Switching to a Temporary Call Auction in Times of High Uncertainty[†]

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ABSTRACT

Madhavan (1992, *The Journal of Finance*, 47, 2, 607-641) recommends a temporary switch to a call auction rather than a trading halt in times of market stress. He predicts the call auction to aggregate information more efficiently and to facilitate the resumption of the continuous session. In this paper, we test the properties of the switching mechanism proposed by Madhavan using data from the Spanish Stock Exchange (SSE). The SSE implements rule-based call auctions to stabilize prices. On the positive side, we find there is price learning during the auction, and price reversals dominate price continuations after the auction. On the negative side, we conclude rule-based auctions do not calm the market and do not reduce information asymmetries, except for small-caps. Our findings suggest the switching mechanism performs better with thinly traded stocks.

1. Introduction

Individual-security trading halts are a very common device in financial markets to deal with periods of high uncertainty. The pros and cons of trading halts have been the subject of an intense debate among academics and regulators. Proponents argue that trading halts provide time for price reassessment and reduce information asymmetries. Moreover, they reduce transitory volatility, offset overreaction, and prevent liquidity traders from incurring in severe losses. In contrast, critics claim that trading halts are an unnecessary impediment for trading, delay price discovery, and may even have the counterproductive effect of exacerbating price changes.[1]

In the most important US markets, firm-specific trading halts are discretionary and, consequently, their timing is generally unpredictable. In the NYSE, trading halts are initiated by the specialist. During NYSE halts, the specialist issues indicator quotes, "trial balloons" to which traders respond submitting commitments to trade. This price exploration stage lasts for more than one hour and finishes with a call auction. Most NYSE halts are delayed openings (Lee et al., 1994). In the Nasdaq, trading halts are initiated by the StockWatch Department. Christie et al. (2002) report durations for the no-trading phase between 30 and 60 minutes. The halt finishes with a 5-minute quotation period for market markers and does not involve a centralized call auction.

The evidence on US discretionary halts suggests they fail to stabilize the market. Lee et al. (1994) report unusual volatility and trading volume in the half hour following NYSE halts. While volatility rapidly decays thereafter, trading volume remains high two days after the halt. They conclude NYSE halts do not "[…] facilitate the type of information transmission that results in cleaner reopening prices". Christie et al. (2002) provide consistent evidence for the Nasdaq case. Post-halt trading activity and volatility are higher than on non-halt days for

[1] Detailed discussions can be found in Lee et al. (1994), Harris (1998), and Kim and Rhee (1997), among others.

up to two hours. For intraday halts, they also report higher than usual post-halt spreads within 30 minutes after the resumption of trading. They conclude that the uncertainty associated with Nasdaq trading halts is not resolved by the time the halt is lifted. Finally, Corwin and Lipson (2000) analyze the order flow around NYSE halts. They show that order submissions and cancellations are extremely high during the halt period, suggesting that investors use the halt to reposition their trading interests. Nonetheless, the unusual order flow remains high for several hours after the halt. They also show that the reopening price is a good predictor of posterior prices, indicating that submissions and cancellations during the halt are a useful source of information. Finally, liquidity, as measured by book depth near the quotes, is unusually low, after NYSE halts.

Madhavan (1992) criticizes those microstructures that propose to use trading halts to reduce market stress in continuous systems. He argues the trading halt may exacerbate the original problem, possibly leading to market failure. Madhavan theoretically compares price formation in financial markets under different trading mechanisms: price-driven and order-driven continuous markets and order-driven periodic auctions. He shows that continuous mechanisms may fail in periods of severe information asymmetry unless there is enough liquidity trading. When information asymmetry is sufficiently grave, liquidity-motivated traders have no incentives to trade since they cannot make nonnegative expected profits. In these circumstances, equilibrium may not exist. In contrast, Madhavan shows that call auctions may still be viable in economies where continuous auctions fail. The call auction equilibrium exists even when public information is so poor that dealers decide not to make market. The reasoning is that pooling orders for simultaneous execution overcomes the costs of information asymmetry. Moreover, call auctions may aggregate information more efficiently than continuous markets. In particular, prices converge to the strong form efficient price as the number of auction participants increases.

In his theoretical framework, Madhavan (1992) concludes that, once halted, it may be difficult or even impossible to restate the trading process unless the degree of information asymmetry is lessened. Instead, Madhavan proposes a temporary switch to a periodic trading phase in times of market stress. The particular timing of the switch would be rule-based (non-discretionary).[2] The allocation price of the auction would serve as a public information signal of the asset value that may facilitate the resumption of the continuous session.

Amihud and Mendelson (1991) provide indirect support to Madhavan's proposition. They use data from the Tokyo Stock Exchange, where the two daily trading sessions are opened with a periodic auction (*Itayose*). These authors show that the daily returns from the opening auction, which is preceded by a non-trading phase, are more volatile than the daily returns from the call auction used to open the afternoon session. Even more, they find that the mid-day auction "may well exhibit the least volatility and the most efficient value discovery process".

In this paper, we provide direct evidence on the efficiency of Madhavan's (1992) proposition using data from the Spanish Stock Exchange (SSE). Since 2001, the SSE uses short-lived rule-based call auctions to deal with unusual volatility levels during the continuous trading session. A so-called "volatility" auction is triggered when prices hit stock-specific price limits. The call auction lasts 5 minutes plus a random end of maximum 30 seconds and, afterwards, the continuous trading session resumes. The SSE system of rule-based call auctions just matches the switching mechanism recommended by Madhavan (1992).[3] We evaluate Madhavan's proposition studying the implications of the SSE switching mechanism in price discovery, market stability, and information asymmetry risk.

[2] In particular, Madhavan (1992) suggests triggering the switching mechanism when the quoted bid-ask spread exceeds a certain critical level based on trading volume and historical spreads.
[3] A similar switching mechanism is implemented in Euronext.

We find that rule-based auctions significantly contribute to price discovery; the market-clearing price of the volatility auction reflects learning in the sense that the allocation price of the auction is more informative about the long-run value of the stock than pre-auction quotations. Although this finding is robust across stocks, we find that volatility auctions are more relevant in the price discovery process of infrequently traded stocks. We also find that price reversals dominate price continuations both during and after rule-based auctions. Our findings therefore disagree with those claiming that circuit breakers systematically delay price discovery. Nonetheless, the rule-based auction is not sufficient to correct the overreaction occurring in the pre-auction period.

As with discretionary US halts, we provide evidence that the switching mechanism proposed by Madhavan (1992) does not calm the market. Volatility, trading activity, and illiquidity levels are unusually high after the auction, meaning that rule-based auctions do not fully resolve price uncertainty. Additionally, we report unusual adverse selection costs levels in the pre-auction period, especially for small-caps. After the rule-based auction, the atypical risk persists during almost two hours among large-caps, but it reverts immediately to non-auction days' levels among small-caps. Our findings therefore suggest the switching mechanism performs better in reducing information asymmetries with thinly traded stocks.

The remainder of the paper is organized as follows. In section 2, we give details on the microstructure of the SSE. In section 3, we review the existing theoretical literature and develop hypotheses we test in posterior sections. In section 4, we describe the database and provide some preliminary statistics. In section 5, we report our empirical findings on the performance of the Madhavan's (1992) switching mechanism. Finally, in section 6, we conclude.

2. Institutional background

The electronic trading platform of the SSE, called SIBE, holds the trading activity of the SSE-listed stocks that, in their most recent past, have satisfied minimum requisites on trading activity and liquidity. The list of stocks admitted to trade through the SIBE is revised every semester. The SIBE is an order-driven market where liquidity is provided by an open limit order book (LOB). Trading is continuous from 9:00 a.m. to 5:30 p.m. There are two fixed daily call auctions; the first one determines the opening price (8:30-9:00 a.m.), and the second one sets the official closing price (5:30-5:35 p.m.). Three basic types of orders are allowed: limit orders, market orders, and market-to-limit orders. Market orders walk up or down the book until they are totally executed. Market-to-limit orders are restricted to the best price on the opposite side of the market. Orders submitted that are not instantaneously executed are stored in the book waiting for a counterparty. The usual price-time priority rule applies. Unexecuted orders can always be cancelled and modified. A trade occurs when an incoming order matches one or more orders on the opposite side of the LOB; thus, every trade involves at least one order stored on the LOB.

Since 5-14-2001, the SSE incorporates a system of intraday price limits and volatility halts directed to handle unusual volatility levels. The "static" price range defines the maximum permitted variation (in either direction) around the so-called "static" price. The static price is the allocation price of the last auction performed. Static price limits remain in force throughout the entire session or until a new auction is triggered. There are standardized categories of possible static ranges: 4%, 5%, 6%, 7% and 8%. There is also a unique 10% range for stocks listed in the "New Market".[4] The range assigned to a particular stock depends on its most recent historical volatility. Static ranges are ordinarily revised every six months. Extraordinary revisions are possible if the situation of the market so requires.

[4] The New Market includes technological and chemical firms, R&D firms, and Internet firms, among others. All firms in this segment of the SIBE are highly volatile.

Whenever an incoming order is to be executed at or above (below) the upper (lower) static price limit, a static halt (henceforth SH) is triggered. A SH lasts only 5 minutes plus a random end of at most 30 seconds.[5] During this interval, a tâtonnement process takes place. As usual, traders can submit, cancel, and modify orders during the tâtonnement, but no trade occurs. When this period finishes, the system sets the allocation price of the auction, if any. Volatility halts are never extended; continuous trading, therefore, resumes after the halt independently of whether a consensus price has been attained.[6] During a SH, the static price is updated and set equal to the price limit that triggered the halt. After the SH, the static price is set equal to the allocation price of the auction, if it exists.[7]

There are some features of SSE switching mechanism that we would like to highlight. First, SSE halts are non-discretionary (rule-based). The decision of halting the continuous double auction trading process and switching to a call auction process does not depend on the discretion of a market maker or any kind of exchange official. Mandatory and objective rules establish when a stock must automatically enter in an auction phase. SSE investors can continuously monitor the distance between the quoted prices and the upper and lower price limits, meaning that static halts can be anticipated up to a certain extent. Second, SSE halts last less than discretionary halts. Corwin and Lipson (2000) report an average halt length of 80 minutes for the NYSE. Christie et al. (2002) report lengths between 31 and 60 minutes for the Nasdaq. Third, Because of the two previous features, volatility halts are very frequent. From May 14th 2001 to December 31st 2003, more than 3000 static halts took place among all

[5] The goal of this random end is to avoid price manipulation.

[6] There is only an exception to this rule. A necessary condition for a price to be the allocation price of an auction is that all market orders and market-to-limit orders submitted during the auction must find counterparty at that price. When no potential allocation price satisfies this condition, market regulators may extend the auction. The length of this extension is, however, totally discretionary.

[7] In addition to static ranges, the SIBE introduced "dynamic" ranges in 5-14-2001. These ranges set the maximum price variation around the last trade price. These price limits are therefore updated each time there is a new trade. By definition, static ranges are always larger than dynamic ranges. A dynamic halt (henceforth DH) is triggered when a dynamic price limit is violated. A violation of the static range implies a dramatic intraday variation in the stock price. On the contrary, a dynamic halt may be triggered by a single and unexpected large-sized order. In this paper, we focus on static halts and we discard days with one or more dynamic halts.

the firms in the SIBE, excluding non-Spanish stocks. Moreover, to observe two or more halts the same day is not a rare event (27.44% of days with static halts have at least two static halts).[8]

3. Literature review and hypotheses

Madhavan (1992) argues that switching to temporary call auctions in times of high uncertainly instead of halting the trading process may result in more efficient reopening prices. He shows that during call auctions, all traders observe a noisy estimate of their aggregated information, in addition to the public or private signals. The resulting allocation price is more efficient as a signal of the asset value the greater the number of participants in the auction. Other theoretical and empirical studies have shown that concentrating orders in a call auction may increase price efficiency (see Biais et al., 2005, pp. 244-245, for a review). Indeed, single call auctions are used in several continuous markets when the uncertainty about fundamentals is large, such as in the pre-opening and pre-closing intervals, or to re-open following a trading halt. In some other markets, infrequently traded and illiquid stocks are traded through periodic trading systems in order to concentrate liquidity.[9] Medrano and Vives (2001) theoretically show that, in the presence of strategic informed traders that manipulate the price discovery process during the call auction, market-clearing prices approach, but do not converge, to the efficient price. However, they prove information revelation exists, and it accelerates towards the close of the auction. Biais et al. (1999) provide consistent empirical evidence. Using data on pre-opening auctions of the Paris Bourse, they show that tentative allocation prices become more efficient in a semi-strong

[8] The effect of the predictability of the static halts on traders' strategies has been studied by Abad and Pascual (2006).

[9] Many European markets have developed market segments for illiquid stocks based on sequences of long-lasting call auctions. In Spain, for example, this segment is called "Fixing". In this market, stocks only trade twice a day, at noon and at 17:30 p.m., and transaction prices are determined through two consecutive single-call auctions. Similar segments are found in Paris, Milan, Amsterdam, Athens, Lisbon etc. Lauterbach (2001) studies stocks in the Tel-Aviv Stock Exchange that were removed from the continuous market and sent back to a single daily auction market. He concludes that continuous trading may be suboptimal for thinly traded stocks.

sense as the auction comes to its end. Medrano and Vives (2001) also show that price discovery benefits from a long tâtonnement process, such as the two and a half hours of the pre-opening period in the Paris Bourse. However, a short duration implies less time for price manipulation by strategic informed traders. As a consequence of this tradeoff, the degree of information revelation during short-lived rule-based auctions remains as an open empirical question. Our first hypothesis is that,

H1 ("Pure learning" hypothesis): Price triggered volatility auctions contribute to price discovery. The allocation price of a short-term rule-based volatility auction is an unbiased estimator of the equilibrium price of the stock (semi-strong price efficiency).

A recurrent argument among circuit breaker critics is that these mechanisms delay price discovery because they interfere with the natural progress of the trading process (e.g., Fama, 1989; Lehman, 1989; Lee et al., 1994). When price movements are constrained by price limits, for example, stocks may be prevented from reaching their equilibrium price. As a result, they have to wait until the resumption of trading to reach their true value. The so-called delayed price discovery hypothesis would therefore predict positive (negative) returns after an upper (lower) limit-hit. Kim and Rhee (1997) and Chen (1998) report overnight price continuations after daily limit-hits, concluding that price limits postpone price discovery. Huang et al. (2001) argue this pattern is also consistent with the overreaction hypothesis. Under this alternative, circuit breakers delay both information revelation and overreaction by noise traders. If we are willing to assume that informed traders only reveal information through trading, that value-motivated trading during the opening is limited or prohibited, and that noise traders may be unable to infer the intrinsic value of the stock during the overnight because of the lack of trading, then, overnight price continuations could be explained by noise traders overreacting to new information. This overreaction will be gradually reversed afterwards. Consistently, Huang et al. (2001) find overnight continuations after limit-hits and price reversals the day after in the Taiwan Stock Exchange.

In a market like the SSE, where price limits activate a temporary switch to a call auction, limit-hits interrupt the continuous session for a while but, as discussed earlier, do not necessarily prevent price discovery. Moreover, value-motivated activity is not limited during the auction phase. Therefore, both information revelation and overreaction may concur during the auction. In the SSE, however, the allocation price of the auction is limited. The auction static limits, computed over pre-hit static limit, are in force during the 5-minute volatility auction. If the intrinsic value of the stock is above (below) the upper (lower) limit during the auction, price discovery and overreaction may be still delayed until the resumption of the continuous trading. Moreover, the auction may fail to prevent overreaction if it is too short or if the volume allocated at the market-clearing price is insufficient to satisfy the demands of noise traders.

Finally, suppose call auctions are efficient in revealing information (i.e., H1 is not rejected). In this scenery, the risk supported by an informed trader would augment near the price limit, encouraging her to anticipate trades, and increasing adverse selection costs. Kim and Sweeney (2002) develop a model where an informed investor faces binding daily price limits. In their model, the informed investor delays her profit-motivated trades from one day to the next when the current price is near, but the equilibrium price is substantially beyond, today’s limit. The reasoning is that by trading today, the informed investors can profit from only a small price rise. Moreover, if today’s trading reveals so much information that trading tomorrow is not worthwhile, then the informed investor bears a high opportunity cost. However, if the amount of information leaked overnight is excessive, so that trades tomorrow would be not profitable, or the limit price is close to the equilibrium price, the investor would be less likely to wait. Therefore, this model would also predict that when a limit-hit does not stop trading but activates an alternative trading device that could reveal new information, informed investors would be more willing to anticipate their trading programs.

Given all previous arguments, we must conclude that the effectiveness of Madhavan's (1992) rule-based auctions in preventing overreaction and delayed value-motivated trading is an open empirical question. Hence, we formulate the following hypotheses to be tested empirically in the next sections,

H2: In venues where limit-hits activate temporary switches from continuous to periodic trading, there is no price continuation after the auction.

H3: In venues where limit-hits activate temporary switches from continuous to periodic trading, adverse selection costs are not unusually large after the auction.

Concentration of trades and orders in a single call auction in times of market stress could be particularly beneficial for infrequently traded stocks. It is well known that stocks of large firms use to be covered by many analysts and investors. Therefore, they are likely to be subject to less information asymmetries than are stocks of small firms.[10] Biais et al. (1999) build on Copeland and Galai's (1983) theoretical framework to argue that for thinly-traded stocks mandated call auctions can minimize information asymmetries at the time of trade and lead to greater risk sharing. The rationale is that posted limit orders for infrequently traded stocks bear a high information asymmetry risk because the arrival rate of information is superior to the arrival rate of orders. A mandated call auction allows limit order traders to submit their orders right before the known time of the call, collecting all the information revealed during the tâtonnement process. Moreover, the call auction promotes the clustering of the thin order flow that otherwise would be spread over the continuous session.

[10] Clarke and Shastri (2001) report a negative relationship between several proxies of adverse selection costs and the number of analysts assessing a stock. Easley et al. (1996) find the probability of information-based trading to be lower for high volume stocks. Easley et al. (2002) find higher illiquidity premiums in stock returns of small-cap stocks in the NYSE. Abad and Rubia (2005) corroborate this finding for the case of the SSE. See Stoll (2000) for further evidence on the highest transaction costs of infrequently traded stocks.

Concentration favors liquidity and risk sharing, and helps to aggregate individual pieces of information. In contrast, when the arrival rate of orders is high relative to the arrival rate of information, as would be the case in frequently traded stocks, the gains from rule-based calls could be small or even offset by the costs to traders of not being able to rebalance their portfolios in continuous time. Therefore, we would expect the Madhavan's (1992) switching mechanism to better aggregate disperse information in small-cap infrequently traded stocks. Explicitly, we hypothesize that,

H4: Rule-based call auctions are more efficient in resolving information asymmetries when stocks are thinly traded.

4. Data and preliminary statistics

The database consists of limit order book files and trade files for 114 SSE-listed stocks, from June 2001 to December 2003. We consider stocks handled by the continuous electronic platform of the SSE. Book files comprise the 5 best ask and bid quotes, the quoted depth, and the number of orders supporting each quote. Book registers are time stamped to the nearest hundredth of a second, and updated each time the book changes. Trade files provide the price, size, and the time-stamp of each trade. We identify market orders, limit orders, and cancellations by matching the book and trade files using an algorithm originally developed by Pardo and Pascual (2005). The distinction between buyer-initiated and seller-initiated trades is straightforward since all trades consume liquidity either at the offer or at the bid side of the book.

We will pay special attention to two sets of stocks: (a) "IDX" stocks were constituents of the official SSE index (IBEX-35) during the whole sample period; (b) "NIDX" stocks never belonged to the IBEX-35. There are 32 IDX stocks and 70 NIDX stocks. These sets of stocks represent the two archetypes of stock that can be found in the SSE: IDX stocks are frequently traded and highly liquid; NIDX stocks are less frequently traded and can be considered as illiquid. The other 12 stocks went in and out of the IBEX portfolio at least once during the whole sample period.

Our sample comprises 2735 static halts. However, we eliminate the 9-11-2001 halts (71) because of the unique circumstances involved. We discard 33 halts lasting more than 5 minutes. Finally, we eliminate 7 halts of RIO (12-30-2002) because they took place uninterruptedly. From the remaining 2624 halts, 1460 are upper-limit halts and 1164 are lower-limit halts.

Table I provides sample statistics. Panel A in Table 1 reports cross-sectional daily statistics on several market indicators. This panel shows that IDX stocks are, in median terms, more active and liquid than the average stock. They also have a smaller relative tick size. Volatility indicators, however, are higher for IDX stocks than for NIDX. This possibly amazing finding is the consequence of (a) a far more intense flow of orders and (b) the inclusion of high-tech firms among the IDX stocks.

[Table I]

Panel B in Table I provides statistics about static halts. Upper-limit halts are more common than lower-limit halts, particularly among the NIDX stocks. The volume traded at the equilibrium price of the auction represents a median 1.45% of the volume negotiated during the continuous session. This same figure for the closing auctions, that also last 5 minutes, is more than 3 times larger (4.55%). This comparison is more dramatic for the IDX stocks (1.05% versus 10.74%) than for the NIDX stocks (1.98% versus 2.35%). Table I therefore suggests that volatility auctions may play a more important role in the price discovery process of NIDX stocks. Sometimes, auction participants do not reach a consensus about the equilibrium price of the stock. Since static halts are never extended, the auction finishes without an allocation price and, therefore, without trading. We call these auctions zero-volume halts. In our sample, 153 volatility auctions over 2624 are zero-volume halts. In relative terms, zero-volume halts are more frequent among the NIDX stocks.

Figure 1 shows the intraday distribution of static halts. We split the trading session into 17 half-hour intervals. Figure 1 reveals remarkable differences between IDX halts and NIDX halts. Static halts during the first (last) intervals of the trading session are more common among NIDX (IDX) stocks. The break point in the IDX halts distribution coincides with the opening of the NYSE (15:30 Spanish Time). These patterns suggest that the motives that use to cause IDX stocks to reach the price limits and trigger a static halt may be unlike in nature to those that give rise to a NIDX static halt.

[Figure 1]

5. Empirical evidence on the efficiency of the switching mechanism

5.1. Price discovery during short-lived rule-based call auctions

In this subsection, we test hypothesis H1 in section 3. This hypothesis states that short-term volatility auctions triggered by limit-hits contribute to price discovery, and their market-clearing prices are semi-strongly efficient. The analysis design follows a procedure proposed by Biais et al. (1999), henceforth BHS, based on unbiased regressions. BSH study the learning process during the 8:30-10:00 a.m. pre-opening auction in the Paris Bourse by analyzing the information content in the sequence of tentative allocation prices. As in the SSE auctions, pre-opening orders can be submitted, cancelled, or modified before the allocation price is determined. Therefore, these orders might fail to be firm and informative. Consequently, indicative prices could reflect noise. BSH test this hypothesis against the alternative that indicative prices reflect learning. Under the alternative hypothesis, indicative prices are unbiased predictors of the true value of the stock, and their precision increases as the pre-opening period advances.

The "pure" noise and the "pure" learning hypotheses could be formulated as follows,

$$H_0 : q_t = E\left(m \middle| I_0\right) + \varepsilon_t \quad [1]$$

$$H_1 : q_t = E\left(m \middle| I_t\right) \quad [2]$$

where m is the long-term value of the security; q_t is the indicative price at time *t*; I_0 is the public information set before the pre-opening period starts; I_t is the public information set at time *t*; ε_t is a noise term, independent from m. Under hypothesis [1], hereafter referred as the pure noise hypothesis, no new information has been processed into q_t since the start of the auction. Under hypothesis [2], hereafter referred as the pure learning hypothesis, q_t is a martingale process.

BHS test the former hypotheses estimating the following unbiased regression,

$$m - E\left(m \middle| I_0\right) = \alpha + \beta\left[q_i - E\left(m \middle| I_0\right)\right] + w_i \quad [3]$$

The pure learning hypothesis posits that q_i is the conditional expectation of m; changes in q_i are entirely informative about the value of the security. Therefore, under the pure learning hypothesis $\beta = 1$. Contrarily, under the pure noise hypothesis $\beta = 0$, since changes in q_t have no informational content. BHS interpret α as a risk premium associated with the uncertainty about *m*. BHS estimate equation [3] across days for each indicative price made public during the pre-opening period. They consider the closing price of the session as the proxy for m, and the previous close as the proxy for $E\left(m \middle| I_0\right)$.

Our analysis differs from BHS in that SSE volatility auctions are short-lived and interrupt the continuous session. Therefore, traders have less time to submit and cancel orders, either manipulative or informative, and to discover the equilibrium value of the stock. However, volatility auctions are preceded by a length-varying continuous trading interval during which learning may have progressed. These differences suggest that BHS conclusions regarding the long-term pre-opening period in the Paris Bourse might not be applicable to the case of the price-triggered short-term volatility auctions of the SSE.

We do not have information about indicative prices during the volatility auction; therefore, we estimate equation [3] only for the allocation price (q_t). As BHS, we consider the allocation price of the closing auction as the proxy for the equilibrium value of the stock (m). We differ from BHS, however, in that we consider the time-weighted quote midpoint in the 5-minute interval before the auction to proxy for $E\left(m|I_0\right)$. In this manner, we account for the learning occurred from the start of the opening auction (8:30 a.m.) to the start of the volatility auction. All prices are expressed in logs.

Table II summarizes the estimation of equation [3] by OLS with White robust standard errors. We provide the results for the whole sample of volatility auctions and also for the auctions of IDX and NIDX stocks separately. We discard zero-volume auctions because, by definition, they have no market-clearing price. In addition, we separate the auctions in three groups depending on their starting time. We consider the time intervals (open 11:00], (11:00 15:30], and (15:30 close]. Since our proxy for m is the allocation price of the closing auction, we would expect β to artificially increase from the first to the third time interval.[11]

[Table II]

Table II provides the estimated coefficients α and β in [3] and the F-values of testing the nulls $\beta = 0$ and $\beta = 1$. Table II shows that the pure noise hypothesis in [1] ($\beta = 0$) is always

[11] Reboredo (2004) also studies price discovery during SSE volatility auctions. He considers, however, a smaller sample of auctions, does not distinguish static from dynamic auctions, and does not control for the starting time of the auction.

rejected at the 1% level. The market-clearing prices therefore reflect learning, meaning there is a significant contribution to price discovery during volatility auctions. This finding is robust across subsamples and time intervals. Moreover, the pure learning hypothesis ($\beta = 1$) is never rejected for the sample of IDX stocks. Despite the estimated β coefficients are also high, the null $\beta = 1$ is generally rejected for the NIDX stocks. Table II therefore suggests that allocation prices of NIDX auctions may be noisier than allocation prices of IDX auctions. Nonetheless, since IDX volatility auctions are more common towards the end of the session (see Figure 1), and our proxy for the long-run value of the stock is the closing price of the session, this finding could be explained by our particular experimental design. Looking exclusively at the auctions located between 11:00 a.m. and 3:30 p.m., the estimated betas for IDX and NIDX stocks are almost identical, though the null of $\beta = 1$ is still rejected for the NIDX stocks. For the auctions triggered after 3:30 p.m., the learning hypothesis is accepted for both NIDX and IDX stocks.

Table II also reports a measurement of the uncertainty remaining about the value of the security once the information revealed during the volatility auction has been taken into account. Our proxy is the ratio of the residual mean square error (RSME) of [3] over the mean square error of $m - E\left(m \middle| I_0\right)$. All ratios are above 80%, confirming there is a significant learning during the auction, but also meaning that, regardless of the auction, there is still a considerable amount of uncertainty to be resolved. A remarkable point is that the residual variance is smaller for NIDX stocks. RSME ratios are generally below 90% for NIDX stocks and above 90% for IDX stocks. This finding suggests that volatility auctions may be more important for the price discovery process of the less frequently traded and liquid SSE stocks.

Table II provides support to hypothesis H1 in section 3, suggesting that switching to a call auction in times of market stress may facilitate price discovery. Madhavan (1992) also predicts that the efficiency of the allocation price should increase with the number of participants in the auction. Unfortunately, our database does not include information about the number of participants in each auction. However, a proxy of investors' participation could be the volume traded at the allocation price. We compute for each rule-based auction the ratio of allocated volume over total volume traded during the corresponding continuous session. Using the 25% and 75% percentiles of the empirical distribution of that variable, we classify our events into low-volume auctions (below or equal to the 25% percentile), high-volume auctions (above the 75% percentile), and medium-volume auctions (between the 25% and the 75% percentiles). We repeat the estimation of equation [3] for each volume-based set of auctions. Our findings are inconclusive. Inconsistently with Madhavan (1992) proposition, we find that both the IDX and NIDX subsamples have lower betas among the high-volume class of auctions (0.82 and 0.74) than among the low-volume class of auctions (0.9 and 0.87). Moreover, for the NIDX stocks, the learning hypothesis is rejected at the 1% level for the high-volume auctions, but cannot be rejected for the low-volume auctions. However, the RSME ratio is smaller for the high-volume auctions (89.4 and 81.3) than for the low-volume auctions (98.3 and 87.1). These findings could be influenced by the intraday distribution of high-volume and low-volume auctions. If low-volume auctions are located towards the end of the day and high-volume auctions towards the beginning, our analysis will be biased in the direction of accepting low-volume auctions to be more efficient. However, neither low-volume auctions nor high-volume auctions are more frequent in the 15:30-close interval than in the open-11:00 a.m. interval. Finally, the validity of our analysis depends on the quality of the proxy used.

5.2. Liquidity, activity, and volatility around rule-based call auctions

Empirical evidence on US discretionary halts (see Lee et al., 1994, Corwin and Lipson, 2000, and Christie et al., 2002) reports unusually high volatility and trading activity levels, and irregularly low liquidity levels, persisting several hours after the resumption of the continuous session. These studies conclude that the uncertainty is not resolved by US trading halts.

As a second step in our study of the performance of Madhavan's (1992) switching mechanism, we replicate former US studies by analyzing volatility, liquidity, and trading activity two hours before and after SSE volatility auctions. For each volatility auction, we consider 5-minute intervals defined from the beginning of the auction backwards, and from the end of the auction forwards. For each 5-minute interval, we compute the accumulated volume (V_t) in shares; the bid-ask spread (S_t) weighted by time; the average displayed depth on the offer and demand sides of the limit order book (D_t) weighted by time, and the midpoint volatility (σ_t), computed using a high-low ratio. All previous variables are expressed as standard deviations from the "ordinary" (without volatility auctions) days' mean per stock and 5-minute interval. For each variable, we stack together the time series of all stocks and estimate the regression model in equation [4] by OLS with White robust standard errors. The D_j^a (D_j^b) dummy variables correspond to the 24 5-minute intervals that go after (precede) the volatility auction.

$$y_t = \alpha_0 + \sum_{j=-24}^{-1} \alpha_j^b D_j^b + \sum_{j=1}^{24} \alpha_j^a D_j^a + u_t \qquad [4]$$

The intercept in [4] captures the average deviation of each variable from ordinary days. The estimated intercepts show that days with volatility auctions are more volatile ($\tilde{\alpha}_0^{\sigma} = 0.39$), less liquid ($\tilde{\alpha}_0^{S} = 0.26$, $\tilde{\alpha}_0^{D} = -0.13$), and more active ($\tilde{\alpha}_0^{V} = 0.35$) than ordinary days, at the 1% level of statistical significance. This finding is confirmed when IDX and NIDX stocks are considered separately. In Figure 2, we display the estimated coefficients of the dummy variables in [1] whenever they are found to be statistically different from zero at the 1% level. We provide the findings for the complete sample (Figure 2.a), and for the IDX stocks (Figure 2.b) and NIDX stocks (Figure 3.c) separately.

[Figure 2]

In general, the patterns shown in Figure 2 do not differ from those previously reported for US discretionary halts. Volatility achieves its maximum level in the 5-minute interval following the auction, a pattern that is consistent across subsamples. Unusual volatility levels persist at least two hours after the auction, but they experience a rapid decay in less than one hour. For example, the average volatility level for IDX (NIDX) stocks five minutes before the auction is 2.5 (4.3) standard deviations larger than the ordinary days' mean for the same time interval. In the five minutes that follow the resumption of the continuous session, volatility reaches a maximum of 2.8 (5.2) standard deviations, but one hour after it is only 0.3 (0.4) standard deviations larger that the ordinary days' mean.

Trading volume attains its highest level in the 5-minute interval before the auction is triggered, but it remains unusually high after the continuous session restarts. It decays from 0.67 (1.02) for the IDX (NIDX) stocks 5 minutes after the auction to 0.25 (0.29) one hour after the auction. Regarding liquidity, the bid-ask spread is wider after the auction than before the auction, but it reverts to the daily mean in 30 minutes for the IDX stocks and in 1 hour for the NIDX stocks. We do not find remarkable differences between the displayed book depth after the auction and before the auction.[12]

As Lee et al. (1994, pg. 185) point out, in the NYSE case the trading cessation and the particular reopening mechanism (call auction) used cannot be considered independently, since both are fundamental features of the NYSE halts. Therefore, higher levels of volume and volatility after NYSE halts may be due to: (a) the lack of recent trading; (b) the inefficiency of

[12] The pattern reported for the book depth should be taken with caution. The SSE allows the submission of partially hidden limit orders. Therefore, the displayed depth is not equal to the total depth available in the LOB. The use of hidden limit orders in the SSE is analyzed by Pardo and Pascual (2004).

the price discovery mechanism, or (c) a combination of both. Something similar occurs with Nasdaq halts, since a trading cessation period is followed by a 5-minute quotation period for market makers used to reopen the continuous trading session. In the SSE case, however, higher volume and volatility after rule-based auctions can only be attributed to the inefficiency of the reopening mechanism since there is no trading cessation period. Our findings suggest that, even with price discovery during the auction, uncertainty is not fully resolved by the switching mechanism. As a consequence, rule-based auctions do not calm the market.

A possible explanation for the failure of the SSE reopening mechanism in calming the market is that volatility auctions are too short. Five minutes may be insufficient to achieve a consensus about the true value of the stock, resulting in a noisy reopening price. Christie et al. (2002) show that Nasdaq halts that reopen the following day with a 90-minute quotation period are associated with significantly dampened volatility and spread effects compared with intraday halts, which reopen with a 5-minute quotation period. They conclude that 90-minute quotation periods are more efficient because they allow for increased information dissemination during the halt. Unfortunately, we cannot test this hypothesis since SSE auctions lasting more than 5 minutes are too rare. Alternatively, the SSE rule-based call auctions may fail to calm the market because the static price limits in place during the auction are binding. However, only 3.7% of the volatility auctions in our sample resulted in a price revision superior than 50% of the distance between the static price and either the upper or the lower limit during the auction. Indeed, only one auction concluded with an allocation price equal to the upper price limit.

5.3. Price continuation during and after rule-based call auctions

In this subsection, we test hypothesis H2. This hypothesis posits that the switching mechanism proposed by Madhavan (1992), implemented by the SSE, is effective in preventing overreaction and not delaying price discovery. In order to test this hypothesis, we investigate whether the price behavior during and after volatility auctions is dominated by price continuations. For each SSE rule-based auction, we use the price limit reached (L_i), the market-clearing price of the auction (A_i), and a post-auction price (C_i) to compute the stock returns during the call auction, $r_i^A = \ln(A_i / L_i)$, and the stock returns following the auction, $r_i^C = \ln(C_i / A_i)$.

The delaying information hypothesis (hereafter DIH) posits that price limits delay price discovery. Under the DIH, the true value of the stock is above (below) the upper (lower) limit that has been reached. Therefore, the DIH predicts price continuations after the circuit breaker is triggered, and no price reversals afterwards. The overreaction hypothesis (hereafter OH) posits the circuit breakers delays information revelation, but also the overreaction of noise traders to new information. Under the OH, the biased expectation of the noise traders about the true value of the stock is above (below) the upper (lower) price limit that has been reached. Therefore, this hypothesis also predicts price continuations after the limit-hit, followed by price reversals afterwards. Under the DIH, efficient learning during SSE volatility auctions should lead to price continuations; that is, $r_i^A > 0$ ($r_i^A < 0$) after an upper-limit (lower-limit) volatility auction. Under the OH, noise traders will continue pushing prices towards their perceived fair price. Therefore, the OH also predicts price continuation during the auction.

To correctly evaluate the performance of SSE price-limits, however, we must also look at the post-auction returns (r_i^C). Suppose an upper-limit auction. If we observe $r_i^A > 0$ and

$r_i^C > 0$, that would signal the switching mechanism either performs poorly in preventing overreaction or delays price discovery. It could be that overreaction is not resolved during the auction because the perceived fair value by noise traders is above the upper limit during the auction; alternatively, the market-clearing price, possibly manipulated, may underestimate the true value of the stock, or perhaps the fair value is above the upper limit during the auction. Whatever the case may be, the conclusion should be that the switching mechanism postpones to resolution of uncertainty until the post-auction period. We consider three alternative proxies for the post-auction price: the quote midpoint 30 minutes after the auction, the quote midpoint 1 hour after the auction, and the allocation price of the closing auction. Once more, we only exclude zero-volume auctions from the analysis. For each auction, we compare r_i^A and r_i^C with the ordinary days' median return during the same time interval.

Table III summarizes our empirical findings. We report the median auction return (r_i^A) and post-auction return (r_i^C) in excess over the ordinary days' median return. We provide separated results for upper-limit and lower-limit triggered auctions. We use the Wilcoxon nonparametric sign-rank test to check whether the auction days' medians and the ordinary days' medians are statistically different. As in previous tables, we report the results for IDX and NIDX stocks separately.

[Table III]

The most remarkable finding in Table III is that during both the auction period and the three post-auction periods, we observe statistically significant price reversals, in median terms. For upper-limit auctions, excess returns are negative during ($r_i^A < 0$) and after ($r_i^C < 0$) the auction, independently of the post-auction interval considered. The opposite pattern is found for lower-limit auctions. In accumulated terms ($r_i^T = r_i^A + r_i^C$), the median excess return over ordinary days is -0.42% (0.63%) from the start of the upper-limit (lower-limit) auction to 30 minutes after the continuous session resumes, and -0.55% (0.75%) up to 1 hour after. This pattern is consistent across subsamples, but stronger for NIDX stocks. For the upper-limit (lower-limit) auctions, the median r_i^A is -0.55% (0.93%) for NIDX stocks, and -0.16% (0.29%) for IDX stocks. In accumulated terms, the excess return up to 30 minutes after the auction is -0.73% (1.10%) for NIDX stocks and -0.24% (0.19%) for IDX stocks. We also find that the trend towards reversion is stronger for lower-limit auctions than for upper-limit auctions. Price reversals during the auction are at odds with the DIH and OH hypotheses. Moreover, price reversals in the post-auction period are inconsistent with the switching mechanism systematically delaying price discovery and overreaction.

In general, Table III suggests that the switching mechanism provides time for price reassessment, but the price adjustment is not completed during the auction. Indeed, price reversals during the auction are followed by further price reversal after the auction. An excessively short call auction or price manipulation by strategic informed traders may explain this price pattern. Our findings sustain hypothesis H2 since price reversals are more common than continuations after volatility auctions, and they are inconsistent with the DIH and OH hypotheses. We report two remarkable asymmetries: price reversions are stronger for lower-limit auctions than for upper-limit auctions and for NIDX stocks than for IDX stocks. These asymmetries suggest overreaction to new information to trigger NIDX rule-based auctions in general, and lower-limit auctions in particular, more frequently than IDX rule-based auctions and upper-limit auctions, respectively.

5.4. Adverse selection costs around rule-based auctions

We finish our empirical analysis on the efficiency of Madhavan's (1992) switching mechanism by testing whether rule-based SSE call auctions improve (reduce) information asymmetries. In particular, we test hypotheses H3 and H4 in section 3. We estimate adverse selection costs using an empirical model of price formation that parallels the model proposed by Brennan and Subrahmanyam (1996), which is actually based on Hasbrouck (1991), and Foster and Viswanathan (1993). We choose this approach because it is valid for a relatively broad range of theoretical specifications. The model is founded on the widespread believe that the average price response to trade-related shocks is a good proxy for the adverse selection component of price changes.[13]

Let q_{t-1} be the logarithm of the quote midpoint right before a trade at time *t*; let x_t be the signed trade size; let $\Delta q_t = q_t - q_{t-1}$ be the price impact of the trade at time *t*, and let D_t be a trade indicator that equals 1 for buyer-initiated trades and -1 for seller initiated trades. The original Brennan and Subrahmanyam's model is,

$$x_t = \alpha_x + \sum_{j=1}^{5} \beta_j x_{t-j} + \sum_{j=1}^{5} \gamma_j \Delta q_{t-j} + w_t \,, \qquad [5]$$

$$\Delta q_t = \alpha_q + \psi(D_t - D_{t-1}) + \lambda w_t + \varepsilon_t \,. \qquad [6]$$

The model is defined in trade time. Equation [5] is the generating process for signed trade sizes. The rational behind this model is that the information content of a trade resides in its unexpected component (w_t), since x_t - w_t is perfectly predictable given the past history of trades and quote changes. The λ coefficient in [6] measures the information content in trade-related shocks, and it proxies for the adverse selection component of price changes. The coefficient on D_t - D_{t-1} is a fixed costs component.

We slightly modify equation [6] so as to accommodate the model to the particularities of our experiment. Foster and Viswanathan (1993) and Brennan and Subrahmanyam (1996) apply the model to transaction prices, using the second term in the RHS of [6] to capture the

[13] See also Huang and Stoll (1997) and Madhavan, Richardson, and Roomans (1997), among others.

bid-ask bounce. Following Hasbrouck (1991), we apply the model to quote midpoints and, therefore, that term is unnecessary. Moreover, we extend the third component in the RHS of [6] to capture unusual levels of λ in the pre-auction and post-auction intervals. Explicitly, we replace [6] by the following alternative equation for the quote midpoint changes (for the case of upper-limit auctions),

$$\Delta q_t = \alpha_q + \left(\lambda + \lambda^u U_t + \sum_{\substack{j=-12 \\ j \neq 0}}^{12} \phi_j^u H_{j,t}^u \right) w_t + \varepsilon_t \,. \qquad [7]$$

The dummy U_t in [7] equals one when the transaction t takes place in a day with a volatility auction triggered by a violation of the upper price limit. Therefore, the coefficient λ^u measures the average risk premium in days with upper-limit auctions with respect to the average risk of the stock (λ). Equation [7] also accounts for the average supplementary risk around rule-based auctions. We consider two hours from the start of the auction backwards, and two hours from the end of the auction forwards, both divided into 10-minute intervals. We use the dummy variables $H_{j,t}^u$, with j from -12 to -1, to control for the distance from the time stamp of the transaction t to the beginning of an upper-limit triggered auction. Similarly, we use the dummy variables $H_{j,t}^u$, with j from 1 to 12, to control for the distance from the resumption of the continuous trading to the time stamp of the transaction t. Thus, positive and significant ϕ_j^u coefficients would signal additional risk during days with rule-based auctions concentrated either in the pre-auction or in the post-auction period. We estimate model [5]-[7] for upper-limit auctions and lower-limit auctions separately. The equation [7] for lower-limit auctions is defined analogously.

The estimation of [5] and [7] proceeds as follows. First, we estimate equation [5] for each stock by OLS, with White robust standard errors, and using transaction data from the ordinary days. Then, we use the estimated coefficients to obtain the unexpected trade-size (w_t) of all transactions executed during event (auction) days. Second, we standardize w_t and q_t per stock using the mean and standard deviation of the ordinary days' transactions. Third, we stack together the time series of all stocks and proceed to estimate [7] also by robust OLS.

The average estimated adverse-selection costs coefficient across stocks for ordinary days (λ) is 0.42. Days with events (rule-based auctions) have a statistically significant positive risk premium of $\lambda^u = 0.027$ for upper-limit auctions, and negative $\lambda^l = -0.042$ for lower-limit auctions. Figure 3.a reports the estimated ϕ_j^i coefficients in equation [7] for the whole sample. We only report the coefficients that are statistically significant at the 1% level. We provide the coefficients for both upper-limit auctions (light bars) and lower-limit auctions (dark bars). Despite that we observe unusual risk more than one hour before the auction is triggered, it achieves its highest level during the pre-auction period in the 10-minute interval preceding the auction. Rather than decreasing, adverse selection costs reach maximum levels in the 10 minute interval following the resumption of the continuous trading, decreasing progressively thereafter. Information asymmetry risk takes almost two hours in revert to its average level. Therefore, we should conclude that the switching mechanism also fails in reducing adverse selection costs, therefore rejecting hypothesis H3 in section 3. Moreover, the high adverse selection costs levels observed during at least one hour after the auction suggest informed traders wait until continuous trading resumes to trade and realize their information advantage. This corroborates our previous conclusion that the rule-based auction does not completely resolve price uncertainty.

[Figure 3]

Figure 3.b and 3.c report the estimated ϕ_j^i coefficients for the IDX and NIDX stocks. NIDX stocks support a more dramatic increase in adverse selection costs, both for lower-limit

and upper-limit auctions, than IDX stocks in the last 10-minute pre-auction interval. The higher pre-auction risk for NIDX stocks suggests the market expects more value-motivated trading in thinly stocks to be advanced in time when a rule-based auction becomes highly likely. This would be in harmony with the superior contribution of the SSE switching mechanism to the price discovery of NIDX stocks shown in subsection 5.1.

Figures 3.b and 3.c also show that post-auction patterns in Figure 3.a. are all due to IDX stocks. For IDX stocks, adverse selection costs remain unusually high for almost two hours after the resumption of the continuous trading, though they decrease progressively. Moreover, the post-auction risk is higher than in the pre-auction period during at least twenty minutes. For NIDX stocks, however, the post-auction information asymmetry risk is not statistically different to the average level observed in the same time interval during ordinary days. Therefore, the SSE switching mechanism performs well in reducing information asymmetries when the stock is infrequently traded. This last finding provides support to hypothesis H4 in section 3.

6. Summary and conclusions

This paper has evaluated the performance of switching from a continuous market to a temporary call auction in times of elevated uncertainty, as proposed by Madhavan (1992). The SSE implements this switching mechanism in the form of non discretionary call auctions. SSE rule-based auctions are short-lived, and they are triggered when either the upper or the lower intraday price limit is triggered. This study complements previous analyses on the performance of US discretionary halts.

Our findings are mixed. On the positive side, we show there is effective price learning during the rule-based auction. The market-clearing price of the auction is more efficient than the quotes in place before the auction is triggered. Moreover, price behavior during and after the auction is dominated by price reversals rather than price continuations. This price pattern is stronger when stocks are thinly traded and the switching mechanism in triggered by the lower price limit. Price reversals during the auction are compatible with the auction preventing overreaction. Price reversals after the auction, however, suggest that SSE 5-minute auctions are not sufficient to correct the pre-auction overreaction.

On the negative side, we find that, as it has already been shown for discretionary halts, switching to a temporary call auction does not calm the market. Unusually high volatility, trading activity, and illiquidity levels persist after rule-based auctions. Finally, we report a significant increase in the information asymmetry risk right before the auction is triggered, suggesting that informed traders may anticipate their trading plans as the rule-based auction becomes imminent. The increase is particularly dramatic for thinly traded stocks, suggesting that the pre-auction risk faced by informed traders is higher in that case. After the auction, adverse selection costs remain unusually high, meaning that rule-based auctions do not reduce information asymmetries. There is, however, a remarkable exception: for thinly traded stocks, the information asymmetry risk reverts immediately to ordinary days' levels.

Our findings suggest the switching mechanism may perform better when stocks are infrequently traded. The evidence we report supports the initiative of those European markets that have created special segments based on sequences of single long-lasting call auctions to handle the trading activity of their least liquid and least active stocks. The failure of SSE rule-based call auctions in calming the market and reducing information asymmetries among frequently traded stocks puts forward that SSE auctions may be too short.

There are a few intriguing findings in this paper. First, we find that more volume allocated at the market-clearing price of the auction does not imply more efficient learning during the auction. A comparative analysis of the performance of zero-volume auctions against high-volume auctions may provide additional insights on this issue. Second, we report asymmetries between upper-limit auctions and lower-limit auctions. Price reversals are stronger during and after upper-limit auctions than during and after lower-limit auctions, respectively. It could be argued this finding is the consequence of noise traders overreacting more frequently to bad news than to good news. In this were the case, the lower limit would be less frequently hit by information-based price movements than the upper limit. Lower-limit auctions would therefore be more likely linked to price reversions than upper-limit auctions. All these issues, however, deserve a more detailed analysis.

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TABLE I
Preliminary Statistics

This table reports statistics on the Spanish stocks and the rule-based (volatility) auctions considered in this study. Panel A provides median daily statistics on the liquidity, the activity, the volatility, and the relative tick size of the 114 stocks in the sample. The sample includes data from June 2001 to December 2003. Stocks are further grouped into index-stocks (IDX) and non-index stocks (NIDX). IDX stocks permanently belonged to the IBEX-35 index; NIDX never belonged to the IBEX-35. Liquidity indicators are the quoted bid-ask spread; the book depth (number of shares displayed) at the 5 best ask plus 5 best bid levels, and the number of limit orders stored at those same book levels. Activity indicators are the daily volume in shares and the daily number of trades. Volatility proxies are the high-low quote midpoint ratio, and the number of quote midpoint changes. The relative tick is computed as the inverse of the daily average price of the stock. Panel A reports the median across days and stocks of all these statistics. Panel B reports the number of rule-based auctions in the sample, distinguishing also between upper-limit (UB) and lower-limit (LB) triggered auctions. We also report some cross-section average statistics for days with rule-based auctions: the volume (in shares) allocated at the market-clearing price of the auction over the total volume traded during the continuous session, and the ratio of the volume (in shares) allocated at the market-clearing price of the closing auction over the total volume traded in the continuous session. Both volatility and closing auctions last 5 minutes plus a random end of maximum 30 seconds. Finally, we report the number of auctions that concluded without achieving an equilibrium price ("zero-volume" halts).

A: General Statistics:		All (114)	IDX (32)	NIDX (70)
Liquidity:	Spread	0.0375	0.0273	0.0567
	Depth	17765	25692.5	14137.5
	Orders	17.5	19.8	15.9
Activity:	Volume (shares)	72398.5	647525	23227
	Trades	52.5	463.5	24
Volatility:	High-Low	0.018	0.0229	0.0149
	Quote Changes	46	401	18
Tick:	1/Price	0.0995	0.0708	0.1191
B: Volatility Auctions Statistics:				
Number of Auctions:	All Auction	2624	639	1619
	UB Auction	1460	329	936
	LB Auction	1164	310	683
Volume Halt /	All Auction	1.45	1.05	1.98
Continuous (%):	UB Auction	1.40	1.04	1.84
	LB Auction	1.55	1.08	2.43
Volume Close Auction /	All Auction	4.55	10.74	2.35
Continuous (%):	UB Auction	3.68	10.41	2.05
	LB Auction	5.96	11.35	3.27
Zero-Volume Auction:	All Auction	153	7	137
	UB Auction	92	5	82
	LB Auction	61	2	55

TABLE II
Price discovery during price-triggered volatility auctions

This table summarizes the estimation of the following regression model by OLS with White robust standard errors,

$$m - E\left(m \middle| I_0\right) = \alpha + \beta\left[q_i - E\left(m \middle| I_0\right)\right] + w_i \ ,$$

with i indexing volatility auctions. As a proxy for the long-run value of the stock (m) we use the closing price of the session. The expectation $E\left(m \middle| I_0\right)$, with I_0 being the the information that is publicly available before the auction, is computed using the time-weighted average of the quote midpoint in the 5-minute interval that precedes the limit-hit that triggers the auction. Finally, q_i refers to the market-clearing price of the auction. The table reports the estimated α and β coefficients for the complete sample ("ALL"), and also for index stocks ("IDX") and non-index stocks ("NIDX") separately. An IDX stock was a constituent of the IBEX-35 during the whole sample period. A NIDX stock never belonged to the IBEX-35. We further split the auctions in terms of time of the limit-hit in three groups: before 11:00 a.m., between 11:00 and 15:30, and between 15:30 and the end of the continuous session. Finally, we also classify auctions attending to the relative volume allocated at the end of the auction. This measure is computed as the ratio of the volume (in shares) traded at the market-clearing price of the auction over the total volume traded during the corresponding continuous session. An auction is considered of "low volume" ("high volume") if the relative volume allocated is below (above) the 25% (75%) value of the empirical distribution of this variable. The table reports the F-value of testing the null $\beta = 0$ (pure noise hypothesis) against the alternative that $\beta \neq 0$, and the null $\beta = 1$ (pure learning hypothesis) against the alternative that $\beta \neq 1$. It also shows the ratio between the residual mean square error and the mean square error of $m - E\left(m \middle| I_0\right)$, a proxy of the uncertainty about m remaining after the auction. The sample includes all the static volatility auctions that took place in the Spanish Stock Exchange between June 2001 and December 2003. We exclude zero-volume auctions, that is, auctions that ended without finding a market-clearing price.

	Coefficients		F tests				
Auctions	β	α	H_0:β=0	H_0:β=1	RMSE (%)	Adj-R^2	Obs.
All							
ALL	0.8311 *	0.0024 *	798.68	32.99	86.84	0.2462	2448
IDX	0.8923 *	0.0006	72.83	1.06 †	94.76	0.1022	632
NIDX	0.8015 *	0.0036 *	413.95	25.38	88.27	0.2207	1459
Before 11:00 a.m.							
ALL	0.8051 *	0.0011	27.23	12.15	85.66	0.2664	569
IDX	0.5778	-0.0044	3.23	1.72 †	95.35	0.0285	77
NIDX	0.7393 *	0.0035	98.97	12.31	89.65	0.1963	402
Between 11:00 a.m. and 15:30 p.m.							
ALL	0.8478 *	0.0027 **	35.04	9.83	88.48	0.2168	1099
IDX	0.8442 *	0.0008	19.56	0.67 †	96.47	0.0688	252
NIDX	0.8478 *	0.0027	214.8	6.93	87.46	0.235	697
After 15:30 p.m.							
ALL	0.9270 *	0.0028 *	280.81	1.74 †	85.77	0.2643	780
IDX	1.0927 *	0.0015	89.38	0.64 †	87.96	0.2264	303
NIDX	0.9056 *	0.0047 *	133.51	1.45 †	85.47	0.2696	360
Low volume							
ALL	0.9570 *	0.0025	344.42	0.7 †	80.01	0.3598	612
IDX	0.9073 **	0.0037	6.42	0.07 †	98.35	0.0327	161
NIDX	0.8721 *	0.0067 **	17.75	2.53 †	87.11	0.2413	368
Medium volume							
ALL	0.7771 *	0.0020	193.68	15.93	92.96	0.136	1225
IDX	0.9931 *	0.0003	38.4	0 †	94.52	0.107	313
NIDX	0.7491 *	0.0020	34.93	15.14	91.87	0.1557	727
High volume							
ALL	0.6810 *	0.0027	258.58	56.73	83.86	0.2969	611
IDX	0.8293 *	-0.0019	40.56	1.72 †	89.38	0.2013	158
NIDX	0.7499 *	0.0033	186.59	20.76	81.34	0.3383	364

*,**: Statistically significant at the 1% and 5% level, respectively.

† The null cannot be rejected at the 1% level.

TABLE III
Price behavior during and after rule-based auctions

This table reports stock returns both during and after rule-based volatility auctions in excess over ordinary days' returns. An ordinary day is a day without events (rule-based auctions). We distinguish between upper-limit auctions and lower-limit auctions. We compute different continuously compounded returns: (a) the return from the price limit triggered to the market-clearing price of the auction; (b) the return from the allocation price of the auction to the quote midpoint 30 minutes and 60 minutes after the continuous session resumes, and (c) the return from the allocation price of the auction to the allocation price of the closing auction. Returns are reported in medians across auctions. We provide tests on the null that the median during event days are statistically different than the median across ordinary days using the Wilcoxon's nonparametric sign rank test. Finally, the analysis is replicated for the IDX subsample (index constituents), and the NIDX subsample (non index stocks) separately.

		Median excess return (x1000)			
Stock		Auction	30 min.	60 min.	Close
All	Upper	-0.9034 *	-3.3016 *	-4.5781 *	-4.0006 *
	Lower	1.3569 *	4.9528 *	6.1578 *	7.5196 *
IDX	Upper	-0.1212	-1.4998 *	-2.3034 *	-0.8696
	Lower	0.6129 *	2.3177 *	1.2961 *	2.0677 **
NIDX	Upper	-1.0217 *	-4.4543 *	-6.2405 *	-6.1071 *
	Lower	1.5044 *	7.8110 *	9.5006 *	10.3954 *

*,**: Statistically significant at the 1% and 5% level, respectively

FIGURE 1
Intraday Distribution of Volatility Auctions

We compute the percentage of static halts located in each half-hour interval of the SSE trading session. We report the resulting distribution for: (a) the whole sample (114 stocks); (b) IDX stocks, that is, those that belonged to the IBEX-35 portfolio during the whole sample period (32 stocks), and (c) NIDX stocks, that is, those that never were included in the IBEX-35 portfolio (70 stocks). Sample period: June 2001 – December 2003.

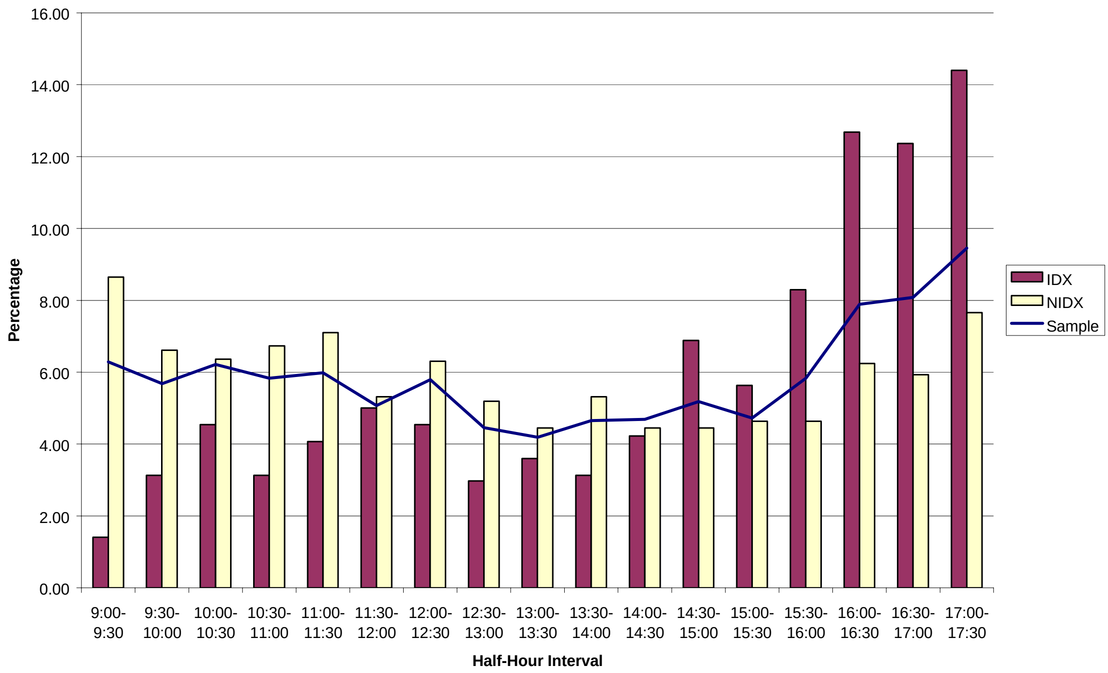


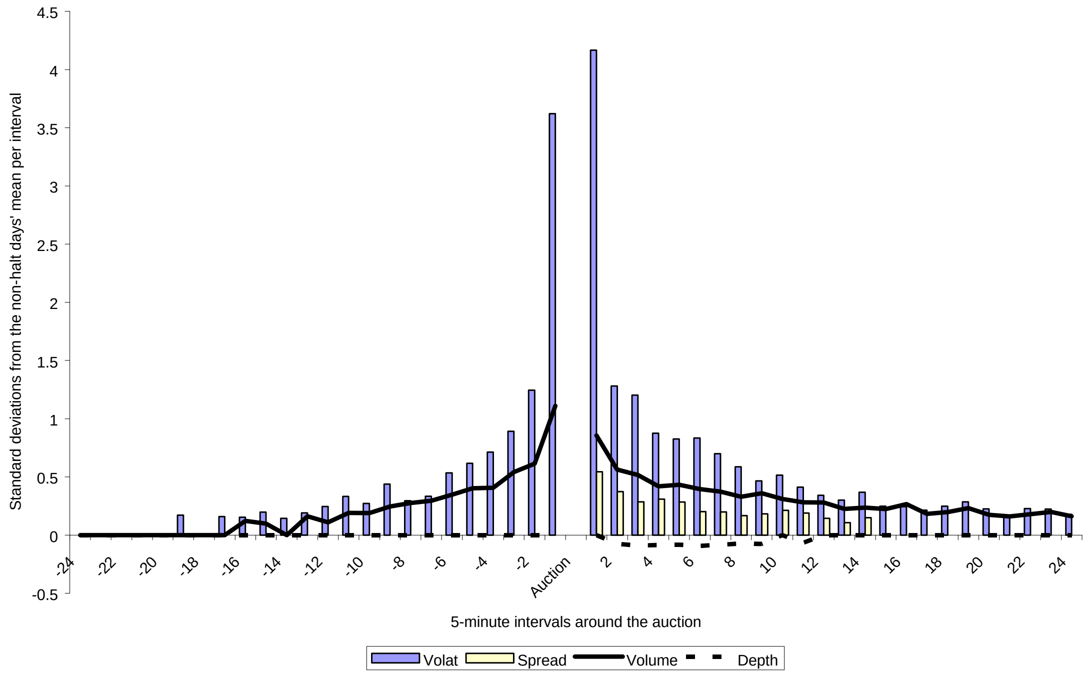
FIGURE 2

Liquidity, volatility and activity around volatility auctions

This table provides the average volatility, liquidity, and trading activity levels around the SSE volatility auctions in our sample. We consider 24 5-minute intervals before and after each auction. Liquidity in each interval is measured by the bid-ask spread and the average displayed depth on offer and demand sides of the book, both weighted by time; trading activity is measured by the accumulated volume in shares, and volatility is computed as the high-low ratio of the quote midpoint. All the statistics are expressed in standard deviations from the ordinary days' mean per stock and 5-minute interval. An ordinary day is a day without volatility auctions. For each statistic, we stack together the time series of the 114 stocks in our sample and estimate the following regression model,

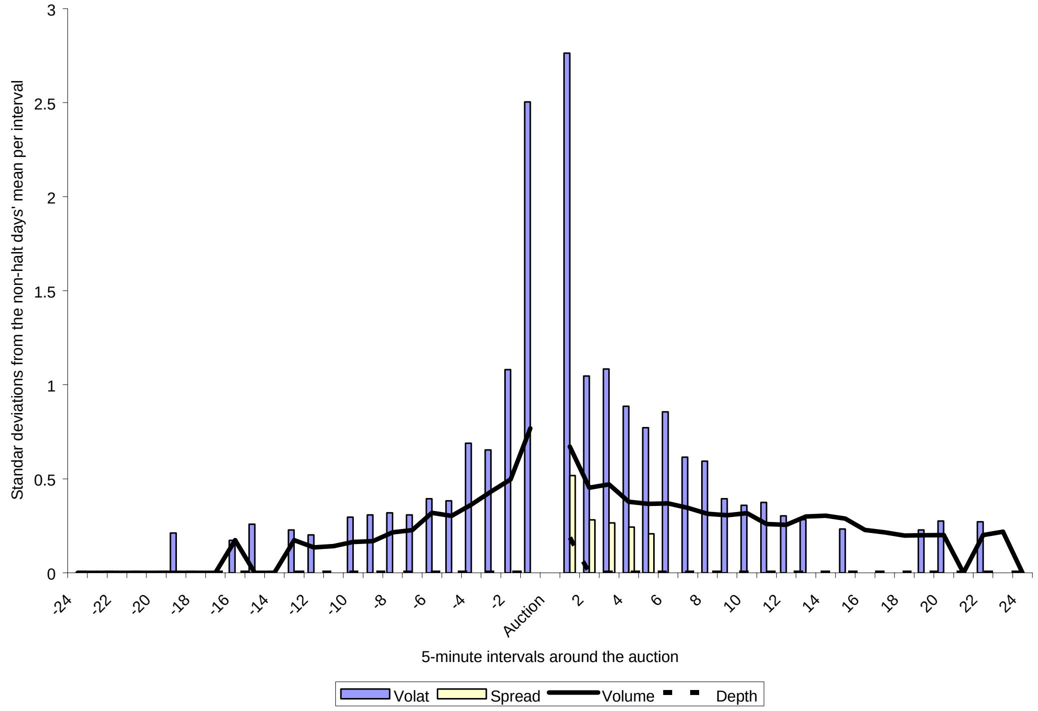
$$y_t = \alpha_0 + \sum_{j=-24}^{-1} \alpha_j^b D_j^b + \sum_{j=1}^{24} \alpha_j^a D_j^a + u_t \qquad [F1]$$

where the RHS variables are dummies that control for the 5-minute intervals before and after the auction. The figure represents the estimated alpha coefficients in [F1] whenever they are statistically significant at the 1% level. Panel (a) shows the findings for the 114 stocks in the sample; panel (b) shows the findings for the IDX stocks, that is, those that belonged to the IBEX-35 portfolio during the whole sample period (32 stocks), and panel (c) reports the findings for the NIDX stocks, that is, those that never were included in the IBEX-35 portfolio (70 stocks). Sample period: June 2001 – December 2003.

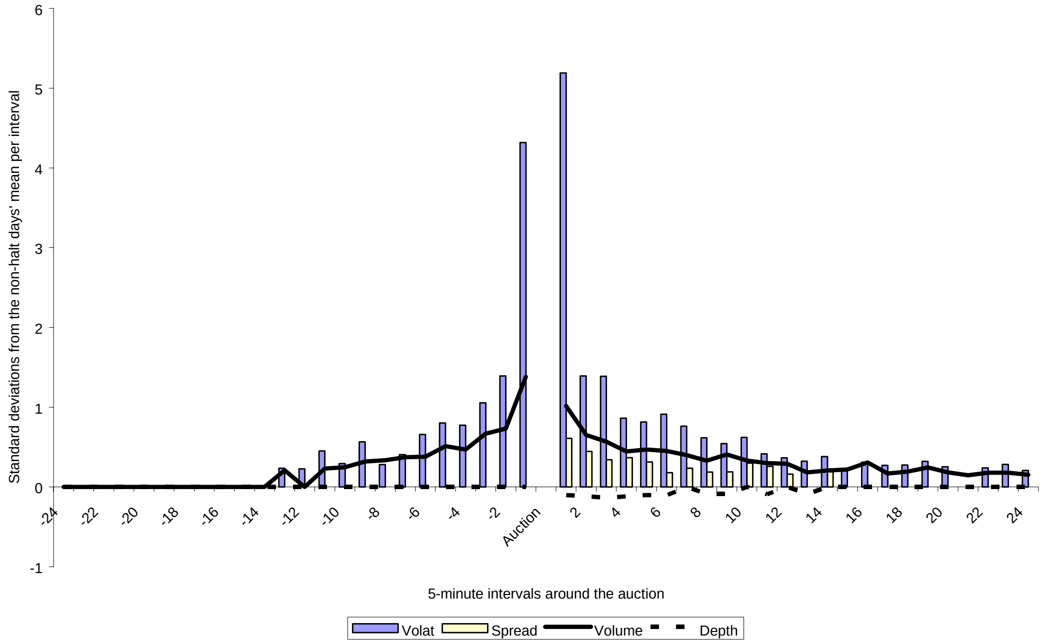


(a) All stocks

FIGURE 2 (Cont.)
Liquidity, volatility and activity around volatility auctions



(b) IDX stocks



(c) NIDX stocks

FIGURE 3

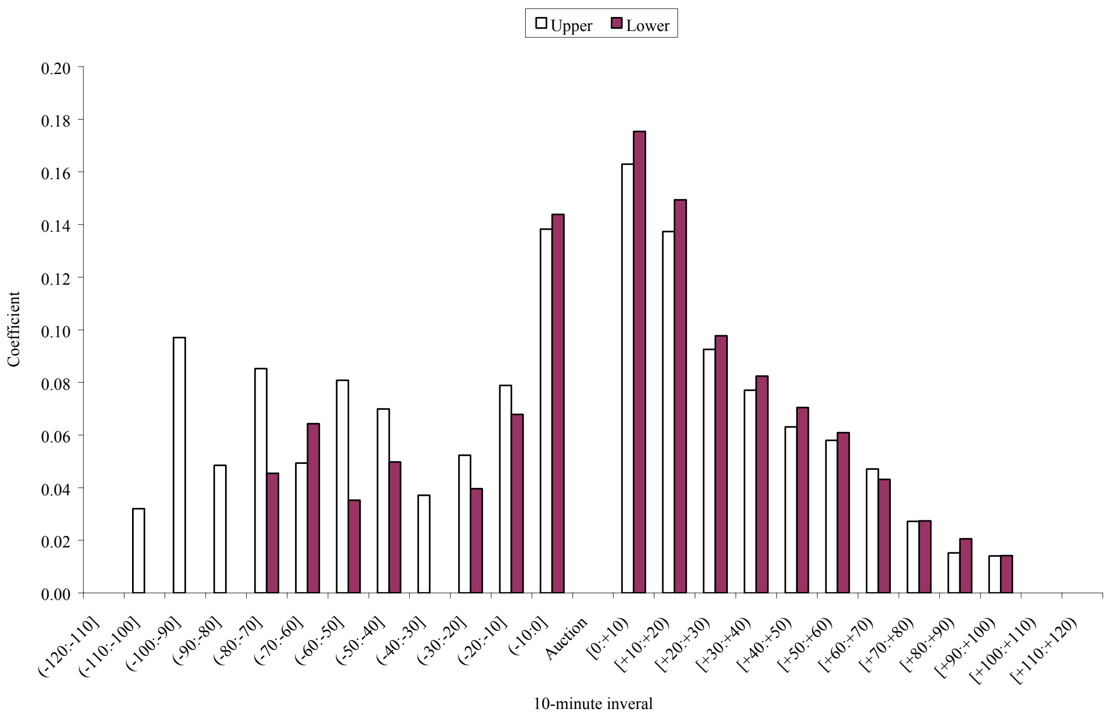
Adverse selection costs around volatility auctions

This table provides the average adverse selection costs levels around SSE rule-based (volatility) auctions. We consider two hours before and after each auction, divided into 10-minute intervals. We estimate adverse selection costs using an empirical model of price formation based on Brennan and Subrahmanyam (1996). The model for upper-limit auctions is given by [F2]-[F3]; the model for lower-limit auctions is defined analogously. It is defined in trade time: x_t is the signed trade size; q_{t-1} is the logarithm of the quote midpoint right before the trade t, and $\Delta q_t = q_t - q_{t-1}$. The dummy U_t equals 1 if the trade t took place in a day with upper-limit volatility auctions. Dummies $H^u_{j,t}$, with j<0 (j>0), accounts for the distance between the time stamp of the trade t and the beginning (end) of the auction.

$$x_t = \alpha_x + \sum_{j=1}^{5} \beta_j x_{t-j} + \sum_{j=1}^{5} \gamma_j \Delta q_{t-j} + w_t \qquad \text{[F2]}$$

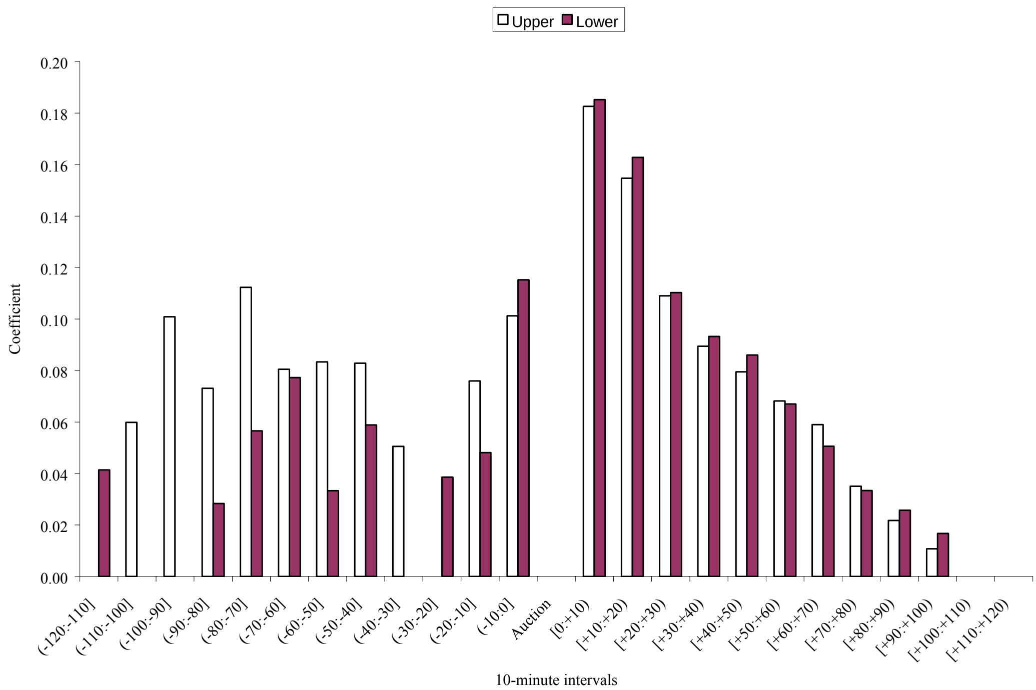
$$\Delta q_t = \alpha_q + \left(\lambda + \lambda^u U_t + \sum_{\substack{j=-12 \\ j\neq 0}}^{12} \phi^u_j H^u_{j,t} \right) w_t + \varepsilon_t \qquad \text{[F3]}$$

The model is estimated in the following steps. First, we estimate [F2] for each stock by OLS with White robust standard errors using data from days without events (rule-based auctions). We use the estimated coefficients to obtain the unexpected trade-size (w_t) for all transactions executed during event days. We standardize the time series of w_t and q_t per stock using the mean and standard deviation of ordinary days' transactions. Finally, we stack together the time series of all stocks in the sample and estimate [F3] also by robust OLS. We represent the estimated ϕ^i_j coefficients, i = {u, l}, in [F3] whenever they are statistically significant at the 1% level. Panel (a) shows the findings for the 114 stocks in the sample; panel (b) shows the findings for the IDX stocks, that is, those that belonged to the IBEX-35 portfolio during the whole sample period (32 stocks), and panel (c) reports the findings for the NIDX stocks, that is, those that never were included in the IBEX-35 portfolio (70 stocks). Sample period: June 2001 – December 2003.

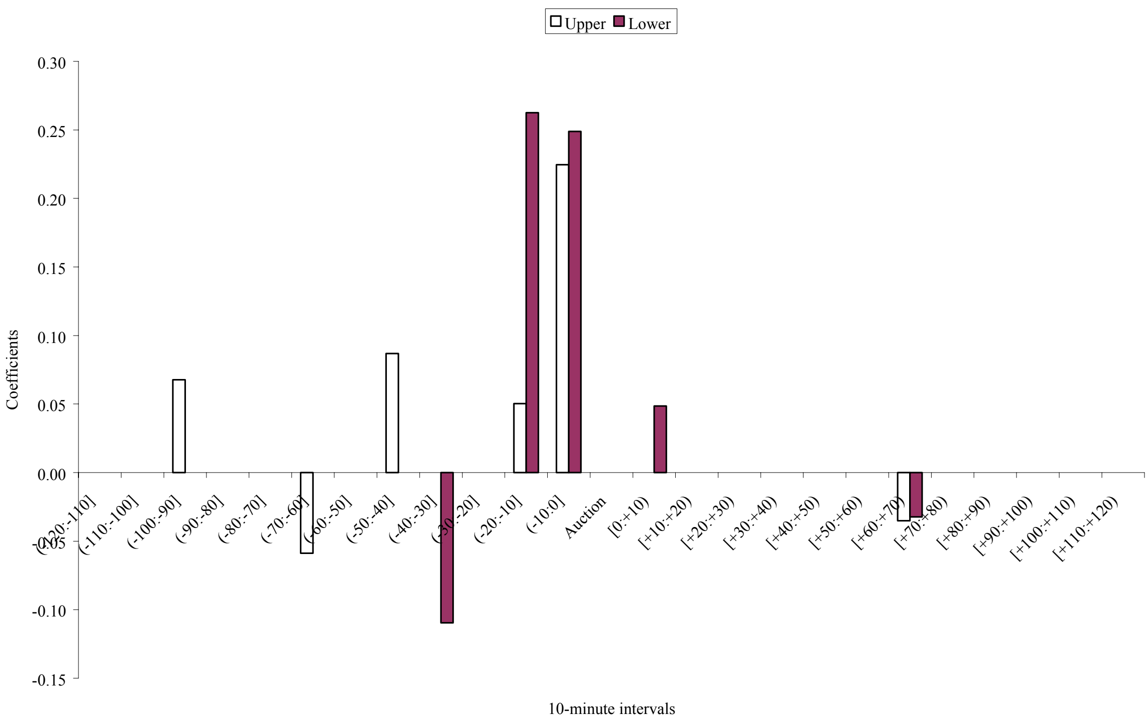


(a) All stocks

FIGURE 3 (Cont.)
Adverse selection costs around volatility auctions



(b) IDX stocks



(c) NIDX stocks