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# Measuring the effectiveness of volatility call auctions

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# Abstract

We propose a method based on synthetic portfolios for event studies and apply it in the context of market microstructure. The method provides a robust data driven approach to build a credible counterfactual. The method is used to evaluate the effectiveness of a volatility call auction using intra day data from the Colombian stock Exchange. With the counterfactual and the observed price after the auction we can analyze if the auction enhances market quality. Results indicate that the synthetic portfolio method provides an accurate approach to build a credible counterfactual that approximates the behavior of the asset if the auction had not taken place. The main results indicate that the volatility call auction does provide a way to reduce the volatility of the asset but their effect on other market quality variables, liquidity and trading activity is ambiguous at best.

*Keywords:* Circuit breakers, synthetic control, event studies, volatility interruptions, tracking portfolios *JEL:* C21, C58, G11, G14

# 1. Introduction

Firm-specific trading halts are widely used in securities markets as means of normalizing the trading process in times of excessive volatility. They belong to the group of circuit breakers, that also includes price limits and market-wide trading halts (Kim and Yang 2004). Firm-specific trading halts

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are a common feature in stock exchanges around the world, such as NYSE, Nasdaq and those of Australia, Canada, Germany, Hong Kong, Israel, UK, Euronext and Spain. However, there is no consensus on the need and effectiveness of trading halts.

In principle, trading halts would be irrelevant in an efficient market since prices should respond immediately to the arrival of new information. However, market microstructure considerations might make them desirable. Specifically, trading halts has been justified as a way of mitigating the information disadvantage of uninformed traders or designated market makers, enabling the market to better accommodate large volume shocks (Greenwald and Stein, 1988, 1991). Trading halts might also provide a "cooling off" period that supposedly allow investors to better process the incoming information (Kim, Yage and Yang, 2008). This line of reasoning is supported by theoretical models. Madhavan (1992), modelling a continuous market versus call auctions, finds that "the periodic auction aggregates information efficiently and is more robust to problems of information asymmetry in that it can operate where continuous market fail" (p. 609). Spiegel and Subrahmanyam (2002) offer a model in which trading halts signal large information asymmetry affecting not only the halted stock but also informationally related securities.

However, some academics oppose trading halts as undesired intrusions in a free market. Fama (1989) claims against the "cooling off" arguing that any investors who wants to do so can just remain outside the market. Grossman (1990) states that investors, as "consenting adults" should not be hindered to trade as they please. Grundy and McNichols (1989) propose a model of learning through trading that imply that in absence of continuous trading potential traders are less able or willing to reveal their demands and information. Moreover, the theoretical analysis of Subrahmanyam (1994) finds that trading halts might have the perverse effect of exacerbating volatility, since traders might sub-optimally advance their trades in anticipation.

We study the effect on market quality of a type of trading halt in the Colombian Stock Exchange (BVC): the rule-based volatility auction. As detailed below, volatility auctions in BVC are triggered by the imminence of a trade outside price collars switching continuous trading to a short-lived call auction. Like those of Spanish Stock Exchange (SIBE) after May 2001, trading halts in BVC have two fundamental differences with those in NYSE, Nasdaq, Montreal and ASE. First, trading halts in BVC are not subjectively imposed by a regulator, or requested by the firm, but mechanically activated by the trading system when the price of a forthcoming trade lays outside the established range. Second, trading itself is not completely stopped but switched to a short-lived call auction (between 2-3 minutes), where investors can incorporate their preferences and information by posting limit orders. Thus, price discovery can still take place in a organized fashion. In that sense a volatility auction can act as a leveler of the playing field between informed and noise traders.

This type of trading halt is also used in the Xetra trading system owned by Deutsche Börse, under the name of volatility interruptions. They are regarded as a way of dealing with volatility spikes while allowing for a smooth price discovery. In words of the Deutsche Börse CEO: The auction concentrates liquidity, and the message that is sent to all market participants attracts further liquidity. This increase in liquidity in and of itself improves the price discovery process (Francioni, 2013 p.27). They can also be found in stock markets of Paris and Euronext (Reboredo, 2012).

The evidence on the effectiveness of trading halts is mixed. Motivated by the October 1987 crash the early literature focus on US Markets. Lee, Ready and Seguin (1994) report that trading halts in NYSE are associated with increasing trading activity and volatility afterwards. Christie, Corwin and Harris (2002) study information dissemination on NASDAQ halts of different duration. They find increasing volatility and volume and bid-ask spreads after the 5-minute halts but none upon overnight halts. They interpret this as evidence of the importance of the increased information transmission during the halt. Corwin and Lipson (2000) studying the NYSE trading halts also report increasing trading activity and volatility and reduced liquidity after the halt. However, they also find two desirable consequences: First, traders take advantage of the halt to revise their trading intentions by cancelling and submitting orders. Second, the clearing price that resumes trading after the halt is informative of the future price.

The evidence on international markets is also mixed. Studying exchangeimposed halts Kryzanowski and Nemiroff (1998) reports increasing volatility and volume in the Montreal Stock exchange. Frino, Lecce and Segara (2011) additionally finds larger bid-ask spreads and lower depths in the Australian Stock Exchange (ASE). Studies on the Spanish Stock Exchange (SIBE) deal with two types of trading halts. Until May 2001, firm-specific trading halts were imposed by exchange officials when price instability or incoming news required so, like those in US, Canada and Australia. From May 2001 onwards, trading halts were replaced with rule-based volatility auctions, triggered by prespecified price collars. Studying the trading halts with data up to April 2001, Kim, Yage and Yang (2008) find an overall beneficial effect: trading activity increases and the bid-ask spread is narrower, although volatility remains the same.

The evidence on volatility auctions is somewhat more favorable. Studying the SIBE volatility auctions Reboredo (2012) finds improvement on price formation and reduction in volatility, particularly for thinly traded stocks. Abad and Pascual (2010), also in SIBE, finds increasing volatility, volume and information asymmetry, but acknowledge the lack of a proper counterfactual. Gomber, Lutat, Haferkorn and Zimmermann (2011) study the effect of volatility auctions on the German Xetra stock market as well as in a satellite market, the London based Chi-X MTF. They find a decline on stock volatility in both markets, at expense of increasing bid-ask spreads. Moreover, the market quality and price discovery in the satellite market decreases during the volatility auction. Zimmermann (2013) uses a set of 1,800 volatility auctions also in Xetra. Using the Corwin and Lipson (2000) methodology, he finds that volatility auctions improve price discovery, in a degree similar to the Xetra midday auction. Besides, he also reports benefits on market quality, using the midday auctions as a control group, revealed in a decrease on volatility and proportional bid-ask spread following the volatility auction.

The contribution of this paper is twofold. First, to our knowledge this is the first paper to study the effect of volatility auctions in the market quality of an emerging market. It is well established in the literature that issues of thin trading, excessive volatility and asymmetric information are pervasive in emerging stock markets, leading occasionally to market failure and limiting their development over time. Those problems are likely to be compounded in small emerging markets as Colombia. Since trading halts have been justified as a way to reduce information asymmetry, protect uninformed investors, and mitigate excessive volatility, a stock market as BVC, seems an ideal case of study.

Second, this paper presents as a methodological contribution to the study of market microstructure events: We use a synthetic portfolio as a contemporaneous counterfactual for the stock affected by the volatility auction. As described in Section 3, we estimate it in a pre-event period, as the portfolio of stocks not involved in a trading halt that better replicates the variable of interest (returns). Thus we compare the change of the variable of interest in the halted stock around the event against the change on the synthetic portfolio. The synthetic portfolio methodology is adapted from existing methods for causal inference in applied microeconomics (Abadie, Diamond and Hainmuller,2010), but to the extent of our knowledge, it has not been used in intraday market data studies. These quasi-experimental methods are starting to spur interest in finance and accounting research (Gow, Larcker and Reiss, 2016). The main reason is that accounting and financial research does also address questions that are causal in nature but the methodologies that have been used for a long time, like event studies, have yet to include methodological advances in causal inference coming from other disciplines.

Stock matching is the most widely used approach in this type of studies. For example, Jian, McInish and Upson (2009) study firm specific trading halts in NYSE, pairing each halted stock with one informationally related stock in the same four-digit SIC industry, and with close correlation of returns, volume, volatility and adverse selection of the spread. At plain sight, this methodology can hardly been applied in a small stock market. In turn, the pseudo match methodology of Lee, Ready and Seguin (1994) pairs the halted period with a different period of the same stock. However this approach omits any systematic effect on the market quality variables around the trading halt. We deem that the proposed methodology can overcome the limitation of both approaches particularly in the context of a thinly traded stock market by taking advantage of the availability of high frequency data and new research design methods. The two most related studies to the present one are those of Gomber et al (2011) and Zimmerman (2013) on the German Xetra stock market. However this study is different not only in the sample data but also in the methodological approach. In Zimmermann (2013) there is no stock matching and in Gomber et al (2011) the matching is with respect to the same stock in different times (mid day auction).

Our findings can be summarized as follows, the volatility call auction has a statistically and quantitatively significant effect on attenuating price uncertainty once continuous trading restarts. In the absence of the call auction volatility is significantly larger. The synthetic portfolio provides a simple yet accurate strategy to proxy the behavior of the asset had the auction not taken place. Using the weights estimated from the synthetic portfolio we find no evidence that the auction has a significant effect on other dimensions of market quality such as liquidity, depth or trading activity. The rule based circuit breaker: volatility call auction seems to have the desired effect, that is reduce volatility, without showing any additional externality on other measures of market quality.

The rest of the paper is organized as follows. Section 2 discusses the relevant institutional features of BVC and the hypothesis regarding the volatility call auction mechanism. Section 3 presents the data and the synthetic portfolio approach. Section 4 discuss the empirical results of the intra day event studies. Finally, Section 5 concludes.

# 2. Hypothesis

In 2009 the Bolsa de Valores de Colombia (BVC), the Colombian Stock Exchange launched a new electronic stock trading platform, incorporating features such as volatility call auctions. The purpose of these rule based market interruptions is to allow investors a chance to receive and react to market information, to form price in an orderly manner, and hence to mitigate excess volatility. Specifically, a volatility call auction is triggered by an order that could eventually lead to a transaction outside a predetermined price range. The price range is set around the closing price of the previous day, with a width in one of three sizes (6.5%, 5.5%) and 4%) where the stock has been classified based on its past volatility (Figure 1). As soon as the auction begins, outstanding orders are withdrawn from the book (except for the order that caused the auction), the duration of the auction is two and a half minutes and has a 30 seconds random closure. When the auction ends the equilibrium price is calculated, as the one that maximizes trading volume. The price range is recalculated around the price of the auction. There is not a maximum number of volatility auctions and an auction can start in the very moment that another auction ends.

We are not aware of any theoretical model specifically devoted to volatility call auctions. However, as mentioned in the introduction Greenwald and Stein (1988,1991), Madhavan (1992) and Spiegel and Subrahmanyam (2002) show that trading halts facilitate price discovery and foster trading activity in an environment where asymmetric information leads to significant transaction price risk or market failure. The results from these theoretical models are aligned to the "cooling off hypothesis". Since the mechanism is designed specifically to reduce volatility, our fist hypothesis will focus on that outcome.

**Hypothesis 1:** The volatility call auction effectively reduce volatility. That is, volatility diminishes after the continuous market is resumed.

In the call auction orders are batched together and there is simultaneous execution, there is a better price discovery process in comparison to continuous trading. The more accurate price mitigates the need for further subsequent price adjustments (unless another call auction starts immediately after the first one) and in doing so avoids excessive volatility in the market. This has been an important argument in favor of opening and closing markets with call auctions (Pagano, Peng and Schwartz, 2013). However, it is important to keep in mind the difference between volatility call auctions, trading halts and open and closing call auctions<sup>1</sup>.

As we have seen in the introduction the empirical evidence is mixed regarding circuit breakers (trading halts and volatility call auctions), in particular regarding whether the interruptions are themselves a source of excessive price changes as is found in a number of studies (Kryzanowski and Nemiroff, 1998; Christie, Corwin and Harris, 2002; Kim, Yage and Yang, 2008; Abad and Pascual, 2010). These results cast a shadow of doubt on the usefulness of the mechanism. More recently there is renewed interest in the usefulness of the mechanism specially due to the incremental use of algorithmic trading and the possibility of malfunctioning algorithms. Both the European Securities Market Authority and the Securities and Exchange Commission call for further empirical evidence regarding the effectiveness of the mechanism (European Commission, 2010). As mentioned by Zimmermann (2015) one important challenge has been setting up a framework to distinguish the causal coherence between the volatility call auction and the transaction price risk after the auction takes place. This seems to be an important downside, so far, in most of the methodological approaches taken to measure the effectiveness of trading halts.

We further investigate the impact of volatility call auctions in some of

<sup>&</sup>lt;sup>1</sup>Trading halts, like volatility call auctions, can happen at any moment during continuous trading, however their duration can be a couple of minutes, the remainder of the day or even more than one day. On the other hand, opening and closing call auctions have a predefined beginning and end.

the other dimensions of market quality (liquidity and trading activity).

**Hypothesis 2:** Volatility auctions improves other traits of market quality, besides volatility.

According to the theoretical model of Madhavan (1995), volatility auctions should improve liquidity afterwards (e.g. lower bid-ask spreads), by mitigating asymmetric information. Besides, to the extent that volatility auctions increase the visibility of the stock, it might also increase the proportion of non-informed traders leading to improved liquidity and increasing trading activity, in line with classical informed trading models like Kyle (1985) and Glosten and Milgrom (1985). Results in this direction have been found by Zimmermann (2013) in the German Xetra stock market.

Alternatively, volatility auctions might impair liquidity as reported by Gomber, Lutat, Haferkorn and Zimmermann (2011) in Xetra and Abad and Pascual (2010) in SIBE. This could be explained in two ways. First, according to the "learning through trading" models cited by Lee et al. (1994), the absence of trading prices during the call auction (or halt) might discourage potential traders to reveal their demands. The demands manifests when continuous trading resumes increasing trading volume, volatility and bid-ask spreads. Second, market quality can decrease if the call auction does not last enough for a proper information dissemination prior to the reopening of the continuous market. This hypothesis is proposed and empirically tested by Christie et al. (2002). They find that short halts with only 5 min quotation periods are followed by higher volatility and spreads, while halts with 90 min quotation periods are not.

# 3. Data and methods

# 3.1. The sample

We use trade and quote data (TAQ), composed of 45 listed stocks in the Colombian Stock Exchange (BVC) from August 2010 to August 2012. The data contains bid and ask quotes, trades, volume, as well as the time stamp on the beginning and end of the volatility call auction. Volatility call auctions can start at any moment of the trading day, there is no particular time of the day where most auctions take place (Figure 2). In total there are 1062 volatility auctions about 90% are concentrated in no more than 19 assets (Table 1). Our hypothesis are on the effect of the volatility call auctions on different dimensions of market quality; since its expected that effect is limited to a trading day, we measure the effect with intra day data

We define a sample selection criteria to avoid confounding effects from different sources, that can lead to a biased measure and to make sure we have enough information within the day to evaluate the hypothesis. For example, we want to avoid volatility call auctions that take place near the opening 30 minute (8:15) and closing 5 minute auctions (14:55) for the market. In this case we want to avoid the intrusion of other market mechanisms like the opening and closing auctions. Avoiding auctions near the opening of the market also makes sure that we have enough data for estimation in the pre-event window.

We start by the defining the asset space in the market, made up by a total of J securities that are liquid enough to be continuously traded during the day  $(S_1, S_2, S_J)$ . We identified the time and day of the volatility auction affecting security  $S_i$ , with out loss of generality we can define i = 1. That means that trading for security 1 has been switched to a volatility call auction. During the same period there is a set of other securities  $\mathcal{S} = (S_2, \ldots, S_J)$  still traded in a continuous market. We need to apply the following criteria to keep the auction for security 1 in the selected sample: a) discard successive volatility auctions affecting the same security  $S_1$  within the same day; b)verify that the volatility auction was not triggered at the beginning nor the ending of the daily trading session as defined above; c) verify that security 1 has enough trading activity during the day. In addition we must also make sure that securities in the control group ( $\mathcal{S}$ ) have enough trading activity during the day.

Using the previous sample selection criteria on transaction (quote) data the number of auction goes down to 184 (441), that is 17% (42%) of the original sample of 1062. Even though there is an important number of observation loss to the sample selection procedure, the reduced sample is still gives a representative sample of the auctions taking place at different times of the trading day (Figure 3). We will perform the analysis to test the hypothesis using separately trade and quote data. For example, we can measure volatility from returns on transaction price or mid price data.

#### 3.2. Method

We will test our hypothesis using an event study methodology that incorporates a synthetic portfolio as a benchmark. The event of interest is the volatility call auction and our purpose is to determine the causal effect of such market mechanism on market quality variables after continuous trading is resumed.

We denote t a intra day time (1 < t < T) and  $t = T_0$  as the time when the auction takes place. Although, the auction approximately last for two and a half minutes, for notational simplicity we turn this interval into a moment in time,  $T_0$ . The pre-event or estimation window is defined by  $t \in [1, T_0)$  and the post-event or forecast window is defined by  $t \in (T_0, T]$  (figure 4). To test the hypothesis we look at specific variable  $Y_{i,t}$  for security i at time t (return, bid-ask spreads and, turnover) to measure the effects on the different dimensions of market quality (volatility, liquidity, trading activity).

The main challenge to determine the causal effect of the volatility call auctions on the asset of interest is the construction of a potential outcome or counterfactual. This tries to capture what would have happened to the asset had the volatility call auction not taken place.

In traditional event studies (MacKinlay, 1997) the effect of a particular event on a security's price, is measured as the abnormal returns AR. For simplicity suppose that security 1 is the only one affected by the event

$$AR_{1,t} = R_{1,t} - E(R_{1,t} \mid X_t), t \in (T_0, T]$$
(1)

where  $R_{1,t}$  is the actual return and  $E(R_{1,t} | X_t)$  is the expected return. There are two common choices for modeling the expected return: the constant mean return model and the market model. In both cases information on the preevent window is used to quantify the normal return. In the constant mean return model the potential outcome is the simple average of the variable of interest in the pre-vent window  $\frac{1}{T_0-1}\sum_{t=1}^{T_0-1}R_{1,t}$ . In the market model the potential outcome is given by  $E(R_{1,t} | R_{m,t}) = \hat{\beta}R_{m,t}$ , where  $R_{m,t}$  is the excess market return at time t, and  $\hat{\beta}$  is the estimated slope in the following regression, estimated with data from t = 1 to  $T_0 - 1$ .

$$R_{1,t} = \hat{\alpha}_i + \beta_i R_{m,t} \tag{2}$$

This traditional approach is not suitable to study the case in hand. Clearly, the event (volatility auction) is not exogenous to the variable we want to measure (volatility) but triggered by it. In order to build a credible potential outcome it is important to guarantee the principle of stable treatment assumption (Imberns and Rubin, 2015), characterized by two properties. The first property requires that the event (treatment) affecting the unit of interest does not affect the outcome for the units that could potentially be used to build the potential outcome (no interference property). In traditional event study approach the use a of the variable of interest in the construction of the potential outcome violates this property. The second property requires that there is no hidden variation due to the indirect exposure to the effect (treatment), that means that there should no be any significant externalities in the other securities from the control group S due to the volatility call auction affecting the security of interest  $S_1$ .

The synthetic portfolio method, is very general and doesn't require a natural experiment or to find a *ad-hoc* criterion to select the securities in the control group, therefore it can be used in many types of event studies. The idea behind the approach is very simple and all the technical details are explained in the appendix. In order to build the potential outcome we use the information for all other available securities (the control group) that are not affected by the volatility call auction  $(Y_2, \ldots, Y_J)$ , in this case  $Y_{i,t}$  denotes returns of asset i at time t. Recall that for convenience we had assumed that security 1 is the only one affected by the volatility call auction (the treatment). Using the information from the pre-event/estimation window we estimate the best tracking portfolio for asset 1 using the securities in the control group. The best tracking portfolio provides a set of optimal weights that better tracks the returns of security 1,  $R_{1,t}$  in the pre-event window. Then in the post-event window we used the estimated weights and the evolution of the control group to forecast (in-sample) a synthetic return that is the best proxy of the evolution of the returns of security 1 had the volatility call auction not taken place, that is this our estimate of the potential outcome for security 1. Figure 4 provides a graphical illustration of how the method works, the continuous line shows the observed evolution of returns for security 1 before and after the event, while the doted line shows the evolution of the synthetic portfolio. Note that in the pre-event window the synthetic portfolio provides a good tracking performance of the security 1 as it clearly replicates the return of the security of interest. If this is so then we have a strong proxy for security 1 just before the volatility call auction. Once the volatility call auction is resolved and a new equilibrium price is obtained continuous trading resumes in the post event window and the observed evolution of the returns of security 1 that has been affected or treated by the volatility call auction. Thus, the post-event return of the synthetic portfolio  $R_{P,t}$  becomes a proxy for the unobserved potential outcome of the behavior of security 1 had the volatility call auction not taken place or in other words the state of the world where security 1 is not exposed to the volatility call auction (the treatment). Lets emphasize that the securities in the synthetic portfolio have not been affected by the volatility call auction and hence have received no treatment.

Using the synthetic portfolio method, the causal effect of the volatility call auction is the following, abnormal returns:

$$AR_{1,t} = R_{1,t} - R_{P,t} \tag{3}$$

$$= R_{1,t} - \sum_{j=2}^{J} w_j^* R_{j,t}, t \in (T_0, T]$$
(4)

Where  $w_j^*$  denotes the weights estimated for each of the J-1 securities <sup>2</sup>. For the case of volatility we obtain 5 minutes realized volatility estimates based on the synthetic returns and the returns of asset 1 to determine the effect of the volatility call auction. We use the weights on the synthetic portfolio returns to build synthetic indicators of the other variables of interest (bid-ask spreads, depths, and turnover). We can generalize the previous measure of abnormal returns to a measure of the effect of volatility call auction over any

<sup>&</sup>lt;sup>2</sup>When comparing the synthetic portfolio approach to traditional event study approaches we find: First, unlike the constant mean model we perform a cross sectional average across the control units that are not affected by the event, rather than a simple time series average for the security of interest before the event takes place. Second, in the market model we estimate the best tracking portfolio rather than using the fitted value of the variable of interest on the market portfolio. In both cases, as we have mentioned before our strongest advantage is that we provide a more credible approach to build a potential outcome that is not influenced by the event. Even though, the existence of externalities from halted securities to informational related securities has been empirically supported by the results of Jiang et al. (2009) this can be overcome in the synthetic portfolio approach by having a larger control group and possibly restricting the estimated weights so that no single security can dominate the synthetic portfolio returns and hence the potential outcome.

of the variables that is informative with respect to market quality <sup>3</sup>,

$$\delta_{1,t} = Y_{1,t} - Y_{P,t} \tag{5}$$

$$=Y_{1,t} - \sum_{j=2}^{J} w_j^* Y_{j,t}, t \in (T_0, T]$$
(6)

After we estimate the synthetic portfolio we must validate whether they provide good tracking performance in the pre-event window. We do this by determining if there is a statistically significant difference in the average behavior of the indicator and the asset of interest. This is equivalent to testing the null hypothesis that the tracking error of the portfolio is statistically different than zero in the pre-event window. We also use a test based on the ratio of the synthetic portfolio estimate versus the observed security  $S_1$ , for the indicator of interest (volatility, bid-ask spread, turnover), and test the null hypothesis that the ratio is statistically different than 1. We will only use the volatility call auctions where there is good tracking performance based on these testing strategies to determine the effectiveness of the mechanism and its effect on market quality.

# 4. Empirical analysis

#### 4.1. The synthetic portfolio

For each of the auctions our empirical strategy requires that we build a synthetic portfolio that provides an accurate tracking performance of the asset of interest before the auction, then we use this portfolio to trace out the potential outcome (in the post event window) for the same asset had the auction not taken place. We illustrate the method by picking out two auctions (figure 5). The fist auction takes place on the 16 of November of 2010 at 11 : 50 : 39, affecting the stock an oil and gas company (ticker: ECOPETL). The second auction takes place on the 9 of August of 2011 at 12 : 25 : 43, affecting the stock a commercial bank (ticker: PFBCOLO). In both cases, in the top panel, we observed how the synthetic portfolio (dashed line) is able to track the five minute returns of the stock during the estimation window. The vertical line indicates the beginning and end of the

<sup>&</sup>lt;sup>3</sup>Since most of the indicators of market quality have a strictly positive support we must transform the weights of the synthetic portfolio returns so that they are positive,  $w_i^* \geq 0$ .

auction<sup>4</sup>. After the auction ended we observe, in the post event window, the deviation between the observed returns (the treated case) of the asset and the returns of the synthetic portfolio acting as the potential outcome (non-trated case). As we can see in the case of ticker PFBCOLO there is large variation in the returns of the synthetic portfolio, this is to be expected since the counterfactual is designed to capture an unobserved state of the world where the auction did not take place. For the ticker ECOPETL the difference in the variation of the returns (observed vs synthetic) is smaller than in the previous case.

One advantage of using the intra-day data is that as opposed to daily data there is a smaller chance of other confounding effect that are not due to the volatility auction. Furthermore, the construction of the counterfactual using a synthetic portfolio is more robust. As opposed to other approached in comparative case studies, we are not picking one particular asset or reference group of assets to build the counterfactual but rather choosing an optimal set of weights to replicate the asset of interest using a control group that has not been affected by the auction. Although there is bound to be some externatilities from informationally related securities as identified by Jian, McInish and Upson (2009) our approach is a less biased alternative, since the weights are estimated rather than imposed. The bottom panels (in figure 5), shows the estimated weights that are used to build the synthetic portfolio in the two auctions. Each asset in the control group receives a positive or negative weight. The asset does not necessarily belong to a specific asset class that has similar characteristics to the asset affected by the auction. For example in a number of comparative case studies (Guidolin and La Ferrara, 2007; Acemoglu et al. 2015) the control group is made up of companies in the same sector. The synthetic portfolio is only build on the notion that a particular assets in the control group (not treated by the volatility call action) provides a contribution to tracking the asset of interest (the asset that will be affected by the volatility call auction) before the realization of the event of interest (volatility call auction).

By allowing weights to take negative values we obtain in general a better tracking performance by the synthetic portfolio in the pre-event window. We perform the exercise illustrated by figure 5) using the five minute intraday returns for the 184 and the 441 auctions using transaction prices and

<sup>&</sup>lt;sup>4</sup>The information during the auction is not considered in the pre or post- event windows

mid price data, respectively<sup>5</sup>.

#### 4.2. Volatility impact of volatility call auctions

To assess the volatility impact of the volatility call auction, following the methodology outlined in the previous section, we estimate three measures of five minute realized volatility: of the asset that is affected by the auction (before and after the auction) and that of the synthetic portfolio after the auction. Since we are only using the auctions where there is good tracking performance of the synthetic portfolio with respect to the asset of interest in the pre-event window, we assume that the volatility before the auction is of the same magnitude. If hypothesis 1 is correct and the volatility call auction avoids strong price variation, then the asset that has gone into the auction (treated) has smaller volatility than the potential outcome captured by the synthetic (non treated). Figure 6 suggests that the volatility auction mechanism works and hence hypothesis 1 is true. The plots in figure 6 are scatter plots of the three measures, where each point (circle or triangle) indicate the realized volatility before and after the auction and any point in the 45 degree line (in black) is the situation where the volatility does not change. What we observed is that most triangles are above the 45 degree line, while the circles are more or less below or close to the origin around the line. Since the triangles represents the realized volatility of the synthetic portfolio, proxing the potential outcome of the asset not affected by the auction, then non-treatment leads to larger volatility whereas the treatment to less, at least relatively.

The difference between the plots in figure 6: first the top and bottom panels differs on the information used to estimate the returns and volatilities, transaction prices versus mid prices. Second the difference between the right and left panel is the amount of five minute returns used to estimate the realized volatilities. In the left panel all the information both in the pre-event and post event window is used <sup>6</sup>. In the right panel we only consider five minute returns one hour before and after the auction. In all four

 $<sup>^{5}</sup>$ We obtain similar results using 1 minute and 10 minute intra-day data, however there is some variation regarding the amount of feasible auctions. These results are available upon request to the corresponding author

<sup>&</sup>lt;sup>6</sup>Note that the amount of information in each auction can be different because this depends on the time when the auction takes place during the trading day

cases in figure 6 we observe that the volatility call auction delivers a reduction in volatility, which is in line with the results on the German Xetra stock market (Gombet et al. 2011; Zimmerman 2013) and Spanish stock market (Reboredo, 2010)<sup>7</sup>.

To get an overall measure of the effect of the mechanism we estimate the median percentage change in volatility using the auctions in figure 6. With the TAQ data for the full day, the volatility call auction had no effect on the annualized volatility estimated using transaction prices but it decreased fundamental volatility (quote based) by 92%; whereas in the case of no auction (no treatment) volatility would have increased by 225% or by 469% using quote data (table 2). With the information only one hour before and after the auction, the volatility call auction decreases both transaction and quote based annualized volatility by 67% and 100%, respectively. The alternative of no call auction, would have lead to a volatility increase between 33% and 70% (table 3). The substantial increases for the synthetic portfolio volatility reveal that, the rise in volatility that triggered the call auction in the first place tends to be shared by other stocks (i.e. systemic).

#### 4.3. Liquidity impact of volatility call auctions

Like in volatility, we measure the effect of volatility call auctions in other variables of market quality both for treated stocks, as well as for the corresponding synthetic portfolios. Figure 7 allows to compare the change in the bid-ask spread for the two groups. Top graphs presents the results for the effective bid-ask spread, while the bottom ones do the same for the quoted bid-ask, both defined in Goyenko, Holden and Trzcinka (2009). As before, left panels use all available information in the trading day, while right panels only use one hour before and after the call auction. Apparently, the volatility call auction has no major effect on the bid-ask spread for the treated stock, as the circles appear somewhat evenly distributed above and below the 45 degrees line in all four cases. Interestingly, the liquidity measure seems to decrease after the call auction for the non-treated group, as triangles tend to be below the 45 degrees line, consistently in all the four panels. This

<sup>&</sup>lt;sup>7</sup>We perform robustness test based on 1 minute and 10 minute returns and the results are equivalent with respect to the effectiveness of the mechanism; the only significant difference is that in some cases we have a smaller number of feasible auctions to analyse or because we loose or gain good tracking performance at these different frequencies. These results are available upon request to the authors

preliminary result clearly go against hypothesis that assume that volatility call auctions would also improve liquidity of the treated stocks.

Table 2 presents the median percentage effect of the volatility call auction in the measures of liquidity and trading activity for both groups. There are five liquidity measures, the quoted and effective spreads, the depths at both quotes, and the ratio bid-ask spread over average depth as in Jiang et al. (2009). There is a reduction in the quoted bid-ask spread in both groups, significant at the 5% level, and so in the Spread/Depth ratio. This effect is higher in the portfolio. Moreover, there is a significant reduction in the effective bid-ask spread in the control group, but not in the stock. On the other hand, there is no discernible effect on the depths and in turnover, in either case. Table 3 presents the same results but using only the data one hour before and after the auction. Overall there is no significant effect either in the stock undergoing the auction (treated) or in the synthetic portfolio (nontreated). Although there seems to be a minor effect of liquidity improvement in both the stock and the synthetic portfolio, this can be attributed to the well-known trend of improving liquidity along the trading day. All in all the results in Tables 2 and 3 are not supportive of hypothesis 2. The volatility call auction does not have a discernible effect in the market quality variables the treated stock, other than volatility itself.

# 5. Conclusions

In this paper we address one of the main difficulties in event studies: building a credible counterfactual. Traditional event studies have focused on using the security of interest fitted to the market model (MacKinlay, 1997), building a reference group based on asset with similar characteristics or behavior (Jiang, et al 2009) or defining pseudo events (Reboredo, 2010; Abad and Pascual, 2010).

We suggest a different methodological approach by proposing synthetic portfolio for event studies, this approach allow us to build a more general and robust counterfactual. Our counterfactual is a portfolio build by finding the optimal weights that allows us to track a variable of interest, for example the returns of an asset that have been affected by a particular event. To build the portfolio we can potentially use all other assets that have not been affected by the event.

We use the synthetic portfolio method to test for the effectiveness of a type

of circuit breaker known as a volatility call auction. We use high-frequency Trade and Quote date from the Colombian stock Exchange that uses this mechanism in its trading platform.

For the volatility call auctions observed over two years (2010-2012) we find positive results in terms of the effectiveness of the mechanism. The mechanism has an important impact in mitigating excessive volatility during the trading day and in addition we do not find an effect on other dimensions of market quality, such as liquidity, depth and trading activity.

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#### Appendix: Synthetic portfolio method

The estimation of the synthetic portfolio is quite straight forward and it is based on synthetic control methods (Abadie, et al. 2010). The synthetic control is a weighted average of the available control units, that makes explicit: the contribution of each unit to the potential outcome of interest and the similarities (or lack thereof) between the unit affected by the event or the intervention of interest and the syntectic control in terms of the preintervention outcomes and other predictors of post-intervention outcomes. In synthetic control methods a set of predictors is used to determined the aforementioned similarities between the control units and the unit of interest. We avoid using predictors by tracking the behavior of the asset of interest using a weighted average of the assets in the control group, hence we call our method synthetic portfolio.

For the event study,  $Y_{1,t}$  is the security of interest. In other words the security whose trading had been halted because of the volatility auction (the intervention). On the other hand the syntectic portfolio is build by using the other securities (those in continuous trading, before, and after the intervention) to replicate the performance of the security of interest.

The methodology is very simple since we only need to obtain the portfolio weights  $(w_j^*)$  by solving the tracking problem,

$$\mathbf{w}^* = argmin_{\mathbf{w}} \sum_{t=1}^{T_0} \left( Y_{1,t} - \sum_{j=2}^J w_j Y_{j,t} \right)^2$$

For the pre-intervention period  $t \in [1, T_0)$ . With the post-intervention data we would estimate the desired effect of the intervention and hence measure the causal effect of volatility call auction.

$$\hat{\alpha}_{1,t} = Y_{1,t} - \sum_{j=2}^{J} w_j^* Y_{j,t}, t \in (T_0, T]$$

# References

- ABADIE, A., DIAMOND, A., HAINMULLER,2010. Synthetic control methods for comparative case studies: Estimating the effect of California's tabacco control program, *Journal of the American Statistical Association*, 105(490), pp.493-505.
- [2] ABAD, D., PASCUAL, R.,2010. Switching to a temporary call auction in times of high uncertainty, *Journal of Financial Research*, 35(1), pp.45-75.
- [3] ACEMOGLU, D., JOHNSON, S., KERMANI, A., KWAK, A., MITTON, T.,2015. The Value of Connections in Turbulent Times: Evidence from the United States, forthcoming *Journal of Financial Economics*, xx(x), pp.xx-xx.
- [4] CHRISTIE, W.G., CORWIN, S.A., HARRIS, J.H., 2002. Nasdaq trading halts: The impact of market mechanisms on prices, trading activity, and execution costs, *Journal of Finance*, 57, pp. 1443-1478.
- [5] CORWIN, S. A., LIPSON, M. L., 2000. Order flow and liquidity around NYSE trading halts, *Journal of Finance*, 55(4), pp. 1771-1801.
- [6] EUROPEAN COMMISSION, 2010. Public consultation, review of the markets in financial instruments directive (mifid). Available at:http://ec.europa.eu/finance/consultations/2010/mifid/docs/consultation\_papes
- [7] FAMA, E.F., 1989. Perspectives on October 1987, Or, What Did We Learn from the Crash?. In SR.W. Kamphuis, Jr., R.C. Kormendi, and J.W.H. Watson. (Eds). Black Monday and the Future of Financial Markets (pp.71-82). Chicago: Mid America Institute for Public Policy Research.
- [8] FRANCIONI, R., 2013. Chapter 2: Mid Day Address. In Schawrz.R.A, Byerne, J.A and Schnee, G. (Eds). The Quality of Our Financial Market. Taking Stock of Where We Stand (pp.17-27). New York, NY: Springer.
- [9] FRINO, A., LECCE, S., AND SEGARA, R., 2011. The impact of trading halts on liquidity and price volatility: Evidence from the Australian Stock Exchange, *Pacific Basin Finance Journal*, 19, pp. 298-307.

- [10] GLOSTEN, L. R., AND MILGROM, P. R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics*, 14(1), pp. 71-100.
- [11] GOMBER, P., 2016. The German Equity Trading Lanscape. Available at:http://safe-frankfurt.de/fileadmin/user\_upload/editor\_common/Policy\_Center/9
- [12] GOMBER, P., LUTAT, M., HAFERKORN, M., ZIMMERMANN, K., 2011. The effect of single-stock circuit breakers on the quality of fragmented markets. Lecture Notes in Business Information Processing, 136 , 71-87.
- [13] GOYENKO, R. Y., HOLDEN, C. W., AND TRZCINKA, C. A., 2009. Do liquidity measures measure liquidity?, *Journal of Financial Economics*, 92(2), pp. 153-181.
- [14] GOW, I.D., LARCKER, D.F., REISS, P.C., 2016. Causal inference in accounting research. Working paper series No. 217, Rock Center for Corporate Governance, Stanford University.
- [15] GREENWALD, B.C. AND J.C. STEIN., 1988. The Task Force Report: The Reasoning Behind the Recommendations, *Journal of Economic Perspectives*, 2, pp. 3-23.
- [16] GREENWALD, B.C. AND J.C. STEIN., 1991. Transactional Risk, Market Crashes, and the Role of Circuit Breakers, *Journal of Business*, 64, pp. 443-462.
- [17] GROSSMAN, S.J., 1990. Introduction to NBER Symposium on the October 1987 Crash. *Review of Financial Studies*, 3, pp. 1-3.
- [18] GRUNDY, B.D. AND MCNICHOLS, M., 1989. Trade and revelation of information through prices and direct disclosure. *Review of Financial Studies*, 2, pp. 495-526.
- [19] GUIDOLIN, M., LA FERRARA, E., 2007. Diamonds Are Forever, Wars Are Not: Is Conflict Bad for Private Firms?, *The American Economic Review*, 97(5), pp.1978-1993.
- [20] IMBENS, G.W. AND RUBIN, D.B., 2015. Causal inference for statistics, social and biomedical sciences: an introduction. New York, NY: Cambridge University Press.

- [21] JIANG, C., MCINISH, T., UPSON, J., 2009. The information content of trading halts, *Journal of Financial Markets*, 12, pp.703-726.
- [22] KIM, Y. H., YAGE, J., AND YANG, J. J., 2008. Relative performance of trading halts and price limits: Evidence from the Spanish Stock Exchange, *International Review of Economics and Finance*, 17, pp.197-215.
- [23] KIM, Y. H., AND YANG, J. J., 2004. What Makes Circuit Breakers Attractive to Financial Markets? A Survey, *Financial Markets, Institu*tions and Instruments, 13(3), pp.109-146.
- [24] KRYZANOWSKI, L., AND NEMIROFF, H., 1998. Price discovery around trading halts on the Montreal Exchange using trade-by-trade data, *Fi*nancial Review, 33, pp.195-212.
- [25] KYLE, A. S., 1985. Continuous Auctions and Insider Trading, Econometrica, 53(6), pp.1315-1335.
- [26] LEE, C. M. C., READY, M. J., AND SEGUIN, P. J, 1994. Volume, Volatility, and New York Stock Exchange Trading Halts, *Journal of Finance*, 49(1), pp.183-214.
- [27] MACKINLAY, A.C., 1997. Event studies in economics and finance, Journal of Economic Literature, 35(March), pp.13-39.
- [28] MADHAVAN A, 1992. Trading Mechanisms in Securities Markets, Journal of Finance, 47(2), pp.607-641.
- [29] PAGANO, M.S., PENG, L., SCHWARTZ, R., 2013. A call auction's impact on price formation and order routing: Evidence from the NASDAQ stock market, *Journal of Financial Markets*, 16, pp.331-361.
- [30] REBOREDO J., 2012. The switch from continuous to call auction trading in response to a large intraday price movement, *Applied Economics*, 44(8), pp.945-967.
- [31] SPIEGEL, M. AND SUBRAHMANYAM A., 2002. Asymmetric information and news disclosure rules, *Journal of Financial Intermediation*, 9, pp.363-403.

- [32] SUBRAHMANYAM A., 1994. Circuit Breakers and Market Volatility: A Theoretical Perspective, *Journal of Finance*, 49(1), pp.237-254.
- [33] ZIMMERMANN, K., 2013. Price Discovery in European Volatility Interruptions. Available at:http://www.fese.eu/images/documents/deLaVega/PriceDiscoveryinEuropeanVolatility



# Figure 1: Volatility auction mechanism

Notes: Description of the volatility auction mechanism, Bolsa de Valores de Colombia.





Notes: Histogram of all the 1062 auctions identified from August 2010 to August 2012.





Notes: Histogram of 184 auctions identified as viable for the implementation of synthetic portfolio method, from August 2010 to August 2012.



Figure 4: Synthetic portfolio method for event studies in market microstructure Notes: Time line for the event study, based on synthetic control method (Abadie et al. 2010).



(a) Observed and synthetic returns for ECOPETL



(c) Synthetic portfolio weights tracking ECOPETL



(b)Observed and synthetic returns for PFBCOLOR



(d) Synthetic portfolio weights tracking PFBCOLO

# Figure 5: Synthetic portfolio

Note: The top panels (a) and (b) illustrate the 5 minutes observed returns (solid line) and synthetic returns (dashed line) of ECOPETL and PFBCOLO over the day. We observed a call auction (the event) taking place at the time indicated by the red vertical line. The vertical line also determines pre-event/estimation window and the post-event/forecasting window. The bottom panels (c) and (d) indicate the estimated weights of the synthetic portfolio for ECOPETL and PFBCOLO. These weights are estimated using the observed returns in the pre-event window.



(c) Mid price, full day

(d) Mid price, 1h before and after

#### Figure 6: Volatility impact of volatility call auctions

Note: Each panel illustrates a scatter plot of the estimated five minute realized (annualized) volatilities before and after the volatility auctions. Circles in blue indicate the volatility of the asset that is affected by the auction (treated). Triangles in red indicate the volatility before the auction of the asset affected by the auction and the volatility after the auction of the synthetic portfolio that is not affected by the volatility auction (non-treated). That is, the Triangles include a potential (outcome) measure of the volatility in the period after the auction had the auction not taken place. The solid line is a 45 degree line indicating whether volatility does not change (along the line), increases (above the line), decreases (below the line) after the volatility call auction. In panels (c) and (d) the realized volatilities are estimated using 5 minutes returns based on mid prices (quote data). In panels (a) and (c) the realized volatilities before and after the auction are measured with the continuous trading information of all the day. In panels (b) and (d) the realized volatilities before and after the auction.



(c) Quote Bid-Ask spread, full day

(d) Quote Bid-Ask spread, 1h before and after

#### Figure 7: Liquidity impact of volatility call auctions

Note: Each panel illustrates a scatter plot of the average spread before and after the volatility auctions. Circles in blue indicate the spread of the asset that is affected by the auction (treated). Triangles in red indicate the spread before the auction of the asset affected by the auction and the spread after the auction of the synthetic portfolio that is not affected by the volatility auction (non-treated). That is, the Triangles include a potential (outcome) measure of the spread in the period after the auction had the auction not taken place. The solid line is a 45 degree line indicating whether spread does not change (along the line), increases (above the line), decreases (below the line) after the volatility call auction. In panels (a) and (b) the spreads are measured using the effective spread based on transaction prices and quotes. In panels (c) and (d) the spreads are measured using bid and ask prices (quote data). In panels (a) and (c) the average spreads before and after the auction are measured with the continuous trading information of all the day. In panels (b) and (d) the average spreads before and after the auction are measured with the continuous trading information of only one our before and after the auction.

Nemo	Number of auctions	Percentage	Nemo	Number of auctions	Percentage
BMC	239	22.5	PFCORCOL	7	0.66
VALBAVA	157	14.78	NUTRESA	6	0.56
COLTEJ	92	8.66	INVARGOS	5	0.47
CNEC	78	7.34	PFDAVVND	5	0.47
ENKA	73	6.87	BCOLO	4	0.38
CONCONC	41	3.86	BOGOTA	4	0.38
PFBHELMB	35	3.3	EEB	4	0.38
PREC	33	3.11	GRUPOSUR	4	0.38
ETB	30	2.82	ECOPETL	3	0.28
MINEROS	30	2.82	PFBCOLO	3	0.28
ODINSA	30	2.82	ISA	2	0.19
TABLEMA	25	2.35	PAZRIO	1	0.09
FABRI	19	1.79	BBVACOL	0	0
BIOMAX	18	1.69	CARTON	0	0
CELSIA	16	1.51	GASNAT	0	0
EXITO	16	1.51	IMUSA	0	0
AVAL	15	1.41	OCCID	0	0
BVC	15	1.41	POPULA	0	0
ISAGEN	13	1.22	PROMIG	0	0
SIE	12	1.13	PROTECC	0	0
CEMARGOS	10	0.94	SANTAN	0	0
CORFICOL	9	0.85	SOCBOL	0	0
INTBOL	8	0.75			

Table 1: Numbers of auctions per asset

Note: The table reports the number of auctions observed for each of the 45 assets analyzed in the complete sample from August 2010 to August 2012.

	Before / After Auction (%)	Troptod	Non Troated
	Delore/Alter Auction (70)	Ileateu	Non-meated
Volatility	Transaction prices	0.00	$2.25^{***}$
	Mid price	-0.92***	$4.69^{***}$
Liquidity	Quote bid-ask spread	-0.23**	-0.33***
	Effective spread	-0.14	-0.43***
	Bid depth	-0.20	-0.01
	Ask depth	0.15	0.01
	$\mathbf{Spread}/\mathbf{Depth}$	-0.25**	-0.50***
Trading Act.	Turnover	0.00	-0.10

Note: Standard errors are shown in parentheses. \*,

\*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Impact on market quality of the volatility call auction, full day

	Before/After Auction (%)	Treated	Non-Treated
Volatility	Transaction prices	-0.67*	$0.33^{***}$
	Mid price	-1***	$0.70^{***}$
Liquidity	Quote bid-ask spread	0.01	-0.18
	Effective spread	0.19	-0.29
	Bid depth	-0.18	0.06
	Ask depth	-0.18	0.16
	$\mathbf{Spread}/\mathbf{Depth}$	-0.33	-0.33***
Trading Act.	Turnover	-0.30	-0.35*

Note: Standard errors are shown in parentheses. \*,

\*\*, and \*\*\* denote significance at the 10%, 5%, and

1% levels, respectively.

Table 3: Impact on market quality of the volatility call auction, using data 1 hour before and after the auction