The Impact of the Suspension of Opening and Closing Call Auctions: Evidence from the National Stock Exchange of India[†]

by

Silvio John Camilleri and Christopher J. Green

Camilleri: **University of Malta**
Green: **Department of Economics, Loughborough University**

June 2004

Preliminary Draft: Not for Quotation

[†] Silvio Camilleri is a doctoral candidate in the Department of Economics, Loughborough University.

THE IMPACT OF THE SUSPENSION OF OPENING AND CLOSING CALL AUCTIONS: EVIDENCE FROM THE NATIONAL STOCK EXCHANGE OF INDIA

by

Silvio John Camilleri and Christopher J. Green

Camilleri: University of Malta
Green: Department of Economics, Loughborough University

Preliminary Draft: Not for Quotation

JEL Classification: G12; G14; G18
Keywords: Call Auctions, stock markets, National Stock Exchange of India

ABSTRACT

A hotly debated issue in the market microstructure literature is the effectiveness of call auctions as against continuous trading systems. In this paper we investigate this issue by studying the impact of the suspension of opening and closing call auctions by the National Stock Exchange of India in 1999. We compare the volatility, efficiency and liquidity (VEL) of securities in the market before and after suspension, and estimate the value of the auctions to traders by carrying out an event study. Contrary to expectation, we find that VEL factors improved following the suspension, and the CARs were significant but were not uniformly positive or negative. As a partial explanation for these results, we find that less liquid stocks traded less in the auctions than did other securities, especially at the opening, and they experienced the most gains following the suspension. This suggests that less liquid stocks did not gain the expected benefits from the auctions, and therefore that it cannot be assumed that a call auction system will improve share trading in a less liquid emerging market. Future research in this area will need to pay attention to the composition of the shares being traded and to the nature of the trading process in different shares in the market.

Correspondence to:
Christopher J. Green, Department of Economics, Loughborough University, Loughborough, Leicestershire, LE11 3TU, United Kingdom
Tel: +44 (0) 1509 222711; *Fax:* +44 (0) 1509 223910;
E-mail: C.J.Green@lboro.ac.uk; S.J.Camilleri@lboro.ac.uk

1. Introduction

Two of the most important topics in market microstructure are the design of trading protocols and the evaluation of their effectiveness. Since trading protocols provide the framework within which markets operate they play a central role in price formation and discovery (Madhavan, 2000). Evaluating the effectiveness of different protocols is therefore a key concern for market authorities and regulators. One of the most hotly debated issues in this area is the effectiveness of call auctions as against continuous trading systems. In theory, call auctions provide an efficient mechanism for aggregating diverse information because trading does not take place until price discovery has occurred (Economides and Schwartz, 1995), whereas under continuous trading, price discovery and trading take place simultaneously implying that trades may occur at "false" prices (Schwartz, 2000). Conversely, it can be argued that continuous trading is preferable to call auctions because the former involves greater immediacy and therefore less price risk. In an auction, there is a delay in establishing the trading price, and so the "true" price may change between the submission and execution of an order (Madhavan, 1992).

So far, the balance of empirical evidence comparing call auctions and continuous trading is inconclusive. Ellul, Shin and Tonks (2003) found that price discovery at the London Stock Exchange (LSE) tended to be higher during call auctions than within the dealer market transactions taking place concurrently off the exchange. In contrast, Amihud, Mendelson and Lauterbach (1997) document large increases in asset values on the Tel Aviv Stock Exchange for stocks which moved from a daily call auction to more continuous trading, implying that investors valued continuous trading more highly. We review related research in section 2 of the paper. Meanwhile, there are several possible reasons for this mixed evidence. First, call auctions vary in structure and different call auction structures may have different effects. Second, different markets have a range of different trading protocols, and it may be that similarly-structured auctions have different effects in a different market context. Kairys, Kruza and Kumpins (2000b) point out that different exchanges adopt different listing requirements, price limits, and minimum tick sizes, all of which may affect the workings of an auction. Third, comparisons between call auctions and continuous trading will be difficult because the two systems being compared rarely share a common set of trading protocols (Madhavan, 2000). For example, much of the evidence on the effectiveness of call auctions is gleaned from markets where auctions are used to begin or end trading, but Amihud, Mendelson and Murgia (1990) show that, in Milan, there was little to choose in terms of efficiency as between continuous trading and call auctions which were not held at the beginning of the day. Many studies look at the impact of the replacement of call auctions by continuous trading on an exchange (Amihud *et. al.* 1997), but such changes typically involve other reforms to the trading system making it difficult to conclude if costs or benefits are due to the switch to continuous trading or to other factors.

A further limitation of the existing empirical literature on call auctions is that it is mostly concerned with the stock markets of the major industrial countries. Exceptionally, Shastri, Shastri and Sirodom (1995) investigated the impact of the opening call auction on the Bangkok stock exchange, and found that prices at the opening call were more volatile than during the rest of the day. This could be because uncertainty and therefore volatility are at their maximum early in the day following the overnight closing rather than because of deficiencies in the call auction system *per se*, and this tends to be supported by the results of Amihud *et. al.* (1990). In general though, there has been very little comparable research on stock exchanges in emerging markets. This is an important omission because a central characteristic of most emerging stock markets is that they are less liquid than the major industrial countries, and it has been argued that call auctions are particularly suited for trading less liquid stocks (Madhavan, 1992). This suggests that in emerging markets call auctions may have advantages over continuous trading systems in fostering the efficient trading of relatively illiquid securities. However, this argument also underlines a further difficulty in comparing call auctions and continuous trading: if the effectiveness of an auction depends on the thinness of the market, a proper comparison must control for variations in market thinness, and possibly other factors.

In this paper we adopt a novel approach to the call-auction/continuous-trading debate. We investigate the impact of the suspension of opening and closing call auctions by the National Stock Exchange of India (NSE) on the 9th June 1999[1]. As far as we are aware, this is the first study of the impact of a suspension rather than a comprehensive permanent change in trading arrangements. The suspension of the auctions was part of a series of experiments by the NSE which had as its ultimate objective the establishment of call auctions alongside continuous trading arrangements. An important aspect of this event is that other market protocols and arrangements were not changed at the suspension. This makes for a relatively clean comparison between the two systems. Furthermore, continuous trading was in effect before and after the suspension. Therefore the call auctions did not limit immediacy in the market given that stocks still traded continuously for most of the day. We are not therefore comparing two systems with a range of different trading protocols. Moreover, the NSE is an emerging market and includes a significant proportion of less liquid securities. This enables us to investigate any differences in the effect of the suspension as between more and less liquid securities in the market.

Our paper has two main objectives. The first is to estimate the impact of the suspension of the call auctions at the NSE and therefore to infer the contribution of the auctions to the organisation of market activity. We do this by comparing the volatility, efficiency and liquidity (VEL) of traded securities in the market before and after suspension. The second objective is to estimate the value of the call auctions to traders. This we do by means of an event study.

Under the circumstances of the NSE, auctions might be considered as value-increasing by market participants, and therefore their suspension as value-decreasing, given that they should help in the price discovery process without preventing continuous trading for most of the trading day.[2] Pagano and Schwartz (2003) found that the introduction of a closing call auction at the Paris Bourse created improvements in the price discovery process, without any

1 The NSE circular announcing this change was issued on the same day.
2 Upon the suspension of the call auction on NSE, the time devoted to continuous trading was unchanged.

negative effects during the continuous trading session. If our expectations are correct, following suspension, we should observe higher excess volatility, a reduction in open and close price efficiency, and perhaps lower liquidity. In addition, following the argument that call auctions are particularly suited for trading less liquid stocks, we should observe that the less liquid stocks in the sample experience a more severe deterioration in these factors as compared to the other ones. In fact, the results of the comparison analysis and of the event study are not in line with our expectations. We therefore conducted further tests to examine the relationships between the response to the auction suspension and the composition of the sample securities, particularly in respect of their initial betas and liquidity. It turns out that the latter variable is a relevant factor in explaining the results which we obtain.

The rest of the paper is structured as follows. In section 2 we review relevant theoretical and empirical literature concentrating on comparisons between call auctions and continuous trading. Section 3 sets out some background material on the NSE and describes the data used in this study. In section 4, we investigate the impact of the suspension of call auctions on volatility, efficiency and liquidity. Two different tests are undertaken for assessing the changes for each of these factors. It turns out that these tests point to a significant overall improvement in VEL factors, contrary to what might be expected. The event study is discussed in secion 5 and the CARs, though significant, exhibit a different pattern from that which would be expected following the results of the changes in VEL factors. Therefore, we undertake further tests to check if these results can be explained by the composition of the sampled stocks. A concluding discussion and evaluation is given in section 6.

2. Research Background

The central issue in the debate between call auctions and continuous trading is the trade-off between information efficiency and immediacy. A sequence of call auctions aggregates information more efficiently, especially where asymmetric information is a particular problem and dealers are reluctant to take the opposite side of trades. However, periodic auctions lack continuity and therefore reduce the immediacy of trading. They may also result in higher information costs given that current prices are available less frequently (Madhavan, 1992). However, these arguments are less relevant where call auctions are used solely at the opening or closing, since trading still occurs continuously for the rest of the day. Moreover, lack of immediacy is an issue in any setting in which trades cluster to one specific point or short period, and this may occur independently of an auction. Admati and Pfeliderer (1988) give a theoretical example in which uninformed traders choose to transact in the lowest cost period. Similarly, traders who submit orders prior to the market opening have to wait for execution until the opening. Thus, it can be argued that an opeing call auction. such as we analyse for the NSE, is unlikely to have an effect on immediacy, as compared with continuous trading (Vayanos, 1999).

Thus, theory would suggest that an opening call auction will bring improved pricing efficiency with little loss of immediacy as compared with continuous trading. Several researchers have investigated the properties of opening call auctions. In a study of the pre-open call auction of the (former) Paris Bourse, Biais, Hillion and Spatt (1999) identified a clear price discovery process as orders posted successively later during the call contained increasing amounts of information about the true price, while those posted early could be classified as noise. Evidence against the pricing efficiency of an opening call auction was reported by Amihud and Mendelson (1987) who compared the opening call auction with the continuous trading session on the NYSE. They found that opening returns exhibited greater dispersion, higher negative autocorrelation and a larger residual error component than closing returns. Similarly, Shastri, Shastri and Sirodom (1995) found that opening prices on the Thailand Stock Exchange, which are determined through a call auction, tended to be more volatile than those of the rest of the day. However, since uncertainty is typically at its peak during the opening of a trading session, these results may emanate from the initial uncertainty, rather than any inherent inefficiency of auctions, and this argument is supported by the results of Amihud, *et. al.* (1990) and Amihud and Mendelson (1991), who analysed call auctions which were not held at the start of the trading day and found that the auctions were no less efficient than continuous trading.

In general, the relative efficiency of call auctions depends on the trading structure with which they are compared. In a study of the NASDAQ, Angel and Wu (2001) suggest that a dealer market may be better equipped than call auctions to handle the random nature of order imbalances, although they themselves advocate a hybrid trading mechanism incorporating the best features of call auctions and dealer markets. Furthermore, Ellul, Shin and Tonks (2003), found that price discovery tended to be higher during the LSE call auctions as compared to the contemporaneous dealership market transactions taking place off the exchange. Call auctions should increase liquidity and reduce trading costs by batching transactions which might have otherwise been executed sequentially (Economides and Schwartz, 1995). Kehr, Krahnen and Theissen (2001) examined the difference in trading costs between call auctions and continuous trading sessions on the Frankfurt Stock Exchange. They found that auctions provided transaction cost savings for small transactions, but not for large transactions. Similarly, Ellul, Shin and Tonks (2003) found that small orders were cheaper to execute in the call auction, but larger orders tended to be cheaper to execute in the dealership market.

The issue of whether call auctions constitute a better trading method for less liquid stocks has also been debated. It can be argued that less liquid stocks are subject to a greater degree of asymmetric information (Barry and Brown, 1984), implying that call auctions are especially suitable for trading such stocks. Comerton-Forde (1999) compared trading on the Australian Stock Exchange which commences with a call auction, with that on the Jakarta Exchange which commences with continuous trading. He concluded that the auction increased liquidity and reduced volatility in the initial phases of the trading sessions, particularly for less liquid stocks. However, Ellul, Shin and Tonks (2003) found that on the LSE, where trading at the opening and at the closing may take place both through call auctions and the dealership system, less liquid stocks tended to trade in the dealer market more frequently, even if the call auctions offered cost savings and higher pricing efficiency. One possible explanation for this behaviour is that dealers invariably guarantee the availability of a counterparty whereas call auctions depend to a higher degree on co-existing public orders.

Studies of changes in trading systems on a particular exchange generally find that a switch from call auction to continuous trading increases stock values. See for example Muscarella and Piwowar (2001) for the former Paris Bourse; and Amihud *et. al.* (1997) and Lauterbach and Ungar (1997), for Tel Aviv. An event study on its own is a relatively blunt instrument, and these results do not necessarily imply that call auctions are inherently inferior trading systems. Kalay, Wei and Wohl (2002) argued that such results may simply reflect investors' preferences for stocks that trade continuously rather than stocks that trade at auction, although it is likely that causation could be two-way, ie: investor preferencees may also be influenced by the systems by which different stocks are traded.

The changes in VEL factors of stocks when the latter switch from call auctions to continuous trading might also depend on the initial liquidity levels of the stocks. For instance, Kairys, Kruza, and Kumpins (2000a) found that when the Riga Stock Exchange shifted from a call auction to a continuous trading system the overall liquidity impact was positive, yet the benefits accrued to stocks which were already liquid whilst the volumes of smaller company stocks declined.

3. Data and Notation

The National Stock Exchange of India (NSE) was established in 1994 and is one of two major Indian exchanges, together with the Bombay (Mumbai) Stock Exchange (BSE). During 2000, around 1,300 equities traded on NSE, through 960 brokerage firms[3]. Most major stocks are quoted on both NSE and BSE and these exchanges compete both for listings and order flow. During the period covered by this paper the volume of a typical trading day on the NSE was around 400,000 transactions.

The NSE was set up with on-line, continuous, screen-based, nationwide electronic trading. Subsequently, the exchange introduced as an experiment a pre-opening and post-closing call auction. This followed the basic rule that the resulting price should maximise the total traded

[3] Shah and Sivakumar (2000).

quantity, implying that the gap between demand and supply should be ideally zero. Orders which included bargain conditions such as "All-Or-None" were not considered in the auctions. Orders could also be modified and cancelled during the sessions. Market buy (sell) orders were considered as orders which were prepared to trade at the highest (lowest) available price; they therefore obtained the best price priority and were listed at the top of the order book in the auction sessions. For the rest of the trading day the system continued to function as a continuous pure limit order book market, with time and price priorities applied to incoming orders. There are no market-makers on the NSE, and therefore theories which suggest that market-makers are a factor in determining the relative efficiency of continuous trading *versus* call auctions (Ellul, Shin and Tonks, 2003) are not relevant to this study.

In the period when auctions were in effect, the pre-opening auction was usually held between 09:30 and 09:45, followed by continuous trading until 15:30, and subsequently by a post-closing auction between 15:30 and 15:45. As from 9th June 1999, the initial and closing auctions were suspended. From this date, continuous trading took place between 10:00 and 15:30. Our data period runs from March 2nd through September 4th 1999, or for 63 days either side of June 9th when the auctions were suspended[4].

The NSE offers particular advantages for a study of this kind. First, about 1,100 equities are traded enabling the selection of a large sample of liquid and less liquid stocks for analysis. Second, trading volumes are high for the most liquid stocks, but there is a range of trading volumes, even among the more liquid stocks, and this enables an analysis of the relationships between liquidity and trading protocols.

The data was extracted from the NSE's historical trades data CDs[5]. These include data on the volume and price of all trades carried out on the exchange on a trade-by-trade basis. In selecting the securities to be included in the sample, only equity issues were considered. We aimed to select the most liquid stocks, in order to obtain sufficient observations for analysis.

[4] Our sample period is characterized by occasional minor changes in trading hours

[5] We thank the NSE for providing us with trial copies of these data.

We therefore selected 170 stocks with the highest quantities traded, and a further 170 stocks with the highest Indian Rupee value traded. We combined these samples, deleted the 107 stocks which were duplicated and a further 51 stocks which had missing observations or changes in equity structure (mergers, new share issues or stock splits). The final sample thus consisted of 182 of these more liquid stocks. However, it should be emphasized that this sample does include a wide range of liquidity. We only excluded stocks where trading was sufficiently thin so that there was no trading at all in at least one day of the sample.

Transactions occur at random times and this results in irregular sampling intervals. For the purposes of this study, the data interval was homogenised by using daily observations on prices and volume. For prices, we used the daily last trade prices for each stock, unless otherwise specified. Table 1 shows a summary of the data periods used for the comparison analysis and event study.

Table 1 and 2 about here

To get a preliminary idea of activity in the auctions prior to suspension, we selected three trading days at random from different days of the week and reasonably close to the event date. We split the sample into high, medium and less liquid stocks and calculated some summary statistics of trading activity (table 2). As we would expect, trading frequencies increase as we move from the low to medium and to high liquidity stocks. Furthermore, the level of activity is generally higher for the closing auction than for the opening auction. One possible explanation for this is that any unexecuted orders at the end of the continuous session are automatically carried forward to the closing call, whereas this does not happen in case of the opening auctions, as unexecuted orders are often cancelled at the end of the trading day. This might suggest that the closing auction contributed more to trading than did the opening auction, notwithstanding the argument noted in section 2 that an opening auction brings improved efficiency with little loss of immediacy as compared with continuous trading.

4. *The Impact of Auction Suspension on Volatility, Efficiency and Liquidity*

4.1 *Volatility*

The impact of the suspension of the call auctions on market volatility is assessed through a comparison of the scaled intra-day price difference and reversals of overnight returns, for the pre-event and post-event data. These measures focus on short-term volatility, given that any expected impacts of call auctions on price stability are essentially of a short-term nature.

The ***scaled intra-day price difference*** is an indicator of intra-day volatility and is given by:

$$D_{i,t} = (P_{high\ i,t} - P_{low\ i,t}) \,/\, P_{open\ i,t} \tag{1}$$

where $P_{high\ i,t}$, $P_{low\ i,t}$ and $P_{open\ i,t}$ are the highest, lowest and opening prices for security i on day t respectively. Contrary to expectations, intra-day volatility decreased in the post-event period, and the hypothesis of no difference between the pre-event and post event $D_{i,t}$ is clearly rejected (table 3). We also tested the difference between the standard deviations of $D_{i,t}$ for each stock but no significant change in this statistic is evident.

Table 3 about here

We next consider ***overnight return reversals*** which are a measure of inter-day volatility, ie. that between trading days. If the opening and closing auctions help in price discovery, we would expect lower overnight volatility during the period when auctions were held. However, a direct comparison between overnight returns in the pre-event and post-event periods is potentially misleading as higher price changes in one period might be justified by the news in that period. Thus we concentrate on the reversal of price movements. If price movements overnight and during the subsequent day are driven independently by the news in each respective period then we would expect there to be no systematic relation between overnight and next-day returns. If however, overnight price movements are systematically reversed next day, this implies that the overnight movement was excessive and provides evidence for excess volatility. To test for this we regress the daily return ($r_{i,t}$)on the previous overnight return ($r^{O}{}_{i,t}$):

$$r_{i,t} = \mu_i + \pi_i r^{o}{}_{i,t} + \varepsilon_{i,t} \tag{2}$$

A significant negative π_i provides evidence of price reversals during the day and therefore of excess volatility between the previous closing and subsequent opening. We do not test for longer-horizon reversals because we expect the main effect of call auctions to be on short-term volatility.

From table 3, we see that the mean of the slope coefficient (π) is negative in both the pre-event and post-event period. However, the t-test shows that there was a highly significant increase in $|\pi|$ following suspension of the auctions implying, on this measure, an increase in volatility as we would expect.

We checked that there were no additional events which might have impacted on volatility during this period by reviewing relevant NSE circulars. The only possible event was that on June 16th the National Securities Clearing Corporation (NSCC) applied additional volatility margins in respect of outstanding positions of trading members in highly volatile stocks. This might have discouraged trading members from taking or increasing positions in volatile stocks, and if anything might be expected to reduce volatility as between the pre-event and post-event period. Furthermore only four of the affected stocks are included in our sample, indicating that the additional volatility margins were unlikely to have affected our results.

4.2 Pricing Efficiency

Two different tests of pricing efficiency are conducted: Relative Return Dispersion (RRD) and the Serial Correlation of Returns. RRD is calculated by averaging the squared residuals of the market model (Amihud, *et. al*., 1997), and is defined as:

$$RRD_t = \frac{1}{n}\sum_{i=1}^{n} \varepsilon^2{}_{it} \tag{3}$$

where, RRD_t is ***Relative Return Dispersion*** across the sampled securities during time t, ε_{it} are the residuals from the market model for security i at time t, and n is the number of sampled securities. A lower RRD_t indicates a lower pricing error and therefore greater efficiency. The results in table 4 indicate that, in fact, RRD_t decreased very significantly suggesting that pricing became more efficient following suspension of the auctions.

Table 4 about here

Pricing inefficiency can also be measured using the ***serial correlation of returns*** for, if prices adjust fully to new information, price changes should be uncorrelated provided that the flow of news is also an uncorrelated series. For this purpose, we calculated first-order autocorrelation coefficients for each individual stock. For most stocks the first order autocorrelation was insignificant, both in the pre-event and in the post-event estimation, suggesting that these stocks were mostly quite efficiently priced. The correlation coefficient does show a significant change as between the pre-event and post-event period (table 4), but this is largely due to the fact that the correlations change from being predominantly negative to predominantly positive. We therefore calculated the squared correlation coefficients for each firm and found that there was a small increase in pricing efficiency measured by the decrease in the squared correlation coefficient but, perhaps not surprisingly, this change was not significant. However, once again the direction of change is unexpected, with the suspension of the call auctions being associated with increased efficiency.

4.3 Liquidity

Two measures were selected to assess the impact of call auction suspension on market liquidity: the number of shares traded and the volume per unit of return. The ***number of shares traded*** is a direct measure of volume: higher activity is associated with a more liquid market. According to this measure there was a significant increase in volume following suspension (table 5). ***Volume per unit of return*** (the ratio of volume to the absolute return) is an estimate of how many shares traded are associated with a unit share price change. This measure assesses the resiliency aspect of liquidity: how much activity is required to generate a unit price change. The more resilient is the market, the greater is the activity required to change the share price in either direction. We see from table 5 that this statistic also indicates a significant increase in market liquidity following the suspension of the call auctions. Of course it is possible that improved resilience may have been partly due to the lower intra-day volatility that we identified earlier, but we can still rule out any deterioration in liquidity following the suspension.

Table 5 about here

---

5. The Value of Opening and Closing Auctions to Shareholders

5.1 Method

We turn next to an event study to assess the value to shareholders (positive or negative) of the suspension of the call auctions. Event study methods are explained in detail in several places, for example by MacKinley (1997). Here we content ourselves with a brief summary.

Following Green, Manos, Murinde, and Suppakitjarak (2003), we used the market model adjusted for calendar time effects as our model of normal returns:

$$r'_{i,t} = \alpha_{i,t} + \beta_i r'_{m,t} + \varepsilon_{i,t} \tag{4}$$

where: $r_{i,t}$ is the return of stock i on day t; $r_{m,t}$ is the market return; $r'_{i,t} = r_{i,t} / k_t$; $r'_{m,t} = r_{m,t} / k_t$; k is the return interval in calendar days; α_i and β_i are the estimated coefficients; and $\varepsilon_{i,t}$ is the error term. Although the market model has been criticised in event study applications (Coutts, Mills, and Roberts, 1994), the current consensus would appear to be that more elaborate methods do not in practise yield significant gains in efficiency or unbiasedness in measurement of the abnormal returns which are the key output of an event study. See, *inter* *alia*, Brown and Warner (1980), MacKinlay (1997), and Cable and Holland (1999). Although the stocks in our sample vary considerably in degree of liquidity, we do not have a thin trading problem in that all the stocks were traded every day in the sample period. Therefore, no further adjustments were necessary to allow for this.

Daily abnormal returns for each firm in the event window ($AR_{i,t}$) are calculated as:

$$AR_{i,t} = [r'_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i r'_{m,t})]k_t \tag{5}$$

The ARs are then cumulated over time to obtain the cumulative abnormal returns (CARs):

$$CAR_{t,i} = \sum_{t=T-2}^{T+15} AR_{t,i} \tag{6}$$

Finally, the CARs may be averaged across the n firms in the sample to obtain the mean CARs (MCAR). This helps eliminate noise from firm-specific news, which is unrelated to the event.

$$MCAR_t = \frac{1}{n}\sum_{i=1}^{n} CAR_{i,t} \tag{7}$$

For this study, the event date ($t = T$) is June 9th 1999. Around this, we used an 18 day event window; from *T–2* to *T+15*. The choice of a short pre-event window is suggested by the fact that the suspension was not trailed in advance, and that the shorter the event window, in general, the more powerful are the tests on the ARs (MacKinley, 1997). We nevertheless do choose a somewhat longer post-event window than might be strictly necessary. This covers the possibility that this market microstructure change might take some time for the markets to evaluate, at least in part because it might be interpreted differently by different market participants, especially given our evidence reported so far. Alternatively, some participants may classify the change as irrelevant, as it would not be expected to change fundamental values of securities in terms of the earnings and risk of the underlying firms.

Conventionally, the estimation window precedes the event window. However, this may create post-selection bias, if the event is conditional on the characteristics of the securities. For instance, Amihud, *et. al.* (1997) used a post-event estimation window in their study of the impact of a market microstructure reform on selected stocks on the Tel Aviv Stock Exchange on the basis of their "marketability". In the current study, a pre-event estimation window covering the period *T–62* to *T–3* was used as the event under review was not conditional on stock characteristics.

We used as market index the BSE-500, a 500-security index quoted by BSE. We took the view that it was desirable to use a broad-based index and both the key indices quoted on the NSE during the sample period comprised just 50 stocks each[6]. We believe that this choice of index is reasonable, given that major Indian stocks are quoted on both NSE and BSE, and both exchanges are subject to the same systemic risk. There were five instances when the BSE-500 closing price was unavailable, because the BSE was closed. These trading days were omitted from the sample.

Daily data create a particular set of problems in event studies (Brown and Warner, 1985). The main concern for this study is the typical non-normality of daily stock returns which creates problems for accurate inferences concerning the ARs, and suggests that we should not rely exclusively on standard t-tests. We pursue this issue in section 5.2 next.

5.2 Results

OLS estimates of the market model and relevant diagnostics show that, in general, the model performed very well with the standard F test indicating that almost all the regressions have a good overall fit (table 6). The betas are also generally plausible. There is no serious evidence of misspecification or structural breaks in the Reset test, the Predictive Failure test or the Chow test. This is important for our research, given that a frequent criticism of event studies is that inferences may be flawed because of time-changing *betas*. These tests indicate that *betas* were generally stable over our sample period. The results of the predictive failure test are particularly strong in this respect, given that the 18 out-of sample observations in the

---

6 The major indices on NSE during the sample period were the NIFTY (NSE-50 Index) and NIFTY Junior (Midcap-50 Index). Nifty was the main index and it included the 50 most liquid stocks which accounted for around 50% of the market capitalisation. Nifty Junior accounted for a further 10% of market capitalisation.

event window were used for the test. It suggests that we can be reasonably confident that the model did not change following the event. The autocorrelation and heteroscedasticity tests do not reject the null hypothesis for most stocks. Moreover, Brown and Warner (1985) argue that adjustments for serial correlation in the calculation of test statistics typically bring only small improvements in performance.

Table 6 about here

The only diagnostic which seems problematic is the normality test where the null of a normally distributed error is rejected for 51% of the stocks. On closer inspection it transpired that there were a few abnormally high Jarque-Bera statistics. For the 6 highest, the fitted model mimicked actual market movements reasonably well, except for a few outliers. Most of these were positive suggesting company announcements as a possible cause. Apart from the outliers, most of the residuals were close to zero, and almost uniformly distributed. This suggests that the estimated coefficients will be close to their true values, and the main objective in dealing with this non-normality should be to enhance the power of the significance tests, rather than obtaining better estimates of the regression coefficients.

To assess the significance of the ARs, we want to compare the residuals in the market model in the estimation period, to the errors obtained when using the model to predict normal returns in the event window. In the absence of normally-distributed errors, we do not rely on standard t-ratios. Instead, we follow MacKinnon (2002) who argues that bootstrap tests usually perform better in these circumstances in assessing statistical significance and establishing confidence intervals. The advantage of bootstrapping in the present context is that it relies only on the assumption of random sampling from the data at hand, and does not require any distributional assumptions.

Since we are interested in the significance of the ARs rather than their sign, we compare the error sum of squares in the estimation period to that in the event window for each stock. For a valid comparison, we rescale the latter by (60/18) in proportion to the numbers of observations in the estimation window and the event window respectively. Hence, defining $S.S.R.E_{i,est}$ and $S.S.R.E_{i,event}$ as the Sum of Squared Rescaled Errors for stock i, in the estimation period and in the event window respectively, we have:

$$S.S.R.E_{i,est} = \sum_{t=T-62}^{T-3} \varepsilon_{i,t}^{\,2} \tag{8}$$

$$S.S.R.E_{i,event} = \frac{60}{18} \sum_{t=T-2}^{T+15} \left[\varepsilon_{i,t}\right]^2 \tag{9}$$

The mean $S.S.R.E_{est}$ was 0.0787 whilst the mean $S.S.R.E_{event}$ was 0.2429; a mean difference of 0.16419. To test the significance of this difference, we combined the *S.S.R.E.s* for all stocks in the estimation period and the event period, into a single sample: 364 *S.S.R.E.s* in all. Observations were then randomly drawn without replacement from this population, creating two sub-samples, each having 182 observations. The difference between means of these two sub-samples was recorded, and the random drawing repeated 5,000 times[7]. The results are summarized in Figure 1 where we see that 0.16419 actually lies outside the bootstrapped distribution, implying that we can reject the null hypothesis of equal means at the 99.98% level[8] (at least) and conclude that the ARs are highly significant.

Figures 1, 2, 3 about here

The cross-section average CARs for all stocks are shown in figure 2. The sample was then randomly split into 5 equal sub-samples[9] and the average CARs recalculated for each sub-sample (Figure 3). The plots of the five sub-samples are acceptably similar to the overall pattern of figure 2, suggesting that the general behaviour of the CARs is similar across all securities: after a short initial increase, the CARs decrease until around T+9; and finally drift

7 The bootstrap routine was obtained from http://www.resample.com/content/about.shtml (accessed 1st March 2004).
8 That is: the probability of obtaining the reported mean difference by coincidence is less than 1 in 5000.
9 Three of the sub-samples consisted of 36 stocks, whilst the other two contained 37 stocks.

upwards again. We conclude that call auction suspension was associated with a significant and consistent pattern of CARs. However, it is not immediately clear how this pattern is related to the general improvement in VEL factors following the auction suspension. Therefore, in the next section we consider the possible linkages.

5.3. CARs and Volatility, Efficiency and Liquidity

We consider the linkages between the CARs and changes in underlying VEL factors associated with the auction suspension by performing two sets of cross-section regressions. First, we check if the changes in VEL factors among stocks are related to the betas and liquidity levels of these stocks. Second, we seek to explain directly the cross-sectional variation in the CARs by changes in VEL factors, betas and liquidity levels.

Table 7 about here

To study the determinants of changes in VEL we regressed 4 of our 6 different VEL factors on two sets of dummy variables, the first measuring pre-event risk in three tranches: low, medium and high beta stocks; the second measuring pre-event liquidity, again in three tranches: low, medium and high liquidity stocks. Given that our two measures of volatility gave different results as to the effect of the auction suspension, both indicators were used as regressands. For efficiency and liquidity, since both measures showed the same qualitative effect of the auction suspension, only one of each measure was used as regressand: the change in Relative Return Dispersion and the change in the Volume-Return Ratio[10]. We see in table 7 that all these regressions have low explanatory power and none of the dummy variables are significant. Therefore, the observed VEL changes seem to be unrelated either to the betas or liquidity of stocks[11]. This is contrary to the results of Kairys, Kruza, and Kumpins (2000a) who found that in Riga, increased liquidity largely accrued to the already most-liquid stocks.

---

[10] These each had a higher significance level in the VEL comparisons than did the alternative measure.

[11] The latter result is thus inconsistent with the findings of Kairys, Kruza, and Kumpins (2000a) cited above, who found that increased liquidity largely accrued to the most liquid stocks.

Table 8 about here

We turn next to the regressions explaining the CARs (table 8). We note that, although the CARs are statistically significant, there is a increasing and a decreasing portion, and the mean value at the end of the event window is very close to zero (figures 2 and 3). We therefore distinguished between the increasing and decreasing portion of the CARs in the regressions. First, the increasing CARs from T+9 through T+15 were regressed on changes in VEL factors which showed an improvement, excluding and then including the pre-event beta and liquidity dummies as regressors. Second, the decreasing CARs from t=T through T+8 were regressed on the overnight return reversal coefficient (π) which indicated an increase in volatility, again excluding and then including the pre-event beta and liquidity dummies.

For the increasing CARs (Panel A), the Scaled Intra-Day Price Difference is significant but with an unexpected sign, Relative Return Dispersion is insignificant and with the expected sign, whilst the Volume Return Ratio is significant and with the expected sign. The beta and liquidity dummies are all insignificant, confirming that initial beta and liquidity were not relevant in determining the positive aspect of the market response to the suspension. For the decreasing CARs (Panel B), Overnight Return Reversals are positive as expected and significant at the 90% level. The dummy for less liquid stocks is also significant and suggests that less liquid stocks experienced higher CARs following abolition of the auctions. However, as the dummy for more liquid stocks is also positive but insignificant, we cannot conclude that there is a well-defined linear relationship between liquidity and the CARs.

To check these results we split the whole sample into high, medium and less liquid stocks and recalculated the mean CARs (Figure 4). This confirms that there is indeed a significant difference between the CARs of the less liquid stocks (Sample A) and those of medium and high liquidity stocks, while the difference between the CARs of medium and high liquidity stocks is relatively small. These results run contrary to the findings of some other researchers that less liquid stocks tend to benefit more from call auctions (Comerton-Forde, 1999; and Kairys, Kruza, and Kumpins, 2000a).

Figure 4 about here

---

6. Further Discussion and Conclusions

6.1 Some Possible Explanations

Table 9 summarizes the main findings in terms of changes in VEL factors following the suspension of call auctions on the NSE. The volatility tests present conflicting indications but, overall, it seems safe to conclude that the suspension of call auctions was associated with an identifiable improvement in market performance. Why should this be? We consider several possible explanations.

Table 9 about here

First, improvements in VEL may have been priced in before t=T, even though the suspension was only announced on the event day. The event window does show small positive CARs in days T-2 and T-1. This may be consistent with insider trading, or that the suspension was expected by the market. The latter is possible because it is generally agreed that the NSE suspended the auctions because of problems related to software[12]. However, changes which affect the structure of trading can be difficult to price in fully before the event because the volume and composition of trading after the event is not known for certain beforehand.

Second, the finding of a general improvement in VEL following the call auction suspension is at odds with the observed pattern of CARs: first decreasing then increasing, and overall

[12] We thank Susan Thomas for helpful correspondence on this point.

negative for most companies for most of the post-event window. The cross-section regressions provide limited support for the impact of VEL improvements in that the increasing part of the CARs are explained to some extent by the positive changes in VEL factors, but not all with the expected sign. One possibility is that the initial downward sloping part of the CARs was an over-reaction which was subsequently reversed. However, it is not easy to explain why there should be such an overreaction, especially as this did not occur in the less liquid stocks. Therefore the possibility of an overreaction followed by a correction is not really supported by the data.

Third, the results indicate that intra-day volatility decreased whilst overnight volatility increased. A possible explanation for this is that the opening auctions were not successful in reducing intra-day volatility, whilst the closing auctions were contributing towards reducing overnight volatility. This is consistent with the results of Pagano and Schwartz (2003). There was less activity at the opening call auction than the closing call (table 2), particularly for less liquid stocks. Thus, we may hypothesise that whilst closing auctions helped to establish more efficient prices and reduce overnight volatility, this was not happening at the opening auctions because of insufficient activity, particularly for less liquid stocks.

Fourth and finally, the results could be related directly to the different liquidity of the shares and the performance of the auctions. The CARs for the less liquid stocks were unambiguously positive, whereas the high and medium liquidity stocks exhibited initially small positive CARs then larger negative CARs (figure 4). This is consistent with the argument that higher liquidity stocks <u>did</u> benefit from the call auctions but low liquidity stocks did not. This too could be because the less liquid stocks traded much less actively in the call auctions and therefore had little to lose from suspension. However, this hypothesis does not explain why the VEL factors all improved following suspension and that there is no clear cross-sectional relationship between liquidity and any of the VEL factors.

None of these explanations is entirely satisfactory, but together, they do suggest that the call auctions, especially at the opening were not as effective as might have been expected, particularly for less liquid stocks. This is consistent with the observation of Schwartz (2000) that it is essential that call auctions attract a "critical mass" of order flow, otherwise they may fail.

6.2 Summary of Conclusions

To our knowledge this is the first study to compare call auctions and continuous trading following a suspension, where no other changes in market protocols took place. It is also concerned with an emerging market where low liquidity is more of a potential problem than in the major industrial countries. Our main conclusions from the study can be summarised as follows. First, we confirm the prevailing wisdom that market microstructure changes do have measurable and significant effects on stock prices and on the characteristics of market performance such as volatility, efficiency and liquidity. However, contrary to expectations, we found that the VEL factors broadly improved following the suspension and the CARs were significant but did not exhibit a uniformly positive or negative pattern.

Second, we cannot accept the hypothesis that the main disadvantage of call auctions is that they prohibit stocks from trading continuously for we find evidence that call auctions also had a largely negative impact on VEL factors as well as any direct impact on immediacy. As a corollary, it is evident that call auctions do not necessarily lead to an improvement in VEL factors as suggested *inter alia* by Madhavan (1992), for we find the reverse to be true.

Third, we do not find a clear-cut market reaction to the suspension. The CARs are significant but initially they decrease and then subsequently increase. The cross-sectional relationships between the CARs and the underlying VEL factors are also imprecise. Stocks which experienced the most improvements in efficiency and liquidity also experienced higher CARs, although the efficiency effect was not significant. However, the change in <u>intra-day</u> volatility had a positive impact on the cross-section of CARs, but the change in <u>inter-day</u> volatility had the expected negative effect.

Fourth, we conjecture that a source of these conflicting findings may lie in the liquidity composition of the sample securities. We find that there is a significant difference in the response to the auction suspension as between less liquid stocks and medium and highly liquid stocks. Less liquid stocks traded less in the auctions then other securities, especially at the opening, and they experience the most gains following the suspension. The results suggest that the less liquid stocks did not gain the expected benefits from the auction system, and that the closing auction may have been more effective than the opening. This could be because there exists a liquidity threshold which stocks have to pass to reap the information benefits of an auction (Schwartz, 2000). Given that suspension was related to software problems, it could also be that the structure of the auction contributed to the problems apparently experienced by less liquid stocks.

These results have some important general implications. In particular, the evidence favouring continuous trading over call auctions may in part be attributable either to the composition of the shares being compared, or more specifically to low call auction activity in the shares, or to the timing of the auction(s) during the working day, rather than to a generic flaw in the auction process. This suggests that future research will need to pay more careful attention to these issues and delve more deeply into the nature of the trading process in different shares in the market.

Finally, it is important to emphasize that our results do show that it cannot be taken for granted that a call auction system will improve share trading in a less liquid emerging market, irrespective of whether it is the sole system of trading or operated alongside a continuous system. On the NSE, it appears to have been precisely the less liquid securities which gained least from the call auction.

References

Admati, A. and Pfleiderer, P., 1988. A Theory of Intraday Patterns: Volume and Price Variability, *Review of Financial Studies*, 1(1), 3-40, Spring.

Amihud, Y. and Mendelson, H., 1987. Trading Mechanisms and Stock Returns: An Empirical Investigation, *Journal of Finance*, 42(3), 533-553.

Amihud, Y. and Mendelson, H., 1991. Volatility, Efficiency and Trading: Evidence from the Japanese Stock Market, *Journal of Finance*, 46, 1765-1789.

Amihud, Y., Mendelson, H. & Lauterbach, B., 1997. Market Microstructure and Securities Values: Evidence from the Tel Aviv Stock Exchange, *Journal of Financial Economics*, 45, 365-390.

Amihud, Y., Mendelson, H. & Murgia, M., 1990. Stock Market Microstructure and Return Volatility: Evidence from Italy, *Journal of Banking and Finance*, 14, 423-440.

Angel, J.J. and Wu, S.Z., 2001. Calling the Open: Price Discovery Evidence from Nasdaq, *Georgetown University Working Paper*.

Barry, C. and Brown, S., 1984. Differential Information and the Small Firm Effect, *Journal of Financial Economics*, 13(2), 283-294.

Biais, B., Hillion, P. and Spatt, C., 1999. Price Discovery and Learning during the Preopening Period in the Paris Bourse, *Journal of Political Economy*, 107 (6), 1218-1248.

Breusch, T.S. and Pagan, A.R., 1980. The Lagrange Multiplier Test and its Application to Model Specifications in Econometrics, *Review of Economic Studies*, 47, 239-253.

Brown, S.J. and Warner, J.B. (1980). Measuring Security Price Performance, *Journal of Financial Economics*, 8, 205-258.

Brown, S.J. and Warner, J.B., 1985. Using Daily Stock Returns: The Case of Event Studies, *Journal of Financial Economics*, 14, 3-31.

Cable, J. and Holland, K., 1999. Modelling Normal Returns In Event Studies: A Model-Selection Approach And Pilot Study, *The European Journal Of Finance*, 5, 331–341.

Chow, G.C., 1960. Tests of Equality Between Sets of Coefficients in Two Linear Regressions, *Econometrica*, 28(3), 591-605.

Comerton-Forde, C., 1999. Do Trading Rules Impact on Market Efficiency? A Comparison of Opening Procedures on the Australian and Jakarta Stock Exchanges, *Pacific-Basin Finance Journal*, 7, 495-521.

Coutts, J.A., Mills, T.C. and Roberts, J., 1994. The Market Model and the Event Study Method: A Synthesis of the Econometric Criticisms, *International Review of Financial Analysis*, 3 (2), 149-171.

Economides, N. and Schwartz, R.A., 1995. Electronic Call Market Trading, *Journal of Portfolio Management*, 21 (3), 10-18.

Ellul, A., Shin, H.S. and Tonks, I., 2003. How to Open and Close the Market: Lessons from the London Stock Exchange, *Unpublished Working Paper*.

Green C.J., Manos, R., Murinde, V. and Suppakitjarak, J., 2003. The Impact of Microstructure Innovations in Emerging Stock Markets: Evidence from Mumbai, India, *Working Paper ERP03-04,* Department of Economics, Loughborough University.

Jarque, C.M. and Bera, A.K., 1980. Efficient Tests for Normality, Homoscedasticity, and Serial Independence of Regression Residuals, *Economics Letters*, 6, 255-259.

Kairys, J.P. Jr., Kruza, R. and Kumpins, R., 2000a. Winners and losers from the introduction of continuous variable price trading: Evidence from the Riga Stock Exchange, *Journal of Banking and Finance*, 24, 603-624.

Kairys, J.P. Jr., Kruza, R. and Kumpins, R., 2000b. A Tale of Three Cities: Is an Electronic Public Order Book Appropriate for Transition Economies? Unpublished Working Paper.

Kalay, A., Wei, L. and Wohl, A., 2002. Continuous Trading or Call Auctions: Revealed Preferences of Investors at the Tel Aviv Stock Exchange, *Journal of Finance*, 52 (1), 523-542.

Kehr, C.H., Krahnen, J.P. and Theissen, E., 2001. The Anatomy of a Call Market, *Journal of Financial Intermediation*, 10, 249-270.

Lauterbach, B. and Ungar, M., 1997. Switching to Continuous Trading and its Impact on Return Behavior and Volume of Trade, *Journal of Financial Services Research*, 12 (1), 39-50.

MacKinlay, A.C., 1997. Event Studies in Economics and Finance, *Journal of Economic Literature*, 35, 13-39.

MacKinnon, J.G., 2002. Bootstrap Inference in Econometrics, *Canadian Journal of Economics*, 35(4), 615-645.

Madhavan, A., 1992. Trading Mechanisms in Securities Markets, *Journal of Finance*, 47(2), 607-641.

Madhavan, A., 2000. Market microstructure: A survey, *Journal of Financial Markets*, 3, 205-258.

Muscarella, C.J. and Piwowar, M.S., 2001. Market Microstructure and Securities Values: Evidence from the Paris Bourse, *Journal of Financial Markets*, 4, 209-229.

Pagano, M. and Schwartz, R., 2003. A Closing Call's Impact on Market Quality at Euronext Paris, *Journal of Financial Economics*, 68(3), 439-484.

Ramsey, J.B., 1969. Tests for Specification Errors in Classical Linear Least-Squares Regression Analysis, *Journal of the Royal Statistical Society B*, 31(2), 350-371.

Schwartz, R.A., 2000. Building a Better Stock Market: New Solutions to Old Problems, *Working Paper*, AEI-Brookings Joint Center For Regulatory Studies.

Shah, A. and Sivakumar, S., 2000. Changing Liquidity in the Indian Equity Market. *Emerging Markets Quarterly*, 62-71, Summer.

Shastri, K.A., Shastri, K. and Sirodom, K., 1995. Trading Mechanisms and Return Volatility: An Empirical Analysis of the Stock Exchange of Thailand, *Pacific-Basin Finance Journal*, 3, 357–370.

Vayanos, D., 1999. Strategic Trading and Welfare in a Dynamic Market, *Review of Economic Studies*, 66 (2), April, 219-254.

Table 1: Data Periods Used for the Comparison Analysis and Event Study

Panel A: Pre-Event and post-Event periods used for the comparison analyses[1,2]								
	First day		Last day		Number of days in period			
	Event Time	Date	Event Time	Date	Open days	Closed days[3]	Week-days	Total days
Pre-Event period[4]	T-62	3rd March 1999	T-1	8th June 1999	62	8	70	98
Post-Event period[4]	T+1	10th June 1999	T+62	3rd Sept. 1999	62	0	62	86
Panel B: Estimation period and event window used for the event study								
Period	**First day**		**Last day**		**Number of days in period**			
	Event Time	**Date**	**Event Time**	**Date**	**Open days**	**Closed days[3]**	**Week-days**	**Total days**
Estimation Period	T-62	3rd March 1999	T-3	4th June 1999	60	8	68	94
Event Window	T-2	7th June 1999	T+15	30th June 1999	18	0	18	24

Notes

1. Call auctions were suspended on 9th June 1999. This date is denoted: t=T. All other days are denoted in relation to this date; for instance T+5 refers to 5 trading days after the event day.
2. The comparison analyses include the tests of the differences in volatility, efficiency and liquidity,
3. Closed days exclude Weekends
4. When working with intra-day prices, rather than returns, one further observation was available and therefore data from T-63 until T-1 was used for the pre-event period and data from T+1 till T+63 was used for the post event period.

Table 2: Summary Statistics for Call Auctions

	Monday 3 May 1999		Thursday 27 May 1999		Friday 4 June 1999	
	Open	**Close**	**Open**	**Close**	**Open**	**Close**
Transactions	1,274	2,995	1,446	13,361	3,392	5,642
Sample A						
Trades (%)	7%	46%	13.6%	88%	18.6%	72.9%
ATS (Z)	0.4	1.6	0.5	7.8	0.6	10.1
ATS (NoZ)	5.3	3.4	3.5	8.8	3.3	13.8
AUT (Z)	49	217	34	1,307	141	830
AUT (NoZ)	725	473	254	1,482	755	1,140
Sample B						
Trades (%)	45%	80%	41%	95%	39.7%	81.3%
ATS (Z)	2.0	5.0	1.3	21.3	3.1	6.2
ATS (NoZ)	4.5	6.3	3.2	22.7	8.0	7.6
AUT (Z)	447	891	409	5,118	786	1,095
AUT (NoZ)	986	1,118	1,005	5,459	2,012	1,348
Sample C						
Trades (%)	80%	95%	95%	100%	86.4%	98.3%
ATS (Z)	13.6	28.5	14.7	120.1	42.0	59.9
ATS (NoZ)	17.1	30.0	15.4	120.1	48.5	60.9
AUT (Z)	4,290	8,201	4,117	43,515	15,243	19,912
AUT (NoZ)	5,385	8,640	4,338	43,515	17,634	20,255

Notes

1. The three days were randomly selected from those that were not more than one and a half months distant from the event, and so as to avoid duplication of days of the week.
2. Sample A includes 59 sampled stocks with the lowest liquidity levels in terms of pre-event daily mean volume. Sample C includes the 59 stocks with the highest pre-event daily mean volume. The remaining 64 stocks were allocated to Sample B as "average liquidity" stocks.
3. Transactions = Total Number of Transactions (including unsampled stocks)
   Trades (%) = % of shares which traded in the auction
   ATS (Z) = Average no of Transactions per share (incl. zero observations)
   ATS (NoZ) =Average no of Transactions per share (excl. zero observations)
   AUT (Z) = Average no of Units Traded per share (incl. zero observations)
   AUT (NoZ) = Average no of Units Traded per share (excl. zero observations)

Table 3: Volatility Comparisons

	Scaled Intra-Day Price Differences				Overnight Return Reversals	
	$D_{i,t}$		Std Deviations of $D_{i,t}$		π	
	Pre-Event	Post-Event	Pre-Event	Post-Event	Pre-Event	Post-Event
Mean	0.0632	0.0564	0.033166	0.033157	-0.3439	-0.3970
Standard Deviation	0.0211	0.0226	0.0165	0.0491	0.1726	0.2288
t value	7.6443***		0.0027		2.9097***	

Notes

1. $D_{i,t}$ is the scaled intra-day price difference defined for each firm as $D_{i,t} = (P_{high\ i,t} - P_{low\ i,t}) / P_{open\ i,t}$, where: $P_{high\ i,t}$, $P_{low\ i,t}$ and $P_{open\ i,t}$ are the highest, lowest and opening prices for security *i* on day *t* respectively.
2. Std. Deviations of $D_{i,t}$ are the standard deviations of each firm's $D_{i,t}$ in the pre- and post-event period.
3. π is the estimated coefficient in a regression of the daily return on the previous overnight return: $r_{i,t} = \mu_i + \pi_i r^o{}_{i,t} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return, and $r^O{}_{i,t}$ is the previous overnight return.
4. The pre-event statistics were calculated using data from T-63 to T-1, and the post event statistics using data from T+1 to T+63. The mean and standard deviation shown for each variable are the cross-section statistics for all firms.
5. t value is the t statistic for the null hypothesis of no difference between pre-and post event data. These are calculated using the paired means test which provides a firm-by-firm comparison; they are not a direct comparison of the means reported in the table.
   *** significant at 99% level; ** significant at 95% level; * significant at 90% level.

	90%	95%	99%
Critical value of t statistic for a two-tail test (n = 182)	1.6533	1.9732	2.6033

Table 4: Efficiency Comparisons

	Relative Return Dispersion		Serial Correlation of Returns			
	RRD_t		ρ		ρ^2	
	Pre-Event	Post-Event	Pre-Event	Post-Event	Pre-Event	Post-Event
Mean	0.1272	0.1017	-0.0169	0.0791	0.0304	0.0292
Standard Deviation	0.1196	0.1127	0.1739	0.1519	0.0409	0.0352
t value	2.9308***		-6.3912***		0.2748	

Notes

1. $RRD_t = \frac{1}{n}\sum_{i=1}^{n} \varepsilon^2_{it}$; where ε_{it} are the residuals from the market model for security *i* at time *t*, and *n* is the number of sampled securities.
2. ρ is the first-order autocorrelation coefficient calculated for each firm
3. ρ^2 is the square of ρ calculated as in note 2.
4 t value is the t statistic for the null hypothesis of no difference between pre-and post event data. These are calculated using the paired means test which provides a firm-by-firm comparison; they are not a direct comparison of the means reported in the table.
*** significant at 99% level; ** significant at 95% level; * significant at 90% level.

	90%	95%	99%
Critical value of t statistic for a two-tail test (n = 182)	1.6533	1.9732	2.6033

Table 5: Liquidity Comparisons

	Number of Shares Traded		Volume/Return Ratio	
	Pre-Event	Post-Event	Pre-Event	Post-Event
Mean	322,391	367,123	108,730	141,148
Standard Deviation	986,908	942,824	284,978	338,722
t value	-1.9422*		-4.4228***	

Notes

1. Number of shares traded is calculated for each firm in the pre-event and post-event periods.
2. Volume/return ratio is the ratio of the number of shares traded in each firm to the daily absolute return. The daily returns include zeroes whereas the volumes do not. Therefore, we first computed daily return/volume ratios for each firm, then calculated the firm means, and finally the reciprocals of the means. This gave (mean) volume/return ratios for each firm in the pre- and post-event periods. The cross-section means and standard deviations of these ratios are reported in table 4; and the cross-section t-tests were performed on the volume/return ratios.
3. t value is the t statistic for the null hypothesis of no difference between pre-and post event data. These are calculated using the paired means test which provides a firm-by-firm comparison; they are not a direct comparison of the means reported in the table.
*** significant at 99% level; ** significant at 95% level; * significant at 90% level.

	90%	95%	99%
Critical value of t statistic for a two-tail test (n = 182)	1.6533	1.9732	2.6033

Table 6: Market Model Estimates

Summary Statistics						
	Mean	**Median**	**Standard Deviation**	**Min.**	**Max.**	
Intercept: α_i	0.0008	0.0009	0.0041	-0.0118	0.0168	
t-value: t_α	0.1803	0.1958	0.8917	-2.4429	3.3704	
Beta: β_i	1.203	1.2231	0.4433	0.1952	2.6905	
t-value: t_β	4.6648	4.7075	1.7018	0.8237	9.0861	
R^2	0.2724	0.2764	0.1324	0.0116	0.5874	
Diagnostics						
	Mean	**Min.**	**Max.**	**95% CV**	**No. of rejects**	**% rejects**
F-statistic F (1,58)	24.6409	0.6785	82.5571	4.0000	169	93%
Autocorrelation: $\chi^2(1)$	2.2013	0.0004	23.3566	3.8410	36	20%
Reset: F (1,57)	1.4317	0.0000	21.2354	4.0000	21	12%
Normality: $\chi^2(2)$	76.9884	0.0118	6645.50	5.9910	93	51%
Heteroscedasticity: $\chi^2(1)$	1.2330	0.0004	36.3735	3.8410	13	7%
Predictive Failure: F (18,58)	1.0631	0.1022	10.6618	1.8100	23	13%
Chow: F(2,74)	0.9962	0.0040	6.7545	3.1200	13	7%

Notes

Summary statistics

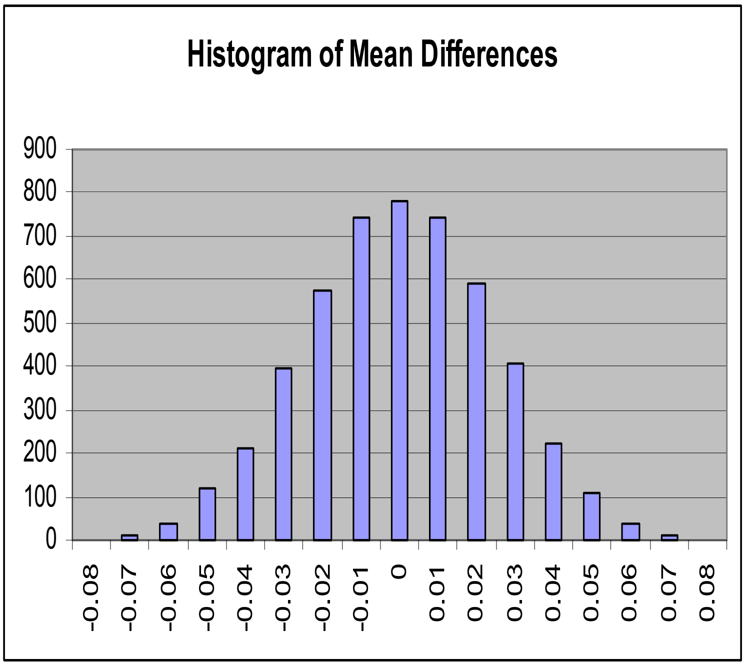
1. Each column gives respectively the cross-section mean, median, standard deviation, minimum and maximum of the firm-specific estimates of the parameters of the market model.

Diagnostics

2. Each column gives respectively, the cross-section mean, minimum and maximum of the corresponding diagnostics from the firm-specific estimates of the market model. "95% CV" is the 95% critical value of each test; "No. of rejects" shows the number of shares where the null hypothesis was rejected at the 95% level indicating a possible misspecification; "% rejects" shows the percentage of shares for which the null hypothesis was rejected at the 95% level
3. F-statistic: F test for zero slopes for the regression as a whole.
4. Autocorrelation: LM test for first-order autocorrelation (Breusch and Pagan, 1980).
5. Reset: Ramsey's test for functional form using squares of the fitted values (Ramsey, 1969).
6. Normality: Jarque and Bera's (1980) test for normality.
7. Heteroscedasticity: LM test for heteroscedasticity (Breusch and Pagan, 1980).
8. Predictive Failure: Chow's second test for structural breaks (Chow, 1960). This was applied to the 18 observations within the event window.
9. Chow: Standard Chow test for structural break at the mid-point of the estimation window.

Figure 1: Mean Differences for S.S.M.E.
Random Sub-Samples in the Bootstrap Procedure.

Bin Centre	Frequency
-0.08	2
-0.07	11
-0.06	37
-0.05	121
-0.04	214
-0.03	397
-0.02	573
-0.01	743
0	780
0.01	743
0.02	589
0.03	407
0.04	222
0.05	109
0.06	39
0.07	11
0.08	2



Notes
1. The histogram shows a summary of the mean differences obtained when the S.S.R.E.s were randomly re-sampled 5000 times from the estimation period and the event window combined. Each bin covers all values within 0.005 of its centre.

Figure 2: Average CARs during the Event Window

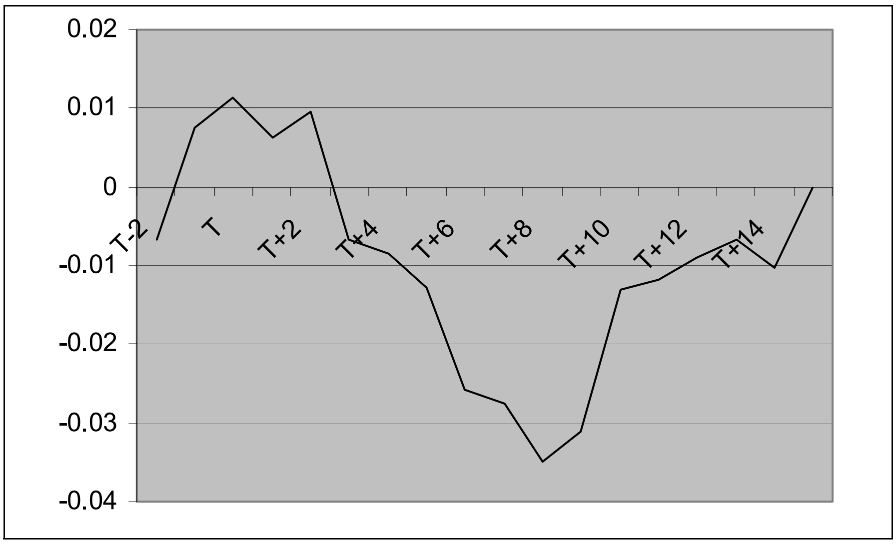


Figure 3: CARs for five Sub-Samples

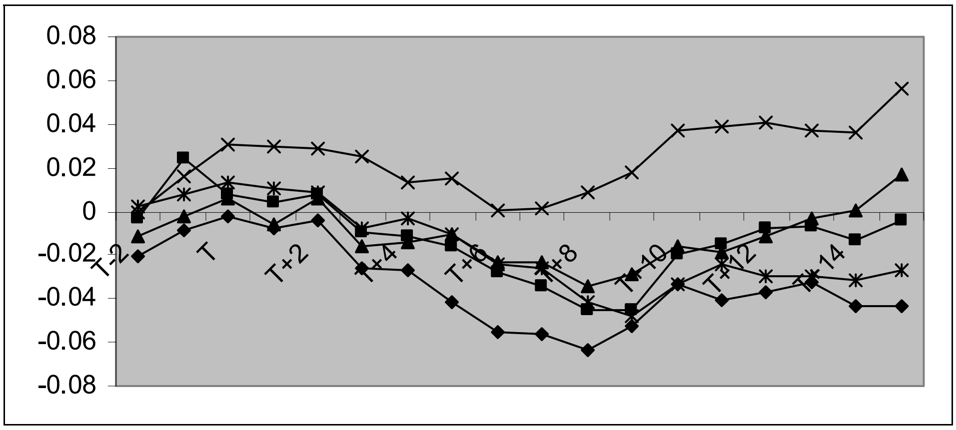


Table 7: Determinants of Changes in Volatility, Efficiency and Liquidity

Dependent Variable	Beta Regressions				Liquidity Regressions			
	C	***βD1***	***βD2***	***R²***	***C***	***LD1***	***LD2***	***R²***
Δ SIDPD	-0.11	0.0165	-0.0067	0.0028	-0.1163	0.0421	-0.022	0.026
(t stat)	(5.29)***	(0.48)	(0.24)		(5.73)***	(1.44)	(0.75)	
ORR	-0.0162	-0.0721	-0.049	0.0129	-0.0427	0.0132	-0.0452	0.0102
(t stat)	(0.52)	(1.40)	(1.19)		(1.39)	(0.30)	(1.02)	
Δ RRD	-0.1348	0.0929	0.0405	0.0013	-0.1136	0.1559	-0.1067	0.0138
(t stat)	(1.16)	(0.49)	(0.27)		(1.00)	(0.95)	(0.65)	
Δ VRR	0.3737	-0.0715	0.2406	0.0158	0.4854	0.2496	-0.295	0.0415
(t stat)	(2.73)***	(0.32)	(1.33)		(3.65)***	(1.30)	(1.54)	

Notes

1. Δ SIDPD is the % change in the Scaled Intra-Day Price Difference as between the pre-event and post-event period (table 2).
2. ORR is the coefficient (π) from the regressions of the daily return on the previous overnight return (table 2).
3. Δ RRD is the % change in the relative return dispersion as between the pre-event and post-event period (table 3).
4. Δ VRR is the % change in the Volume-Return ratio as between the pre-event and post-event period (table 4).
5. *βD1* = 1 for stocks with a pre-event $\beta \leq 0.8$; zero otherwise ("low-beta");
   βD2 = 1 for stocks with a pre-event $\beta \geq 1.25$; zero otherwise ("high-beta").
   The thresholds were set to divide the whole sample into three, approximately equal categories.
6. *LD1* =1 for stocks with pre-event mean daily volume ≤ 40,000 shares; zero otherwise ("less liquid");
   LD2 = 1 for stocks with pre-event mean daily volume ≥ 140,000 shares; zero otherwise ("very liquid").
   The thresholds were set to divide the whole sample into three, approximately equal categories.
7. t statistics are shown in parentheses.
   *** significant at 99% level; ** significant at 95% level; * significant at 90% level.

	90%	95%	99%
Critical value of t statistic for a two-tail test (n = 182)	1.645	1.960	2.576

Table 8: Determinants of CARs

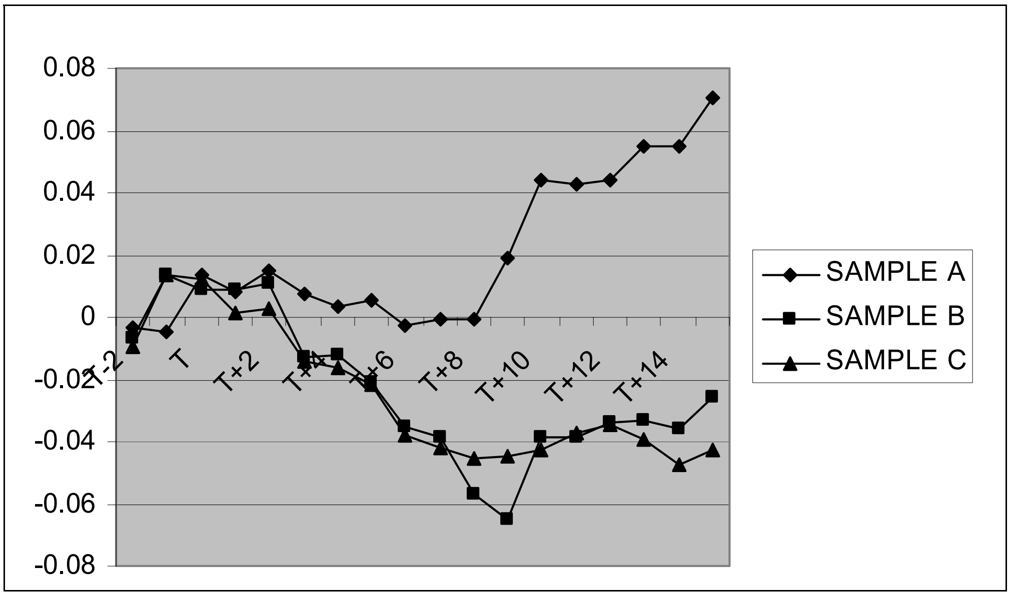
Panel A. Dependent variable: Mean CARs T+9 through T+15								
C	***ΔSIDPD***	***ΔRRD***	***ΔVRR***	***βD1***	***βD2***	***LD1***	***LD2***	***R^2***
0.048	0.225	-0.001	0.024					0.174
(4.00)***	(3.81)***	(0.10)	(3.00)***					
0.057	0.230	-0.001	0.023	-0.031	-0.003			0.184
(3.56)***	(3.90)***	(0.10)	(2.88)***	(1.35)	(0.16)			
0.046	0.216	-0.002	0.021			0.025	-0.018	0.194
(2.88)***	(3.66)***	(0.20)	(2.63)***			(1.25)	(0.90)	
Panel B. Dependent variable: Mean CARs T+0 through T+8								
C	***ORR***	***βD1***	***βD2***	***LD1***	***LD2***			***R^2***
-0.039	0.070							0.018
(3.90)***	(1.84)*							
-0.036	0.070	0.000	-0.005					0.019
(2.25)**	(1.79)*	(0.00)	(0.24)					
-0.068	0.063			0.074	0.015			0.081
(4.53)***	(1.70)*			(3.36)***	(0.68)			

Notes

1. Panel A: regressors are:
   ΔSIDPD = % change in Scaled Intra-Day Price Difference; ΔRRD = % change in Relative Return Dispersion; ΔVRR = % change in Volume-Return Ratio; *βD1, βD2* are the Beta dummy variables as in table 6; and *LD1, LD2* are the Liquidity dummy variables as in table 6
2. Panel B: regressors are:
   ORR is the coefficient (π) from the regressions of the daily return on the previous overnight return; *βD1, βD2* are the Beta dummy variables as in table 6; and *LD1, LD2* are the Liquidity dummy variables as in table 6
3. t statistics are shown in parentheses.
   *** significant at 99% level; ** significant at 95% level; * significant at 90% level.
   Critical values of the t statistic are:

	90%	95%	99%
Critical value of t (n = 182)	1.645	1.960	2.576

Figure 4: Different CAR patterns for stocks with differing liquidity levels



Notes

1. Sample A includes 59 sampled stocks with the lowest liquidity levels in terms of pre-event daily mean volume. Sample C includes the 59 stocks with the highest pre-event daily mean volume. The remaining 64 stocks were allocated to Sample B as "average liquidity" stocks.

Table 9: Summary of Changes in VEL Factors Following Call Auction Suspension

	Test	**Outcome**	
		In favour of:	**Significance**
Volatility	Scaled Intra-Day Price Difference	suspension	Significant (99%)
	Overnight Return Reversal	auctions	Significant (99%)
Efficiency	Relative Return Dispersion	suspension	Significant (99%)
	Return Serial Correlation	suspension	Insignificant
Liquidity	Number of Shares Transacted	suspension	Significant (90%)
	Volume per Unit of Return	suspension	Significant (99%)