of exchanges and regulators in order to prevent market turmoil, deal with excessive volatility and foster market integrity has been the introduction of so-called securities market circuit breaker and volatility interruptions.

Circuit breaker bring continuous trading to a halt by suspending order matching for a certain amount of time if a predetermined price limit is exceeded. Thus, they allow for additional time to reevaluate the current market situation and prohibit disequilibrium trading that would otherwise take place in the non-halt period (Lee, Ready, & Seguin, 1994). However, during this suspension period, no multilateral price coordination or determination is possible until trading continues. Although such mechanisms have proven their utility during the 2010 U.S. Flash Crash, critics claim that such measures represent an unnecessary impediment for trading by postponing price discovery and delaying price changes to subsequent periods. Lee et al. (1994) find volatility after such halts increased by 50 to 115 percent compared to price-matched pseudo-halt situations and likewise increased trading volumes in subsequent periods. Moreover, Cho, Russell, Tiao, and Tsay (2003) find pre-halt stock prices to accelerate towards the circuit breaker price limits, indicating that such measures rather facilitate price distortion than lower price uncertainty. In particular, Corwin and Lipson (2000) argue that the lack of liquidity surrounding the halt causes abnormal volatility.

In contrast Christie, Corwin, and Harris (2002) conclude that foremost increased information transmission during such halt situations could result in reduced post-halt uncertainty as traders are able to coordinate their evaluations right in the situation of the halt. This assumption is in line with the theoretical model of Madhavan (1995). Like Otcchere and Chan (2003), he argues that although continuous markets show higher levels of price efficiency during normal trading activity, they are prone to asymmetric information during periods of price uncertainty. Traditional circuit breaker, that rely on a halt, may intensify this problem as price communication is interrupted and coordination is not possible. Instead, he proposes a temporary switch to a call auction in order to allow for information exchange.

Within the European securities market system, exchange-based circuit breaker are implemented as call auctions, so-called volatility interruptions. In contrast to halt trading, these mechanisms switch to short-lived and non-discretionary call auctions lasting only a few minutes. As market participants can continue price discovery in the auction's open call phase, exchange operators claim that such measures could initiate a return to smooth and orderly trading by dissolving price uncertainty.

Proponents further argue that the auction mechanism could likewise provide time for market participants to reevaluate and coordinate prices among themselves and subsequently reduce successive information asymmetries. However, in regard of the ongoing academic discussion, the effectiveness of volatility interruptions remains disputed and the European Securities Market Authority and likewise the Securities and Exchange Commission call for further empirical evidences (EuropeanCommission, 2010). Critics claim that even volatility interruptions are followed by excessive price changes and increased information asymmetries in the subsequent periods (Abad & Pascual, 2010). In such cases, the switch to a call auction fails to restore trading conditions, does only provide limited price discovery and additionally postpones volatility to the near future. Therefore, volatility interruptions may not contribute to post-auction trading but only impede continuous trading price discovery.

Further fueling this debate, empirical work covering various markets and time periods shows diverging effects on post-interruption volatility, supporting arguments on both sides. Basher, Hassan, and Islam (2007) applied stock-wise GARCH volatility estimation, indicating that although some stocks are followed by decreased price uncertainty, others indicate significantly increased price uncertainty. This dissent is further driven by the lack of a distinct causal coherence between the volatility interruption itself and subsequent market uncertainty levels. As most studies rely on a variety of pre- and post-event market condition comparisons, the subsequent changes in market quality can also be explained by manifold unobserved parameters like rapidly changing trading activity, leaving the impact of the volatility interruption spurious. Additionally, volatility changes conditional to auction results are, so far, not analyzed but would allow for a detailed impulse-response analysis.

In this paper we therefore focus on the volatility interruption's auction itself and its relevance and contribution to price discovery and subsequent market conditions. In particular, we pose the following three questions motivated by the previous introduction. At first, we investigate whether and to what extent volatility interruptions contribute to price uncertainty resolution. We therefore conduct an empirical two-step analysis based on a data sample of approximately 1,800 volatility interruptions of Deutsche Boerse's electronic trading platform Xetra during 2009 and 2012. We empirically show that volatility interruptions are able to dissolve an average of 36 percent of the pre-interruption price uncertainty which is about the same amount observable in traditional Xetra midday auctions. We therefore conclude that volatility interruptions provide incremental price discovery contribution. Within the second question, we strive to answer if this contribution is shaping post-interruption continuous trading by evaluating whether subsequent trading benefits from the auction's price discovery. By applying Xetra midday auctions as a control group, we find that each incremental contribution to price discovery lowers subsequent continuous trading price volatility and market risk compensation. Most interesting, this tranquillizing effect on subsequent price volatility is especially distinct after volatility interruptions compared to midday auctions. In contrast, participants' adaption of their market risk compensation, the order book spread level, happens in accordance with their adaption to price discovery in midday auctions. We therefore conclude that volatility interruptions essentially conduce to a return to smooth and orderly trading if they are able to indicate a price signal that is relevant for future trading. At last, we seek to find the major drivers for price discovery efficacy. Our results give indication that increased participation in volatility interruptions does promote price discovery during the auction.

This paper is structured as follows: At first, we give an overview on the European volatility interruption mechanism, especially at the Deutsche Boerse Xetra system, which is the basis of our data set. Secondly, we propose our empirical setup and approach. At last we will discuss our results and conclude.

European Volatility Interruption Details

The European regulatory bodies so far have neither addressed harmonization nor requirements for circuit breaker or volatility interruption mechanisms in European trading venues. Therefore, neither European Regulated Markets nor Multilateral Trading Facilities are forced to implement such mechanisms on a European level, unless national requirements exist (e.g. German High-Frequency Trading Law). Besides, various European trading venues provide in-house implementations based on very similar volatility interruption models as listed by Gomber, Lutat, Haferkorn, and Zimmermann (2011).

In general, these volatility interruptions apply price bands, allowing trades to be matched in continuous trading within a pre-determined price corridor around a given reference price throughout the trading day. Price bands are normally based on static, i.e., last auction price, or dynamic, i.e., last trade price, reference prices or a combination of both. Therefore, trades are allowed at prices within a symmetrical corridor around the last trade price or last auction price. All European mechanisms are based on such price bands differing only in their reference price specifications and corridors. Whenever such a price band is potentially exceeded by an execution, the current market phase switches to a call auction (volatility interruption / volatility auction). During the indicative phase of this volatility auction traders can continue to submit, cancel and modify orders comparable to regular open-, midday- and close-auctions. The indicative phase is heterogeneously set by each exchange lasting from 2 minutes till up to 15 minutes plus potential random extension if needed. In the case the indicative price lies outside a predetermined range at the end of the call phase, the volatility auction is generally prolonged (extended volatility interruption) until this condition is satisfied. Subsequently, continuous trading restarts with the auction allocation price (Gomber et al., 2011).

Our data sample comprises Deutsche Boerse Xetra volatility interruptions which are applied for each stock traded at the Xetra trading system and follow the aforementioned rules (DeutscheBoerse, 2011). Additionally, market participants at Xetra are notified by this change in the market situation and are therefore aware of the current volatility auction which generally ends after a period of 3 minutes (for DAX/STOXX component shares) (DeutscheBoerse, 1999). Noteworthy within the Xetra market model, Deutsche Boerse obliges the respective share's designated sponsors, i.e., market makers, to contribute and maintain quoting during the call phase thereby adding further liquidity in such situations. Within the next subsection we will give further insights into our volatility interruption sample.

Data Set

We rely on Thomson Reuters Tick History data comprising tick-by-tick order book and execution information for stocks traded at Deutsche Boerse's electronic trading system Xetra. Deutsche Boerse Xetra data comprise trade-by-trade flags for trading phase changes. Most important, in the case of Xetra, Thomson Reuters additionally reports indicators for volatility interruptions for each stock in the time the flag was available. Therefore, we are able to identify every volatility interruption within each stock with millisecond-precise start and end time. Further, the indicator flags allocation price and volume information for each volatility interruption allowing for a cross-sectional analysis of every event. We are therefore able to provide an in-depth analysis of each interruption as well as the respective effect on subsequent continuous trading. Additionally, Thomson Reuters reports changes in the indicative price and volume throughout the auction's call phase relevant for determining the call progress within our last research question. Although Xetra volatility interruptions are active the whole trading day, such events are rare. We therefore rely on German blue chip constituents of the DAX 30 in the years of 2009, 2010, 2011 and early 2012 in order to ensure that enough events are available for the empirical analysis. To be valid for analysis, each interruption must not collide with Xetra open-, mid- or closing-auctions as otherwise intervening biases cannot be excluded. In such situations both auctions are not distinguishable anymore as they blend into each other. In order to be able to further add and compare pre- and post-interruption market conditions, we demand a symmetrical ten minute window of orderly trading before and after each volatility interruption. This approach also excludes double hits, i.e., repeatedly triggered volatility interruptions within a short amount of time. However, only double hits within ten minutes after a volatility interruption are excluded which are fairly rare (four events). We additionally exclude three outliers where the interruption lasts only a fraction of a second or where no auction statistics where provided by Thomson Reuters. This leaves 1,817 volatility interruptions in 32 stocks included in our analysis. Maximum/Minimum number of volatility interruptions per stock is 145/13 (Commerzbank AG/Beiersdorf AG - mean 57) with 23 interruptions in one single day covering 21 stocks (10.08.2011 - Table 1). We collect order book and execution statistics before and after each event in order to measure changes within trading intensity, activity and market quality parameters. Table 1 provides descriptive sample statistics.

Table 1: DESCRIPTIVE STATISTICS

Descriptive results for the volatility interruption sample of 1,817 observations and midday auction sample of 7,690 observations as well as aggregated market quality measures ten minutes before (Pre) and after (Post) the interruption. The sample captures 32 DAX stocks in the years of 2009 to 2012 traded at Deutsche Boerse's electronic order book Xetra. Market quality parameters involve the number of trades (Number of Trades), executed volumes in shares (Executed Volume), Depth(X) measure in accordance to Degryse et al. (2011) ten basis points around the order book midpoint, relative spread (Relative Spread), order book midpoint standard deviation (M. Std. Dev.) and the highest-to-lowest execution price ratio (High-to-Low).

Volatility Interruptions - 1,817 Observations				
	Mean	Std. Dev.	Min.	Max.
Interruptions per Day (#)	3.5	3.3	1.0	23.0
Interruptions per Stock (#)	56.8	36.0	13.0	145.0
Duration (in sec.)	143.3	25.0	119.0	460.0
Executed Volume	26,016.5	73,886.0	3.0	1,326,478.0
Auction Return (in %)	- 0.0130	0.4241	- 5.2500	2.4735
Market Quality around Volatility Interruptions				
	Pre Mean	Post Mean	Pre Std. Dev.	Post Std. Dev.
Number of Trades	292.6	348.9	287.2	340.1
Executed Volume	332,602.6	417,849.3	811,328.6	937,608.3
Depth(10)	9,738.3	9,130.8	26,570.1	24,432.2
Relative Spread (in %)	0.0014	0.0016	0.0016	0.0018
M. Std. Dev.	0.1288	0.1107	0.2674	0.2563
High-to-Low	1.0127	1.0107	0.0101	0.0081
Midday Auctions - 7,690 Observations				
	Mean	Std. Dev.	Min.	Max.
Duration (in sec.)	179.1	92.0	120.0	833.0
Executed Volume	52,602.1	350,647.7	1.0	13,320,623.0
Auction Return (in %)	0.0031	0.0012	- 0.8750	1.5078
Market Quality around Midday Auctions				
	Pre Mean	Post Mean	Pre Std. Dev.	Post Std. Dev.
Number of Trades	55.3	65.5	55.0	62.3
Executed Volume	35,050.1	43,416.2	73,394.1	75,699.7
Depth(10)	6,264.7	6,147.5	10,020.0	10,197.5
Relative Spread (in %)	0.0006	0.0006	0.0003	0.0003
M. Std. Dev.	0.0264	0.0258	0.0926	0.0239
High-to-Low	1.0019	1.0023	0.0013	0.0016

Descriptive statistics in Table 1 indicate that the average volatility interruption lasts about 143 seconds with an average executed amount of 26,017 shares at a slightly negative volatility auction return of -0.013%. The shortest interruption only lasts for two minutes, whereas the longest for about seven minutes, indicating that our sample also comprises extended interruptions. We additionally depict mean market quality statistics during the pre- and post-volatility interruption periods, i.e., the ten minutes before and after each event. Namely, we compute number of executed trades, number of shares traded, order book depth level in accordance to Degryse et al. (2011), Depth(10). Depth(10) indicates the amount of order book liquidity ten basis points around the midpoint. We further calculate the respective order book's mean ten minute relative bid-ask spread, i.e., the difference between the best bid and best ask offer relative to the order book midpoint. The bid-ask spread represents a measure for the risk premium market participants require for being exposed to market risk, i.e., unexpected price fluctuations, while providing liquidity to the market (Harris, 2003). High variability in asset prices indicates large uncertainty about the fundamental value of the underlying asset, thus alienating an investor's valuation opportunity and potentially resulting in incorrect investment decisions when price variability is high (Harris, 2003). We obtain the order book midpoint standard deviation for the respective time windows. In contrast to execution price standard deviation, not every bid and ask execution is incorporated into this measure, so it could be considered more robust towards ordinary trading activity changes. In order to measure maximum price changes within respective periods we additionally rely on a high-to-low measure comparable to Abad and Pascual (2010). In contrast to the midpoint standard deviation, this measure only incorporates the highest and lowest prices of each period and therefore accounts for the maximum price movement within each time window (Abad & Pascual, 2010). The descriptive, unconditional comparison of these measures in Table 1 indicates that the average volatility interruption is followed by slightly reduced price uncertainty (M. Std. Dev. and High-to-Low), whereas market participants demand slightly increased compensation for market risk (Relative Spread). According to K. Kim and Rhee (1997) decreased price variability may indicate that price discovery has continued between both periods. Alongside, trading intensity and activity after the average volatility interruption have increased, while order book depth seems to retain at lower levels. Figure 1 shows the volatility interruption occurrence distribution over the course of the observation years.

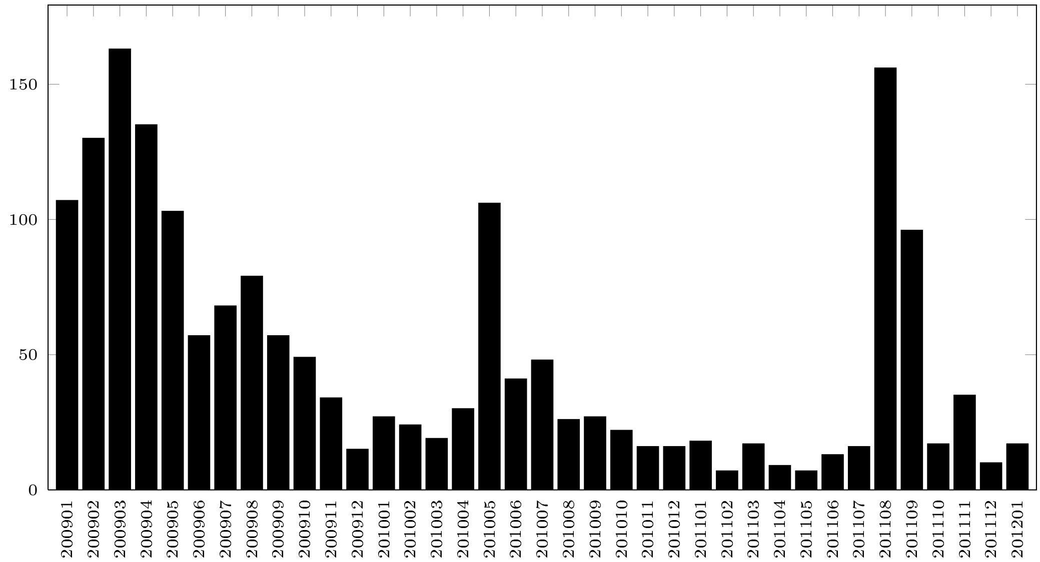

Figure 1. Total Volatility Interruption Occurrence per Month of Observation

In the following section, we will analyze price discovery contribution as well as market quality relevance of volatility interruptions. In order to compare these results to a benchmark, we apply a control group to evaluate the relative magnitude of the respective effects. We therefore rely on Xetra midday auctions within each analyzed stock for every available trading day in the year of 2010. Within the Xetra market system, midday auctions, likewise open and close auctions, show high similarities to the volatility interruption mechanism concerning the auction duration as well as general submission, cancellation and modification possibilities (DeutscheBoerse, 2011). However, midday auctions are triggered always at the same time of the day and not due to threshold breaches. We acquire midday auction and likewise ten minute pre- and post-auction market quality statistics comparable to the volatility interruption subsample. Descriptive summaries are depicted in the lower section of Table 1. Unconditional comparison indicates that market activity, i.e., number of trades and volumes, surrounding the average volatility interruption is far more intensive compared to the average midday auction. Likewise, volatility and spread levels around volatility interruptions tend to be higher/wider than in the control sample supporting the findings of French and Roll (1986), Karpoff (1987) as well as Schwert (1989) that market volatility and spread levels are correlated to respective market intensity levels. Since we do not rely on a pre-post-period comparison, these differences in trading activity and market quality between interruption and midday sample are far less restrictive. However, we will perform each analysis on the mere volatility interruption sample and repeat it on the aggregated volatility interruption and midday auction sample additionally controlling for systematic differences.

Empirical Study

In this section, we summarize our empirical approach, directed to evaluate the effect and efficacy of Xetra volatility interruptions in terms of dissolving price uncertainty and transitory market risk. We start with a general evaluation of the interruption's ability to provide incremental price information by analyzing price discovery during volatility interruptions based on the methodology of Corwin and Lipson (2000). In the second step, we test whether and how this contribution is reflected in subsequent continuous trading market conditions, i.e., if continuous trading benefits from price discovery achieved during the volatility interruption. At last, we will provide a basic setup to test for major determinants of volatility interruption price discovery efficacy.

Price Discovery during Volatility Interruptions

Considering the evaluation of information processing and price discovery during the volatility interruption, we apply the modified two-stage regression methodology of Chakrabarty, Corwin, and Panayides (2011) based on the fundamentals of Corwin and Lipson (2000). The aim of this approach is to evaluate the unique and likewise incremental contribution to price informativeness during the interruption. This way we show that interruption results provide additional information to market participants lowering pre-interruption price uncertainty. In the first stage of this approach, we evaluate the amount of pre-interruption price uncertainty prevailing in the market immediately before the volatility interruption. We assume prices, prior to the volatility interruption to be considered more uncertain, the more they progress in incoherency to a future post-interruption reference price level. That is, a drop in prices prior to the interruption is not considered distorted if the drop is likewise persistently pursuing after the auction. However the more this trend is reverted after the interruption the more prices are considered uncertain. Chakrabarty et al. (2011) estimate this dissonance via the following cross-sectional approach:

$$Stage1 : \ln \frac{P_{ref,i}}{P_{pre,i}} = \alpha_1 + \beta_1 * \ln \frac{P_{last,i}}{P_{pre,i}} + \epsilon_i \tag{1}$$

In contrast to Corwin and Lipson (2000) who choose the price one hour before/after the halt as pre-interruption/reference price, we rely on ten minute average midpoints. In our case P_{pre} is the pre-interruption reference price, the ten minute average order book midpoint before the volatility interruption, P_{ref} the future post-volatility auction reference price level, respectively in our case the ten minute average order book midpoint and P_{last} the last price before the interruption was triggered. Compared to Corwin and Lipson (2000), our interruptions only last for approximately two minutes (Corwin and Lipson (2000) - 81 minutes), so we cannot assume prices within one hour to be affected by the two minute interruption. Further, taking a single price as reference is strongly restrictive, especially considering that the difference between bid and ask price has a large impact in our case as prices do not move quite far within the ten minutes after the interruption. We therefore rely on the ten minute average midpoint. According to Chakrabarty et al. (2011), if the pre-interruption price developments are perfectly anticipating the future reference price level, the intercept of this regression will be zero, the slope will be one, and subsequently the R-square will be one and residuals zero. In this case the market situation in the pre-interruption phase is not considered uncertain at all. If, on the other hand, the P_{pre} provides no information about the future price, the slope and R-square will equal zero, and the intercept will equal the mean pre- to post-interruption reference midpoint return. A slope coefficient β_1 greater than (less than) one suggests that the pre-auction prices tend to undershoot (overshoot) the future reference price level.

Particularly interesting is the residual component ϵ_i of the first stage regression, since it contains the unsystematic dissonances between both returns which cannot be explained by the average linear approximation. Therefore, the larger the dissonances between future reference price and pre-interruption return, the lager the respective residuals will become. In the second stage, we test to which magnitude this dissonance is reverted by the volatility auction return, i.e., if the auction return provides incremental explanatory power capable of dissolving the return dissonances. We therefore regress the volatility auction return on the residuals of the first-stage regression. The second-stage regression takes the following general form:

$$Stage2: \ln \frac{P_{auction,i}}{P_{last,i}} = \alpha_2 + \beta_2 * \epsilon_i + \eta_i \tag{2}$$

Where ϵ_i are the residuals of the first-stage regression and $P_{auction}$ the respective auction allocation price. In the second-stage regression β_2 represents the average incremental price discovery fraction of the volatility interruption. If the volatility auction return is perfectly resolving price uncertainty, we would expect the intercept equal to zero, the slope β_2 to be one, i.e., 100 percent, and again the R-square to be one. β_2 within this regression can therefore be interpreted as fraction of resolved price uncertainty due to the volatility interruption. A negative slope coefficient however, would indicate a systematic aggravation of the price uncertainty through the interruption. The results are illustrated in Table 2. We find the slope coefficient in the first-stage regression β_1 to be

Table 2: PRICE DISCOVERY REGRESSION DURING THE VOLATILITY INTERRUPTION

Regression results based on the two stage ordinary least squares regression approach of Corwin and Lipson (2000) on price discovery during the volatility interruption. Table 2 shows coefficients obtained from regression (1) and (2) respectively based on the 1,817 volatility interruptions of German blue chips stocks traded at Deutsche Boerse Xetra. Values in parenthesis indicate P-values. Control group regression (3) depicts regression results on the second step approach based on the combined volatility interruption and midday auction subsample. The slope coefficient at this stage represents the difference of the midday auction subsample slope compared to the volatility interruption second stage regression slope (2). We apply robust variance estimates following the MacKinnon and White approach.

	Intercept	Slope	R^2	N	Prob > F
First Stage Regression (1)	0.0000 (0.889)	1.002 (0.000)	0.7046	1,817	0.0000
Second Stage Regression (2)	-0.0001 (0.113)	0.3593 (0.000)	0.2599	1,817	0.0000
Control Group Regression (3)	0.0000 (0.005)	0.0621 (0.114)	0.2572	9,507	0.0000

significantly larger zero. This result indicates that prices before the interruption tend towards the reference price and therefore the average price distortion does not seem to be too vast on average. As of the second-stage regression, the slope coefficient is significantly positive and smaller one. Overall, the results in stage two provide evidence that the volatility auction return provides incremental contribution to price discovery narrowing pre-interruption prices towards the respective future reference price. In particular, the results show that about 36 percent (β_2) of the existing price dissonances are reverted during the volatility interruption. On the one hand, these results subsequently indicate that the majority of price discovery is postponed to continuous trading. On the other hand, it raises the question whether 36 percent are a considerable amount worth switching to an auction, especially if the magnitude of price uncertainty is apparently postponed. To answer this question and increase generalizability, we re-run the two-stage approach based on a control group in order to determine if volatility interruption within tense market situations show abnormal behavior in dissolving price uncertainty. Because of this control sample we are able to test if price discovery during volatility interruptions is comparable to price discovery within midday auctions. We report the second stage regression results within Table 2 (3) of the aggregated volatility interruption and midday auction sample. In this stage, the coefficient only determines the difference between the slope coefficients of both auctions (the slope interaction with a dummy variable switching to one if the respective auction was a midday auction) at the second-stage regression. Therefore, a significant positive value determines that midday auctions reveal on average a larger fraction of price uncertainty. Results indicate that midday auctions reveal on average 42 percent of the existent price uncertainty (0.3593 + 0.0621), however this difference is not significantly different from zero so we can conclude that price discovery during volatility interruptions is comparable to midday auction situations and there is no systematic inefficiency coming from the tense market situation. However, even perfect price discovery during volatility interruptions is only relevant if it contributes to subsequent continuous trading by lowering price volatility. Within the next subsection, we will therefore concentrate on each interruptions' contribution to post-auction continuous trading.

Price Discovery Effect on Post-Interruption Continuous Trading

The results of the previous subsections suggest that volatility interruptions contribute to price uncertainty resolution by revealing additional information to the market that is in coherence with the future price level. However, these results call likewise into question if the switch to an auction is indeed desirable and appropriate in such situations as only a minor fraction of price discovery is contributed. In this subsection we therefore concentrate on continuous trading's reaction to the price signal. In particular, we quantify the individual contribution of each interruption to test whether it affects post-interruption market quality. The rational behind this approach follows Christie et al. (2002), we would expect a volatility interruption with good price prediction to calm down subsequent price uncertainty in a better way than an interruption with zero price discovery. If this is not the case, the volatility interruption would be negligible as the newly determined price has apparently no value. We test this assumption by determining market quality after each interruption. In contrast to call auctions, market efficiency and quality in continuous trading can be measured based on execution data and order book changes and thus allow for a comprehensive impact assessment. We again rely on our volatility interruption sample to measure whether post-interruption market conditions benefit from price discovery.

We first focus on the measurement of the incremental price discovery of each volatility interruption. We assume that volatility interruptions that perform better in anticipating future price movements conduce more value to post-interruption trading in contrast to interruptions that massively deviate from the future reference price. We therefore calculate each interruption's contribution based on the individual compliance of volatility auction return and pre-interruption price uncertainty (ϵ). Based on the results of the previous subsection, we calculate this amount based on the following approach:

$$Auc_i = \left[1 - \frac{\left| \epsilon_i - \ln \frac{P_{auction,i}}{P_{last,i}} \right|}{|\epsilon_i|} \right] * |\epsilon_i| \tag{3}$$

Therefore, price discovery Auc of each volatility interruption is calculated as fraction of the existing price dissonance (ϵ) that could successfully be resolved by the volatility auction return. According to (3), if the interruption is perfectly resolving price uncertainty, i.e., depicts the future reference price, price discovery in this auction (Auc) equals the absolute volatility auction return. This implies that interruptions with higher absolute returns, if perfectly revealing the future reference price, deliver higher contribution than auctions with smaller absolute returns in the same situation. However, according to (3), with each incremental over- and undershooting, the overall price discovery decreases. At the point, where dissonances between future reference return and pre-interruption return (ϵ) have not changed, e.g., where the volatility auction return is zero or overshoots the future reference price by the factor two, the auction's contribution Auc is likewise zero. In the case the volatility interruption increases pre-interruption price uncertainty by progressing in incoherency with the future reference price, Auc becomes negative the further it deviates from the future reference price. A positive Auc is therefore associated with price discovery during the respective volatility interruption while higher Auc indicate a higher contribution. Figure 2 shows the relative distribution of Auc in the combined volatility interruption and midday auction sample.

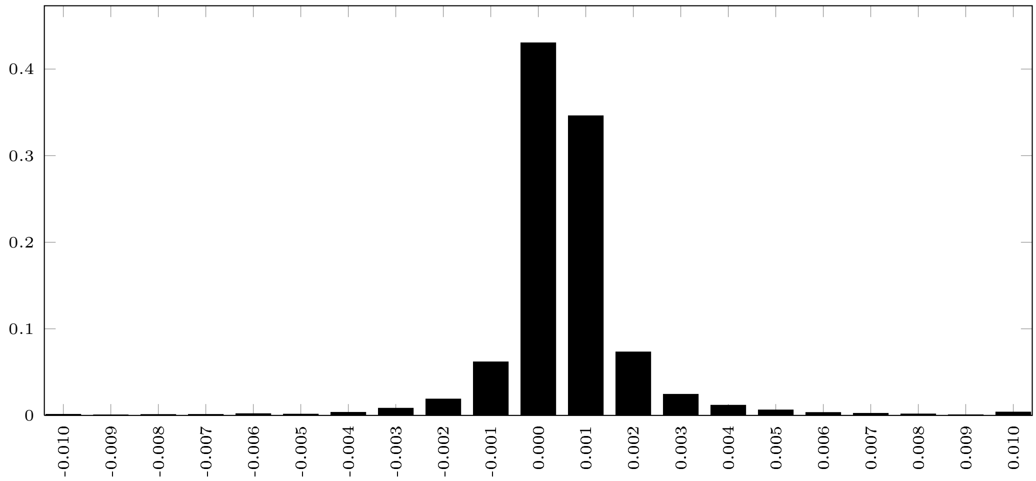

Figure 2. Relative Distribution of the Incremental Price Discovery Measure (Auc) of the Combined Volatility Interruption and Midday Auction Sample

In order to determine the effect of incremental price discovery on continuous trading we perform regression analyses on the market quality parameters proposed in the previous subsection. In this setup we test if continuous trading is affected conditionally on each price discovery contribution, i.e., if Auc significantly contributes to the explanation of post auction market quality levels. The regression takes the following form:

$$Y_i = \theta + \gamma_1 * Auc_i + \sum_{n=2}^{9} \gamma_n * C_{n,i} + \sum_{j=10}^{45} \gamma_j * X_{j,i} + \rho_i \tag{4}$$

Where Y_i captures the respective market quality measure, i.e., average relative spread, high-to-low measure and midpoint standard deviation within ten minutes after the volatility auction. Following French and Roll (1986), Karpoff (1987) as well as Schwert (1989), trading activity and order flow changes are major sources of price variability during comparable periods of trading. In order to evaluate if price discovery contribution is among the driving factors of subsequent price variability, we have to likewise control for changes in trading activity and order flow before and after the interruption. We would expect high price variability if trading intensifies after the interruption. Spread levels, on the other hand, reflect market participants' compensations for staying in the market and are mainly determined by the ability to manage inventory positions, i.e., order book liquidity depth (Harris, 2003). We therefore add controls for order book depth level, executed volume and the number of trades within ten minutes before the interruption as well as each controls' relative change from the pre- to the post volatility interruption period in order to control for omitted variables ($\sum_{n=2}^{9} \gamma_n * C_{n,i}$). We do not rely on trading controls of the contemporary post-interruption period, as simultaneity of the exogenous and endogenous factors could potentially bias our results (this is only done for robustness - results are omitted and available on request but remain robust). We additionally control for the overall absolute level of price uncertainty ϵ prevailing before each respective interruption, as this should clearly be one driving factor of the respective subsequent market quality measures in the case it is a good indicator. We further capture differences within each interruption event by adding dummy variables for each stock (31) and weekday (4) ($\sum_{j=10}^{45} \gamma_j * X_{j,i}$). In order to control for multicollinearity, we report mean and maximum Variance Inflation Factor (VIF) for each regression.

The regression so far would give insight whether continuous trading is reacting to the interruption's price discovery contribution. In order to improve the informativeness of the results, we modify regression (4) by additionally applying the benchmark sample for our volatility interruptions. We therefore seek to evaluate, given the same amount of price discovery, whether we observe an abnormal reaction after the volatility interruption that is not measurable after midday auctions. Such abnormal deviations may give indication if the auction's price signal value for future trading alters in times of increased market distress and whether volatility interruptions are (in-)efficient. We thus recalculate the price discovery contribution proxy Auc for the Xetra midday auction sample. Additionally, we acquire the same market quality measures and auction activity statistics for each midday auction. The regression is modified to the following form:

$$Y_i = \theta + \gamma_1 * Auc_i + \gamma_2 * I_{i,[0;1]} * Auc_i + \gamma_3 * I_{i,[0;1]} + \sum_{n=4}^{11} \gamma_n * C_{n,i} + \sum_{j=12}^{47} \gamma_j * X_{j,i} + \rho_i \quad (5)$$

Where $I_{i,[0;1]}$ is an indicator variable with value one if the respective event was a volatility interruption and zero if otherwise. γ_2 on the interaction term likewise indicates if price discovery affects market quality measures differently in times of market distress. For estimation, we rely on ordinary least square estimation. Each regression on midpoint standard deviation, high-to-low measure and relative spread level is performed three times. First, we just apply the pre-interruption levels of each control. Second, we add the respective changes of each control and third, we add the respective market quality level of the pre-volatility interruption 10 minute period as further control. The approach is repeated with the combined volatility interruption and midday auction sample. Tables 3 and 4 aggregate the results on the market quality regressions.

Table 3: MARKET QUALITY REGRESSION - VOLATILITY INTERRUPTION SUBSAMPLE

Market quality regression on the separate volatility interruption sample. Endogenous variables are: The mean market quality parameters midpoint standard deviation (Mid. Std. Dev.), high-to-low measure (High-to-Low) and relative spread (Relative Spread) ten minutes after the volatility interruption. Exogenous variables based on equation (4) are number of trades ($NumberofTrades$), Depth(10) ($Depth$), executed volume ($ExecutedVolume$) and absolute price uncertainty ϵ ($PriceUncertainty$) within the ten minute pre-interruption interval (Model 1, 2 and 3) as well as respective returns (Δ) of the exogenous variables to the post-interruption period (Model 2 and Model 3). Additional controls for each stock and weekday (Model 1, Model 2 and Model 3) and pre-interruption market quality levels (Pre Mid. Std. Dev., Pre High-to-Low and Pre Relative Spread - Model 3) are applied. Coefficients are reported standardized so that their variances equal one for comparability of coefficients. Values in parenthesis indicate respective P-values. Within each regression we report maximum and mean Variance Inflation Factor (VIF) to control for multicollinearity. We apply robust variance estimates following the MacKinnon and White approach.

	Mid. Std. Dev.			**Relative Spread**			**High-to-Low**		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Auc	-0.1514	-0.1527	-0.1521	-0.1894	-0.2007	-0.0715	-0.2884	-0.2715	-0.2324
	(0.0016)	(0.0015)	(0.0016)	(0.0000)	(0.0000)	(0.0007)	(0.0000)	(0.0000)	(0.0000)
$NumberofTrades$	0.0412	0.0442	0.0392	-0.1980	-0.2274	-0.0855	0.1435	0.1795	0.0360
	(0.1069)	(0.1200)	(0.1665)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2484)
$Depth$	-0.0063	-0.0033	-0.0035	0.3207	0.3227	0.0446	0.0785	0.0766	0.0435
	(0.3557)	(0.6572)	(0.6387)	(0.0000)	(0.0000)	(0.0516)	(0.0738)	(0.0823)	(0.2245)
$ExecutedVolume$	-0.0308	-0.0305	-0.0281	-0.0061	-0.0032	0.0111	0.0539	0.0504	0.0118
	(0.0343)	(0.0353)	(0.0507)	(0.8570)	(0.9282)	(0.3536)	(0.1416)	(0.1843)	(0.5658)
$PriceUncertainty$	0.1754	0.1713	0.1680	0.3624	0.3926	0.1542	0.7329	0.6967	0.5309
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\Delta NumberofTrades$		-0.0617	-0.0599		-0.0832	0.0036		0.1836	0.2409
		(0.2475)	(0.2636)		(0.0351)	(0.8795)		(0.0000)	(0.0000)
$\Delta Depth$		-0.0145	-0.0140		0.0360	0.0065		-0.0004	-0.0102
		(0.5084)	(0.5257)		(0.0887)	(0.5805)		(0.9762)	(0.3748)
$\Delta ExecutedVolume$		0.0902	0.0894		-0.0072	-0.0258		-0.0961	-0.0733
		(0.1156)	(0.1199)		(0.8544)	(0.2279)		(0.0175)	(0.0851)
$PreMid.Std.Dev.$			0.0219						
			(0.2755)						
$PreRelativeSpread$						0.7412			
						(0.0000)			
$PreHigh-to-Low$									0.4248
									(0.0000)
Number of Obs.	1,817	1,817	1,817	1,817	1,817	1,817	1,817	1,817	1,817
R^2	0.110	0.112	0.113	0.503	0.510	0.810	0.550	0.562	0.675
Max VIF	4.09	4.09	4.10	4.09	4.09	4.10	4.09	4.09	4.10
Mean VIF	2.11	2.15	2.14	2.11	2.15	2.17	2.11	2.15	2.16

Table 4: MARKET QUALITY REGRESSION - AGGREGATED SAMPLE

Market quality regression on the aggregated volatility interruption and midday auction sample. Endogenous variables are: The mean market quality parameters midpoint standard deviation (Mid. Std. Dev.), high-to-low measure (High-to-Low) and relative spread (Relative Spread) ten minutes after the volatility interruption. Exogenous variables based on equation (5) are number of trades ($NumberofTrades$), Depth(10) (Depth), executed volume ($ExecutedVolume$) and absolute price uncertainty ϵ ($PriceUncertainty$) within the ten minute pre-interruption interval (Model 1, 2 and 3) as well as respective returns (Δ) of the exogenous variables to the post-interruption period (Model 2 and Model 3). Additional controls for each stock and weekday (Model 1, Model 2 and Model 3) and pre-interruption market quality levels (Pre Mid. Std. Dev., Pre High-to-Low and Pre Relative Spread - Model 3) are applied. $I_{[0;1]}$ denotes a dummy variable with value one if the respective event was a volatility interruption. Coefficients are reported standardized so that their variances equal one for comparability of coefficients. Values in parenthesis indicate respective P-values. Within each regression we report maximum and mean Variance Inflation Factor (VIF) to control for multicollinearity. We apply robust variance estimates following the MacKinnon and White approach.

	Mid. Std. Dev.			**Relative Spread**			**High-to-Low**		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Auc	-0.0691	-0.0698	-0.0686	-0.1220	-0.1198	-0.0419	-0.2168	-0.2184	-0.1821
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$I_{[0;1]}$	0.1756	0.1766	0.1729	0.2994	0.2982	0.0620	0.2430	0.2436	0.1124
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$I_{[0;1]} * Auc$	-0.0875	-0.0851	-0.0854	-0.0462	-0.0536	-0.0165	-0.0184	-0.0124	-0.0243
	(0.0166)	(0.0203)	(0.0198)	(0.2262)	(0.1588)	(0.2860)	(0.3729)	(0.5452)	(0.1723)
$NumberofTrades$	0.0718	0.0773	0.0697	-0.2631	-0.2793	-0.0903	0.1098	0.1232	0.0150
	(0.0036)	(0.0024)	(0.0067)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5183)
$Depth$	-0.0323	-0.0317	-0.0313	0.2372	0.2363	0.0285	0.0680	0.0685	0.0443
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0726)	(0.0162)	(0.0150)	(0.0609)
$ExecutedVolume$	-0.0891	-0.0899	-0.0856	0.0017	0.0044	0.0020	0.0532	0.0509	0.0146
	(0.0000)	(0.0000)	(0.0000)	(0.9524)	(0.8802)	(0.8132)	(0.0488)	(0.0615)	(0.3056)
$PriceUncertainty$	0.2243	0.2187	0.2140	0.4117	0.4275	0.1579	0.6655	0.6524	0.5307
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\Delta NumberofTrades$		0.0203	0.0214		-0.0933	-0.0346		0.0811	0.1109
		(0.1418)	(0.1210)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
$\Delta Depth$		0.0009	0.0010		-0.0062	-0.0206		-0.0053	-0.0041
		(0.8334)	(0.7991)		(0.0807)	(0.6976)		(0.5391)	(0.6541)
$\Delta ExecutedVolume$		0.0074	0.0076		0.0285	0.0097		-0.0290	-0.0290
		(0.5261)	(0.5149)		(0.0052)	(0.1203)		(0.0005)	(0.0008)
$PreMid.Std.Dev.$			0.0389						
			(0.0313)						
$PreRelativeSpread$						0.7703			
						(0.0000)			
$PreHigh-to-Low$									0.3972
									(0.0000)
Number of Obs.	9,507	9,507	9,507	9,507	9,507	9,507	9,507	9,507	9,507
R^2	0.163	0.163	0.165	0.502	0.507	0.827	0.733	0.736	0.794
Max VIF	4.17	4.17	4.19	4.17	4.17	4.19	4.17	4.17	4.19
Mean VIF	2.11	2.12	2.10	2.11	2.12	2.13	2.11	2.12	2.15

Table 3 depicts all regression results on the market quality measures based on approach (4) for the volatility interruption subsample. Concerning the effect on market volatility levels as of midpoint standard deviation and the high-to-low ratio, *Auc* significantly enters all regression models indicating that price discovery during volatility interruptions is significantly shaping the level of subsequent price variability in continuous trading even after controlling for levels and changes in trading intensity. Average price variability as well as maximum price deviations are significantly lower after interruptions with high price discovery. Namely, the more accurately volatility interruptions reveal the future price level, the less volatile and misguided trading prices become in the following. Additionally, market participants adjust their demand for market risk compensation conditional to the level of price discovery. Coefficients in the relative spread regressions are likewise negative in all of our models indicating that liquidity providers skip market risk compensation after volatility interruptions with high price discovery. Equivalently, the coefficient on $PriceUncertainty$ indicates that price volatility and likewise the demand for market risk compensation is higher the more price uncertainty is prevailing in the pre-interruption period. Therefore, if the interruption is able to reduce this price uncertainty, market conditions will improve. Concerning our additional controls, we are able to partially confirm the findings of French and Roll (1986), Karpoff (1987) as well as Schwert (1989) as the respective controls for trading activity and order book depth level significantly enter each regression. Most notably in the spread level regression, high order book depth is associated with wider spread levels, which is apparently non-intuitive. We therefore repeat this approach with the combined sample.

By comparing these results to the combined volatility interruption and midday auction sample in Table 4, we are able to evaluate each effect's magnitude compared to the midday auction benchmark. Given the same level of trading intensity and order book activity in previous continuous trading and zero price discovery, $I_{[0;1]}$ indicates that average price volatility, maximum price deviation and likewise spread levels after volatility interruptions are significantly higher/wider compared to midday auctions. However, the more price discovery is achieved during each auction, the more this situation will change according to our *Auc* and interaction coefficients. First, midpoint standard deviation, spread levels and high-to-low ratio after midday auctions are affected by midday auction price discovery as *Auc* remains significant in all models. However, the tranquillizing effect on midpoint standard deviation is considerably strong in volatility interruptions indicated by the $I_{[0;1]} * Auc$ coefficient. Concerning the effect's magnitude, results show that the coefficient on *Auc* is doubled within the volatility interruption subsample, indicating that the interruption's price signal has superior signaling value to comparable levels of price discovery in midday auctions as midpoint standard deviation is significantly lower. Concerning spread levels and the high-to-low ratio, results are slightly different. Within all models, although the coefficient on $I_{[0;1]} * Auc$ remains negative, differences between the volatility interruption and midday auction sample are reported insignificant. We therefore can only conclude that the effect on spread levels and likewise maximum price deviation is comparable to the effect we observe during midday auctions. All together, our results deliver strong indications that securities market volatility interruptions beneficially contribute to a return to orderly trading as even more inexact price signals are followed by calmer market conditions compared to midday auctions at least for average midpoint standard deviation. However, as also noted by Christie et al. (2002), these effects depend upon the interruption to reveal a relevant price for future trading, in our case a high *Auc*. Within the next subsection we focus on potential drivers facilitating price discovery during volatility interruptions and midday auctions by focusing on the determinants of *Auc*.

Determinants of Price Discovery

The previous subsection shows strong indications that price discovery efficiency during volatility interruptions is a major determinant for market quality within the subsequent continuous trading phase. Therefore, within this third part, we seek to identify the major determinants of price discovery efficiency based on our volatility interruption and midday auction sample. This may be further desirable, as results could potentially provide regulatory adjusting screws for future volatility interruption requirements. As mentioned in section 1, Christie et al. (2002) conclude that foremost increased information transmission during the halt could result in reduced post-halt uncertainty as traders are able to coordinate their evaluations right in the situation of the halt. Within this section, we therefore focus on characteristics and results of the volatility interruption that may indicate or support information transmission during the interruption. We especially concentrate on quoting and indicative price dynamics of the respective interruption's call phase. Y. Kim and Yang (2004), within their volatility hypothesis, consider the time duration during which traders can obtain new information, reassess the market price, and avoid or correct overreactions, crucial for volatility reduction. We therefore include the total duration of the volatility interruption (midday auction), measured in seconds, in the following analysis. Since volatility interruption and midday auction call phases at Deutsche Boerse are determined randomly after a fixed minimum duration as seen in section 2 (durations of volatility interruptions (midday auctions) vary between 119 (120) seconds and 460 (833) seconds), we can evaluate whether longer call phases result in higher price discovery on average. However, as pointed out within the last section, Xetra volatility interruptions are automatically extended in the case the indicative price lies outside a predetermined range at the end of the call phase. This would indicate a serious causality as well as interpretation problem, since interruptions with indicative prices outside the predetermined range may automatically be prolonged just because they do not fulfill these Xetra rules, albeit they may be a perfect predictor of the future reference price.

We further concentrate on the volume, quoting and price dynamics of each interruption, which were not included within the previous analysis so far. Traded volumes and quoting dynamics contain valuable information about the call progress and traders' participation. Madhavan (1995) indicates that larger auction participation would result in more efficient prices as the auction allocation price contains additional trader information and therefore represents a larger consensus among traders. Likewise, an increase in the indicative execution volumes may imply that a larger fraction of buyers and sellers agree on the current evaluation of the indicative price. We therefore proxy traders' participation in the call phase in two ways. First, we count the number of indicative price updates in the call phase of each volatility interruption and midday auction event. The number of updates give a general impression if more activity during an auction's call phase is associated with prices that are of higher relevance for future trading. Second, we identify the first indicative execution volume of each call phase together with the auction execution volume. In the case the ratio, auction execution volume to first indicative execution volume, is larger one, we can conclude that over the course of the call phase traders' participation has increased, while a ratio smaller one would indicate the opposite development. In addition, we add the auction execution volume to proxy for the overall level of participation. At last, we focus on the dynamics of the indicative price during the call phase. Likewise in continuous trading, prices with high variability may indicate value opacity or even disagreement between participants, we therefore control for the absolute auction return as indication for price innovation during the auction. Again, we further capture differences within each interruption event by adding dummy variables for each stock (31) and weekday (4). The regression takes the following form:

$$\begin{aligned} Auc_i = \alpha + \psi_1 * Length_i + \psi_2 * Participation_i + \psi_3 * ParticipationRatio_i \\ + \psi_4 * Updates_i + \psi_5 * AbsReturn_i + \sum_{n=6}^{41} \psi_n * X_{n,i} + \xi_i \end{aligned} \tag{6}$$

Where Auc again is the measure for price discovery contribution, $Length$ the total interruption duration in seconds, $Participation$ the executed stock volume, $ParticipationRatio$ indicates a possible increase or decrease in the indicative execution volume while $Updates$ is the number of indicative price updates. Likewise, $AbsReturn$ is the absolute auction return. We add event specific dummy variables controlling for each respective stock and weekday (X_n). We run this regression on the volatility interruption subsample and again on the aggregated midday auction sample applying indicator variables for each exogenous variable comparable to the previous section in order to determine systematic deviations in either one of both subsamples. Results are aggregated in Table 5: By focusing at first on the volatility interruption subsample, results confirm that participation in the call phase will improve price discovery efficacy. We can therefore conclude, that auctions with high execution volumes deliver on average prices more relevant for future trading. The same applies for auctions that show a strong increase in the indicative execution volume during the course of the call period. On the contrary, indicated by the coefficient on the number of indicative price updates ($Updates$),

Table 5: PRICE DISCOVERY CONTRIBUTION REGRESSION

Price discovery contribution regression on the volatility interruption subsample and the combined volatility interruption and Xetra midday auction sample. Endogenous variable is the auction's contribution to price discovery (Auc) according to equation (3). Exogenous variables based on (6) are the total interruption duration in seconds (Length), the auction's executed stock volume (Participation), the auction execution volume to first indicative execution volume ratio (ParticipationRatio), (Updates) the number of indicative price updates and (AbsReturn) the absolute auction return. ($I_{[0;1]}$) indicates volatility interruptions as one. Coefficients are reported standardized so that their variances equal one. Values in parenthesis indicate respective P-values. Within each regression we report maximum and mean Variance Inflation Factor (VIF) to control for multicollinearity. We apply robust variance estimates following the MacKinnon and White approach.

	Volatility Interruption Sample	Aggregated Sample
$I_{[0;1]}$		-0.1783
		(0.2232)
Participation	0.0914	0.0203
	(0.0932)	(0.1862)
$I_{[0;1]} * Participation$		0.0663
		(0.0941)
ParticipationRatio	0.0319	-0.0051
	(0.0775)	(0.4485)
$I_{[0;1]} * ParticipationRatio$		0.0291
		(0.0599)
Updates	-0.0045	0.0848
	(0.8611)	(0.0000)
$I_{[0;1]} * Updates$		-0.0458
		(0.0869)
Length	0.0342	0.0226
	(0.3000)	(0.2545)
$I_{[0;1]} * Length$		0.1409
		(0.3388)
AbsReturn	0.2376	0.0395
	(0.0010)	(0.3991)
$I_{[0;1]} * AbsReturn$		0.2018
		(0.0150)
Number of Observations	1,817	9,507
R^2	0.10	0.08
Max VIF	3.90	29.61
Mean VIF	2.00	3.27

a high number of submissions, modifications and cancellations is in general negligible for the future relevance of the price. Most interesting, the duration of the call phase (*Length*) yields no significant contribution while a strong price innovation in either direction (*AbsReturn*) seem to have superior reference value for future trading. We re-run the regression including our midday auction subsample in order to compare results and evaluate each contributions magnitude. $I_{i,[0;1]}$ at the aggregated sample indicates that there are no systematic differences within the average price discovery efficiency levels between volatility interruptions and midday auctions, which is in line with our findings in the first subsection. Focusing on the impact of traders' participation on the midday auction's price discovery, we observe that only the number of indicative price updates significantly explain price discovery during the midday auction, while the coefficients on the execution volume proxies remain insignificant. We can therefore conclude that call phase participation is especially desirable during volatility interruption. In accordance with the subsample analysis of the volatility interruptions, we can also conclude, that there is no need to prolong an interruption or auction call phase in order to promote price discovery, the coefficient on *Length* remains insignificant within the aggregated analysis. However, low explanatory power of the exogenous variables indicated by the low R-squared supports the assumption that major exogenous factors are missing within this analysis. Further, the dramatic increase in the correlation between the exogenous variables (indicated in the Variance Inflation Factor) within the aggregated sample regression is a result of the interaction terms and may bias our results. Yet, these results give at least some indication about the importance of traders' consensus during volatility interruptions to initiate a return to smooth and orderly trading.

Conclusion

Financial markets are more than ever coined by investors' tension and the public desire for far-reaching regulation. In 2012, the European member states saw the first vanguards of this development in the implementation of various exchange-based order-to-trade ratios, the German draft legislation of the High-frequency Trading Act as well as the French transaction tax. This change in the regulatory focus from market efficiency, cost reductions and competition, the cornerstones of the Markets in Financial Instruments Directive of 2007, towards market stability, integrity and transparency in MiFID II, indicates a turning point in European market regulation. As of 2013, several regulative proposals discuss the implementation of circuit breakers and likewise volatility interruptions as a major mechanism to prevent market turmoil, deal with excessive volatility and foster market integrity.

In this paper we follow the call of regulatory bodies as well as exchange providers to evaluate the efficiency of volatility interruption mechanisms already implemented at major European trading venues such as Deutsche Boerse, Euronext or the Spain Securities Exchange. Instead of bringing trading to a halt and impede price coordination among participants, these short-lived call auctions concentrate on information allocation and price coordination during the halt. However, academia is still skeptical if such measures are indeed prosperous.

The aim of this paper is therefore to provide evidences how such measures perform in today's markets and if they are capable of initiating a return to smooth and orderly trading. We therefore rely on approximately 1.800 volatility interruptions during 01/2009 to 01/2012 to give insight into the price discovery capabilities of such auctions and how they affect post-interruption trading. We find that volatility interruptions contribute to about 36 percent of pre-interruption price uncertainty revelation. That is, interruption prices provide incremental information for participants helping to return to orderly trading besides prices from pre-interruption continuous trading. These findings are in line with Abad and Pascual (2010), who study a very similar mechanism at the Spanish stock exchange. They find that the allocation price of the interruption reflects efficient learning, indicating that there is price discovery during the volatility interruption. They further find that normal market conditions are reinstated quite rapidly after the interruption, although price uncertainty is not completely resolved by the time the continuous session is restarted. We extend these findings as we show a robust relationship between the amount of auction price discovery and post-interruption market quality. That is, we observe that subsequent price volatility is dependent upon price discovery efficiency during the volatility interruption and is significantly lower in times where the volatility interruption provides a good predictor for further trading prices. Additionally, we show that this effect is considerably strong in volatility interruptions, indicating that allocation prices contain superior influence and referential value in times of market distress concerning midpoint volatility. Our findings also suggest that market participants likewise adjust their demand for market risk compensation in accordance to auction price discovery. However, this effect's magnitude is comparable to their adjustment after midday auctions. We therefore conclude that traders remain more cautious in after volatility interruption although calmer market conditions are reinstated quite rapidly. These results are backed by Basher et al. (2007) who find price uncertainty after volatility interruptions to be sometimes increased or reduced. We therefore conclude that it is wrong to believe that such interruptions would automatically initiate a return to smooth and orderly trading. Instead, it is dependent upon the auction's contribution to price discovery achieved during the open call phase of the volatility auction. Within our last question, we thus ask for the primary drivers of price discovery during volatility interruptions. The results up to now do provide indication that a prolongation of the auction's call phase does not necessarily facilitate price discovery. Moreover, auction participation and traders' consensus do support price discovery especially strong during volatility interruptions. So far however, we are not able to give distinct recommendations about the usefulness of liquidity agreements of market makers during volatility interruptions as such would require additional analysis. However, these findings are in line with Madhavan (1995) and Christie et al. (2002), who conclude that foremost increased information transmission during the halt could result in reduced post-halt uncertainty and facilitate price efficiency. Post-interruption market conditions therefore depend upon the degree of price coordination and the consensus reached by its participants. We would recommend to extend this analysis to more detailed quoting data during volatility interruptions in order to address this question more properly. Our results are relevant for regulators, exchanges and policy markers likewise as we are able to demonstrate the tranquilizing capacities of volatility interruptions in times of tense market situations. Further, compared to circuit breaker that do not allow for price discovery, we show that auctions' coordination capabilities are vital in reinstating market integrity as soon as trading continues as proposed by Christie et al. (2002). We therefore support the theoretic implications of Madhavan (1995) that volatility interruptions are to be preferable to traditional circuit breaker.

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