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The Impact of Microstructure Innovations in Emerging Stock Markets: Evidence from Mumbai, India

by

Christopher J. Green, Ronny Manos, Victor Murinde, and Joy Suppakitjarak.

Green: Department of Economics, Loughborough University

Manos: Department of Economics, Loughborough University

Murinde: Birmingham Business School, The University of Birmingham

Suppakitjarak: University of Westminster

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

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THE IMPACT OF MICROSTRUCTURE INNOVATIONS IN EMERGING STOCK MARKETS: EVIDENCE FROM MUMBAI, INDIA*

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ABSTRACT

We examine the impact on the Mumbai Stock Exchange of the introduction of screen-based trading (the “BOLT”) on 14 March 1995. We use event study methods to investigate if this reform had positive value using two samples of more liquid and less liquid stocks. We find that the impact was substantial: the average CAR for the more liquid A shares was about 4.5%, while that for the less liquid B shares was around 10%. We examine how far this improvement was associated with improvements in liquidity, efficiency and (reduced) volatility (LEV). We find evidence of increased liquidity and efficiency but more ambiguous results for volatility. A regression approach provides evidence that cross-sectional variations in the CARs can be explained by cross-sectional variations in firm-specific LEV improvements. Overall, the results suggest that the introduction of the BOLT improved the market microstructure for both A and B shares, with the effect on B shares being more marked.

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1. Introduction

Over the last 25 years, the subject of market microstructure has become a major sub-discipline within the field of finance. Recent surveys of the subject include Stoll (1999) and Madhavan (2000). Not surprisingly, most empirical research on market microstructure has so far been concerned with the major industrial countries, particularly the USA. Meanwhile, the development of market microstructure as a subject has coincided with a period of establishment of new stock markets and revitalisation of existing markets in many developing and transitional economies. The revitalization of these “emerging” stock markets is typically characterized by institutional reforms, including modernization of the trading and information systems¹, expanding stock market membership, revamping the regulatory framework², and opening access to foreign capital³. The reforms are aimed at improving stock market performance by increasing liquidity and transparency, enhancing efficiency, and reducing volatility and trading costs. The wider goal is to promote the development of local capital markets and facilitate access to long-term capital.

Liquidity and transparency are desirable because they reduce the required return by investors and therefore increase security values. Increased liquidity improves the ability of stock markets to perform their information processing and signalling functions (Amihud and Mendelson, 1986). Increased efficiency improves the aggregation and transmission of information through price signals, and thus allows agents to make more informed investment decisions and spread their risks more effectively (Amihud, Mendelson and Lauterbach, 1997; Caprio and Demirguc-Kunt, 1998). Efficient stock prices and yields provide benchmarks against which the cost of capital for and returns on investment projects can be judged, even if such projects are not financed through the stock market (Green, Maggioni and Murinde, 2000). An efficient price discovery process is traditionally associated with lower fundamental volatility, which promotes stock market effectiveness in allocating resources. High volatility can distort resource allocation by making investors more reluctant to hold stocks. Risk-averse

investors will demand a high risk premium, which increases the cost of capital and reduces market liquidity (Bekaert and Harvey, 1997; Kim and Singal, 2000).

The main issue in emerging markets is whether and how a costly revitalization programme has positive value in terms of liquidity, efficiency, and volatility. In studies of more established markets which have implemented reforms in trading systems, Amihud and Mendelson report that reform had a generally positive impact, creating gains in efficiency of the price discovery process, increased liquidity and lower volatility. These include studies of Milan (Amihud, Mendelson and Murgia, 1990), Tokyo (Amihud and Mendelson, 1991) and Tel Aviv (Amihud, Mendelson and Lauterbach, 1997). Blennerhassett and Bowman (1998) report a fall in transactions costs on the New Zealand stock exchange following the move from open outcry to screen trading, and Majnoni and Massa (2001) report broadly positive results for reforms introduced by the Italian Stock Exchange. There are fewer studies of emerging markets, and their results are more mixed. Some suggest that the entry of foreign investors is a more important factor than internal market reform (although the former may be predicated on the latter), and that this is followed by increased liquidity and enhanced efficiency in the price discovery process, with market volatility either remaining unchanged or declining (Richards, 1996; Kim and Singal, 2000; Ngugi, Murinde, and Green, 2002a, 2002b). However, Chang, Hsu, Huang and Rhee (1999) found no change in liquidity or in the efficiency of the price discovery process, while volatility increased, following the introduction of a continuous auction system in Taipei.

One difficulty in studying emerging markets is that many of the stock exchanges are of recent origin and relatively few stocks are traded. Data from the pre-reform era are often not adequate to carry out a full evaluation of the effects of reform. However, since reform can be costly, it is particularly important to quantify its benefits in countries where there may be many apparently more pressing claims on investment resources.

In this paper we investigate the impact of the revitalisation process on the market microstructure of the Stock Exchange, Mumbai (BSE) in India⁴. The BSE is not a “typical”

emerging stock market, with relatively few quoted companies. It has the second-largest number of domestic quoted companies of any stock exchange in the world after New York, and far more quoted companies than either London or Tokyo, for example. In small markets, a main purposes of revitalisation is to encourage fledgling domestic companies and foreign entrants to begin using the exchange, and thus to stimulate the expansion of the domestic capital market. In India however, the domestic capital market is long-established. Indeed, the BSE dates back to 1875, but until the 1990s it was subject to tight regulatory restrictions. In this setting, revitalisation may be expected to have a more direct impact in generating more efficient trading and allocation of capital for existing companies, as well as the longer-term effect of fostering market expansion.

The sheer size and diversity of the Indian capital market are more than sufficient reasons for investigating the performance of the BSE. However, it also has specific features which make it a particularly interesting laboratory for studying reform in emerging stock markets. First, several major reforms took place during the 1990s. In this paper, we concentrate on the switch from open-outcry to electronic trading which took place in a “big bang” in 1995. Second, general data availability in India is exceptionally good for this type of study. Third, since the market is of long-standing origin, we can obtain a relatively large balanced panel of companies to evaluate the impact of reforms in a consistent way. Fourth, the market consists of a wide range of shares, some of which are relatively heavily traded, others very thinly traded. This enables us to check precisely how reform had the most impact on securities of varying liquidity. While each emerging stock market may be different, an understanding of the impact of reform in India will undoubtedly offer important lessons to other emerging markets.

The revitalisation of the BSE in the last 15 years has involved both institutional and regulatory reform. For an overview, see Shah and Thomas (2001). Key institutional changes include: the establishment of a new regulatory authority, The Securities and Exchange Board of India (SEBI); the formation of a second major stock exchange in competition with Mumbai, the National Stock Exchange of India (NSE); the suspension and subsequent reintroduction of “Carry-Forward” trading, or “badla”, following a stock trading scandal in 1992⁵; and the

introduction of electronic trading, first at the NSE and, shortly thereafter, at the BSE. Regulatory reform interacts with market microstructure, and Nayak (1999) has argued that not enough attention was given to market microstructure issues in the regulation of India's stock markets. The impact of the suspension and subsequent reintroduction of Badla was studied by Berkman and Eleswarapu (1998), who found that the main effects of Badla were to increase both liquidity and noise on the market. Overall however, they concluded that Badla was viewed as value-increasing by the market. Shah and Thomas (1996) compared market performance on the BSE between May-October 1994 and June-November 1995. The two key changes in this period were the commencement of trading at the NSE and the introduction of electronic trading by the NSE and BSE. Shah and Thomas found evidence of improvements in liquidity and efficiency⁶, but their analysis relied on a direct comparison between the two time periods, and they acknowledged that this comparison did not permit a precise identification of the effect of electronic trading on its own.

In this paper we concentrate on the impact on the BSE of its major reform of the trading system: the introduction of electronic trading, the "Bombay On-Line Trading" system or BOLT, which took place in Mumbai in 1995, and was extended to other member exchanges throughout India in 1997. We aim to improve on and extend Shah and Thomas's (1996) research by following Amihud, Mendelson and Lauterbach (1997) and Berkman and Eleswarapu (1998) in using the event study methodology as our principle investigative tool. We also contribute to event study methodology by testing the duration of the event's impact; and we compare more liquid ('A') and less liquid ('B') shares. Thin trading is an important issue in the pre-reform and post-reform eras, and we take care to allow for thin trading in our estimation procedures. Our analysis enables us to pin down more precisely the impact of the introduction of the BOLT on market performance. Our results suggest that the introduction of the BOLT was followed by a significant improvement in market performance. We therefore examine how far this improvement was associated with increased liquidity, increased efficiency, reduced volatility, or a combination of these factors. In addition, we find

interesting and intuitive differences between the two groups of more and less liquid shares in their response to the reforms.

The rest of the paper is structured as follows. In section 2 we summarise the major changes which took place in the BSE during the last 15 years. In section 3 we describe the dataset used in the analysis. The price reactions to the introduction of the BOLT are estimated in section 4. Possible reasons for these reactions are investigated in the next sections: section 5 is concerned with the impact on liquidity; section 6 deals with efficiency improvements; and section 7 considers the effect on volatility. In section 8, we analyse the relative contributions of improved liquidity, efficiency and volatility to the overall price improvements observed in the market. Section 9 contains some concluding remarks. Details of the estimation period are reported in appendix A.

2. The Stock Exchange, Mumbai (BSE)⁷

2.1 Background to Reform

Established in 1875 as *The Native Share and Stockbrokers Association*, the BSE is the oldest stock exchange in Asia. It was the only national stock exchange in India until 1994 when the NSE commenced trading. India now has more than 20 stock exchanges, but most of these have links with the BSE or the NSE, and only these two are regarded as national exchanges.

India has sustained a thriving private sector from the earliest phases of industrialization but, until recently, its economic policies emphasized the role of state planning and intervention. Within this framework, securities markets were governed by three main pieces of legislation. First was the *Capital Issues (Control) Act* of 1947 which authorized the government to control new share issues, type of shares issued, and their issue price. Primary and secondary issues were invariably priced at par. Debenture issues were regulated by ceilings on coupon rates and term to maturity, although these were evaded to some extent by deep discounting of primary issues. Second was the *Securities Contracts (Regulation) Act* of 1956 which provided for statutory control over stock exchanges. Under this act, all securities trading must take place on

a recognised stock exchange, and the rules and listing regulations set by an exchange had to meet the minimum standards laid down in the legislation. Third was *the Companies Act* of 1956 which set out a code of conduct for the corporate sector in relation to the issue, allotment and transfer of securities, and disclosure standards for public issues. It also regulated underwriting, the use of premia or discounts on share issues, substantial acquisitions of shares, payment of interest and dividends, annual reporting, and related issues.

The 1956 acts were mainly regulatory, but the 1947 act was highly restrictive of stock market activity. Moreover, each stock exchange could set its own policy on listing and settlement and regulatory agencies had overlapping responsibilities. This created inconsistencies and lack of transparency in implementation of the regulations. Strict controls on inward investment meant that the market was effectively closed to the rest of the world. Overall, the regulations provided a powerful disincentive for companies to finance their activities through the private capital market⁸.

Historically, the BSE was regarded as a sideshow in the economy, and it had little incentive to modernise. It operated an open outcry trading system on the floor of the exchange, which was characterised by high transactions costs and intermittent trading of a relatively few stocks, often held by a small group of investors. The market for most stocks was quite illiquid, especially as securities lending and derivatives markets were not permitted. The clearing system was fragile, and the settlement procedure was slow and unreliable, based as it was on the shipment of physical security certificates, a process which brokers could manipulate. Barriers to entry inhibited competition, especially in the brokerage industry which operated largely as a cartel⁹.

Until recently, a unique feature of the BSE was its system of leveraged trading on the cash market, called "carry forward" or "badla". Badla trading permitted cash settlement to be postponed to the next account period. When settlement was due, a buyer could borrow funds from and pay interest to the lender, called contango charges ('vyaj badla'). Conversely, a short seller could borrow securities and pay interest called backwardation charges ('undha badla').

For further details see the Patel Committee (1995). Two of the main practical problems with the system as it existed through 1993 were that settlement could in theory be postponed indefinitely, and that there were no formal margin requirements. Thus, badla fostered complex highly leveraged positions which substantially exacerbated settlement risks. In 1992, the BSE was hit by share-dealing manipulation and fraud associated with a sharp rise in prices and subsequent collapse¹⁰. Badla did not directly cause this fraud, but it was generally believed that it did make fraud easier (Shah, 1997) and, following an investigation, SEBI banned all forms of badla in December 1993. A revised form of badla was reintroduced in 1996 on the recommendation of the Patel Committee (1995). Berkman and Eleswarapu (1998) studied the impact on stock returns and market liquidity of the abolition and subsequent reinstatement of badla. They found, *inter alia*, that the abolition of badla produced a significant decrease in market liquidity and that the market subsequently reacted positively to the announcement of the reintroduction of badla, suggesting that badla did improve liquidity and this was valued positively by the market. However, in July 2001 badla was abolished altogether when a T+5 rolling settlement system replaced settlement according to a fixed account period.

2.2 Key Reforms in Regulation and Trading

The main regulatory reform of the capital markets took place in the early 1990s, with the repeal of the *Capital Issues (Control) Act* and the coming into force in January 1992 of the *Securities and Exchange Board of India (SEBI) Act*, which established SEBI as the principal authority governing stock exchanges and a range of other corporate financial activities. Agarwal (1996) describes this act in detail. Subsequently, SEBI introduced several new regulatory measures including capital adequacy rules for brokers, a share depository system involving (from December 1997) progressive dematerialization of securities, and an investor guarantee fund. Derivatives were legalised and capital markets opened up to foreign institutional investors, but stamp duty on share transactions remained in effect. In the same period, the Reserve Bank of India liberalized its credit control regime, and ceilings on debenture coupon rates and other interest rates were abolished.

Institutional reforms took place in the stock markets in the same epoch. The NSE opened in 1994 with a nationwide screen-based trading system, which it presented as more transparent, competitive, efficient and less vulnerable to fraud than the BSE's old system. Bond trading quickly gravitated to the NSE, but the BSE has retained much of the share-trading business, in part because of the reform of its own systems and practises¹¹. Trading reforms on the BSE included: the introduction of odd-lot trading, separate trading in renounced rights and warrants, direct trading in share index baskets, and the reduction of settlement time leading to progressive elimination of the fixed account period. Regulatory reforms by the BSE included the establishment of an investor protection fund with guarantees substantially in excess of the minimum required by SEBI, a trade guarantee fund to eliminate broker-counterparty risk in settlement, a stock exchange brokers' contingency fund to make short-term advances to members facing a temporary mismatch of funds, and a comprehensive insurance policy. These measures were underpinned by the introduction of circuit breakers and improved monitoring of brokers' margin positions by the exchange.

The centrepiece of the modernisation of the BSE was the introduction of its own screen-based trading system: the BOLT¹². Initially, the BOLT was a mixed order-driven and quote-driven trading system which accepted and disseminated two-way price quotations from authorized jobbers¹³, and market and limit orders from authorized brokers which could be matched directly according to the order-book rules in the system. Initially, priority was given to the quote-driven system with the order book functioning as an auxiliary jobber. The order-book allowed for the retention and matching of orders against one another where no quotes existed in the system for a particular security, and it improved the price competitive character of the market in case individual investors were willing to deal at prices better than the best jobber's quote. Over time however, the order book assumed increasing importance, and in 2001 the facility for placing quotes on the system was removed altogether. The BOLT is now strictly an order-driven system. However, during the period relevant to this study it was a mixed system as we have described.

The BOLT was introduced on March 14th 1995 when 818 shares were transferred to electronic trading (all A shares and the most liquid B shares¹⁴). The remaining shares (over 5000) were transferred in stages, and all shares were on the new system by the 50th trading day. On August 30 1997, the BOLT was expanded to provide direct connections with other exchanges in India and by 2000, over 200 locations outside Mumbai were connected to the BSE through the BOLT. The option of dematerialized settlement became available in a limited range of stocks on December 29 1997, and by September 30 2001, all companies were required to sign agreements for the dematerialization of their securities.

At the time of the introduction of the BOLT, securities traded on the BSE were classified into two groups: specified shares (A group) and non-specified shares (B group). Companies with a large capital base, widespread shareholding, a steady dividend, good growth record and a large volume of business in the secondary market were classified as A shares. The number of A shares has risen during the last decade from about 75 to 200 companies¹⁵. The remaining (over 5000) B shares were less well-established or less liquid securities. In 1996, B shares were split into 'B1' and 'B2' to reflect the greater liquidity of the former which consisted of some 700 shares. In 1999, a 'Z' group was introduced to represent companies which have failed to comply fully with listing requirements, have not resolved investor complaints, or have not made the required arrangements for the dematerialization of their securities. By 2003, A and B1 group shares represented 99% of the daily trading volumes at the BSE in terms of value, and consisted of 94% of the market capitalisation.

3. Data

The basic data for this study consist of the daily closing prices for 69 A shares and 83 B shares of non-financial private-sector Indian firms which were quoted continuously on the BSE from September 1 1993 through November 29 1996¹⁶. Table 1 describes the two samples, which we refer to as the A sample and B sample respectively. To the extent that sales are a proxy for size, our two samples reflect the differences between A and B stocks on the BSE. The average size of a firm in the A sample is about 3 times greater than that in the B sample. Similarly, the

average firm in the A sample is nine years older than that in the B sample. Manufacturing firms and business groups dominate our sample, a feature which reflects the population of Indian non-financial companies.

We confined our attention to non-financial firms for two reasons. First, we wanted to focus on privately-owned Indian firms. Public sector or foreign-owned firms may not necessarily respond in the same way to market reforms as would private Indian firms. A high proportion of Indian financial firms are wholly or partly-owned by the public sector, either by the Indian government or by state governments. The remaining sample of private financial firms would be small and not representative of the financial sector. A second reason for omitting financial firms is that insofar as financial and market reforms alter the financial structure and trading patterns of non-financial companies, these changes may have indirect effects on the share price of financial firms because of their impact on the normal lending and borrowing business of such firms. These indirect effects could easily obscure the direct trading effect of market reforms. These considerations suggest that Indian financial firms will not provide a good test-bed for studying the effects of market microstructure changes, although they would undoubtedly be an interesting subject for study in their own right.

Table 1 about here

Table 1 also shows the number of firms in our samples that are included in the various market indices compiled by the BSE. The BSE Sensitive Index (SENSEX), published since 1986, consists of 30 A shares of a selection of large and well-established companies. It currently accounts for about 44% of the market value of the BSE. The BSE100, published since 1989, is a more broad-based index made up of 100 A and B shares. We used the SENSEX as the market index to estimate the market model for the event study. Although it includes a relatively small number of shares, it accounts for a substantial part of the total market capitalization of the BSE, and all its component shares are heavily traded. The components of

the BSE100 include shares which are thinly traded, implying that estimation of betas for individual firms would be subject to a non-synchronous trading problem¹⁷. Two broader indices, the BSE200 and BSE500 were introduced after the data period of our study begins (in 1994 and 1999 respectively), and they include a yet higher proportion of thinly-traded shares.

4 Introduction of the BOLT

4.1 Cumulative abnormal returns (CARs) - Methodology

We begin with an analysis of the impact on share returns of the introduction of the BOLT on March 14 1995 using event study methods. MacKinley (1997) gives a detailed exposition. The basic equilibrium model of security returns is the market model:

$$R_{k,t} = \alpha_k + \beta_k M_t + \varepsilon_{k,t} \quad \dots(1)$$

where: $R_{k,t}$ ($= \ln P_{k,t} - \ln P_{k,t-1}$) is the return on stock k on day t

$P_{k,t}$ is the closing price on stock k

M_t is the daily return on the market index

$\varepsilon_{k,t}$ is the error with variance $= \sigma_k^2$.

The estimation of (1) with daily data and its application to event studies have been widely discussed (Brown and Warner, 1985). French (1980) distinguished between calendar time and trading time models. In the former, returns are generated continuously implying that reported returns distributions will differ as among Mondays, post-holidays, and other working days. In the latter, returns are generated only in trading time and return distributions are therefore the same on each trading day. The trading time hypothesis is invariably rejected by the data but the calendar time hypothesis usually fares little better (Lakonishok and Smidt, 1988). In this paper, we adopt a calendar time approach implying that (1) can be rewritten as:

$$R'_{k,t} = \alpha_k + \beta_k M'_t + \varepsilon_{k,t} \quad \dots(2)$$

where: $R'_{k,t} = R_{k,t}/n_t$ and $M'_t = M_t/n_t$

Now, $R_{k,t}$ is the return on stock k between two consecutive days when the exchange was open for trading, from day $t - n$ to day t , which include n_t calendar-day returns; and M_t is the corresponding return on the market index. Thus $R'_{k,t}$ and M'_t are the returns per calendar day during period n_t on stock k and the market index respectively.

To evaluate the impact of the introduction of the BOLT, the standard event study method involves estimating (2) outside the event window, and then calculating the abnormal return per calendar day ($AR'_{k,t}$) in the event window as:

$$AR'_{k,t} = R'_{k,t} - (\hat{\alpha}_k + \hat{\beta}_k M'_t) \quad \dots(3)$$

The AR on a share for each trading day in the event window ($AR_{k,t}$) is obtained by multiplying $AR'_{k,t}$ by the number of calendar-day returns between successive trading days:

$$AR_{k,t} = AR'_{k,t} n_t \quad \dots(4)$$

Finally, the cumulative abnormal returns ($CAR_{k,t}$) are calculated as:

$$CAR_{k,t} = \sum_{h=T-u}^t AR_{k,t,h}; \quad t = T-u, \dots, T, \dots, T+v \quad \dots(5)$$

where: $t = (T-u, \dots, T, \dots, T+v)$ is the event window, and $t = T$ is the event day. These can then be averaged across shares to obtain the mean CAR for each day in the window.

As observed by Karafiath (1988), an equivalent procedure for calculating the ARs is the event dummy approach. This involves estimating:

$$R'_{k,t} = \alpha_k + \beta_k M'_t + \sum_{h=T-u}^{T+v} \gamma_{k,h} d_{h,t} + \varepsilon_{k,t} \quad \dots(6)$$

across the non-window period and the event window itself using $d_{h,t}$ as daily dummies within the event window ($d_{h,t} = 1$ for $h = t$ and zero otherwise). Standard theory shows that estimates of the market model from (6), $\hat{\alpha}_k, \hat{\beta}_k$ are identical to those arrived at using the more usual method with (2). Likewise, the estimated coefficients ($\hat{\gamma}_{k,h}$) are identical to the abnormal returns obtained by calculating $AR'_{k,t}$ using (3). See Karafiath (1988) for details. To obtain the abnormal return for any period of n_t calendar-day returns, we use (4) as before.

The event dummy approach is not widely used. However, it has the useful property that (6) delivers direct estimates of the significance of the ARs through the t statistics for the dummy variables. It also permits the use of F tests on the estimated dummies to check the length of the event window. This is particularly important in studying the impact of new technology where

market participants may initially incur learning costs in the operation of the system. The full impact of the new system may take some time to be reflected in share prices, and the best length for the event window may therefore be unclear. Plots of the CARs give an informal indication of the true length of the event window, but F statistics provide a more rigorous test.

Amihud, Mendelson, and Lauterbach (1997) and Berkman and Eleswarapu (1998) use a dummy variable approach to calculate certain of their ARs. However, they do not test the length of the event window as we do. Also, they impose a particular time pattern on the ARs by constraining the event dummy parameters to be equal across large segments of the event window¹⁸. It is hard to see the point of this, since the standard methodology does not impose any pattern on the ARs. In theory, this procedure could eliminate idiosyncratic components in each day's AR, but it can only do so if the imposed parameter process corresponds to the true underlying AR process, and there is no *a priori* reason to believe that this is the case. Thus, their procedure is more restrictive than the standard event study method.

Efficient and unbiased estimation of (2) or (6) in daily data is typically plagued by further problems, especially thin trading and non-normality of the returns distribution. Non-trading was endemic in Mumbai at the time of the introduction of BOLT. As shown in table 2, even the most liquid A shares in our sample did not trade on average on 23% of possible trading days when the BSE was open. For the less liquid B shares the figure is even greater at 34% of open days. Dimson (1979) showed that thin trading will tend to bias downwards the OLS estimates of β_k in (2) and proposed instead estimating¹⁹:

$$R'_{k,t} = \alpha_k + \sum_{j=-h}^h \beta_{k,j} M'_{t+j} + \varepsilon_{k,t} \quad \dots(7)$$

Provided non-trading is not too severe, OLS estimation of (7) will deliver unbiased estimates of the true systematic risk using relatively small values of h (typically 3 - 5²⁰). The estimate of systematic risk is just: $\beta_k = \sum_j \beta_{k,j}$.

Table 2 about here

Maynes and Rumsey (1993) advocate instead using trade-to-trade prices of individual stocks to adjust for thin trading. The time intervals between trade-to-trade prices, like those between calendar time prices, vary from period to period, except that the interval (n_t) between the prices of a security (and hence between corresponding values of M_t) is interpreted as the interval between consecutive days in which a trade took place in that security instead of between days on which the exchange is open for business. According to Dimson (1979), there is relatively little difference between the Dimson and trade-to-trade methods in terms of the unbiasedness of the resulting estimate of β_k . In our research, we experimented with both methods, but we found little difference between the results in each case. We therefore report only the results obtained by using the Dimson method²¹.

A second problem with estimation of the market model on daily data is the possibility of non-normality of the returns. Mills, Coutts, and Roberts (1996) have advocated robust estimation methods to deal with non-trading and associated excess kurtosis of returns in the market model. Cable and Holland (2000) point out that the main application of the model in event studies is in the calculation of ARs for a large number of stocks and subsequent averaging of these returns across the portfolio to evaluate the impact of the event under investigation. They note that robust estimation does not necessarily lead to efficiency gains in the presence of skewness which is also common in security returns. Furthermore, they show that the process of averaging ARs across a portfolio typically restores normality for both robust and OLS estimators of the underlying market model. Since this is precisely our application of the model, we proceeded with OLS estimation.

In summary therefore we conduct the event study using the market model, estimated by the Dimson method applied to the event dummy approach. Thus we estimate:

$$R'_{k,t} = \alpha_k + \sum_{j=-h}^h \beta_{k,j} M'_{t+j} + \sum_{h=T-u}^{T+v} \gamma_{k,h} d_{h,t} + \varepsilon_{k,t} \quad \dots(8)$$

To reduce the possibility of *ex-post* selection bias (Brown, Goetzmann and Ross, 1995) we follow Amihud, Mendelson, and Lauterbach (1997) who argued that the equilibrium model for evaluating market microstructure reforms should be estimated on data from the period after the reform took place. In our study, a further reason for post-event estimation is that shares started trading on the NSE on November 4 1994, just before the introduction of the BOLT. Shah and Thomas (1996) concluded that competition from the NSE had a negative impact on liquidity on the BSE. Using pre-event data to estimate the market model for our study could therefore bias the CARs upwards.

For the length of the estimation period we experimented with a 12 month period (March 1995 to February 1996) and an 18 month period (March 1995 to August 1996). Panel 1 of appendix table 1A gives details. However, as the two periods gave very similar results, we only report the results for the longer estimation period of 18 months.

We chose the event window to be $t = T - 5, \dots, T + 50$, where T is the date of the introduction of the BOLT (14 March 1995). We used a 5 day window prior to the introduction of the BOLT as we were interested in the effect of the BOLT *per se* and not the effect of the announcements which preceded its introduction. The 50 day post-introduction window concludes on the date that the transfer of stocks to the BOLT was completed. The event window is therefore the 56 days that the BSE was open for trading from day T-5 (7 March 1995) to T+50 (6 June 1995). See panel 1 of appendix table 1A.

The length of the event window could be criticised on the grounds that all the most liquid A shares and many of the more liquid B shares were transferred to the BOLT on its opening day²². It could thus be argued that most of the effects of the transfer would occur in the early part of the window. However, a long event window should shed light on the permanency of the effect of automation on stock prices (Amihud, Mendelson and Lauterbach, 1997). Moreover, as we argued above, the transfer process itself could create a shadow over trading

on shares which were transferred earlier to the electronic system. Dealers would need time and resources to adjust to the new system and to trade with the old and new systems simultaneously. These factors could affect the speed with which any gains from the new system were realized. Furthermore, non-trading was endemic in Mumbai at this time and even the most liquid A shares did not trade on approximately 23% of possible trading days. Thus we worked with the 56-day window. However, we did test the length of the window using F tests on the estimated event dummies, $\gamma_{k,h}$, particularly to help determine if days towards the end of the post-event window should be excluded.

4.2 Cumulative abnormal returns - Results and implications

Before turning attention to the time series of average CARs over the event window, it is useful to examine the market model regressions that were used to generate these data (table 3). It is reassuring that the mean estimate of the constant (alpha) in the market model is close to zero for both A and B shares. Likewise, the mean estimates of beta are positive and not significantly different from unity for both A and B shares as we would expect in a large portfolio. We calculated the mean of the t-statistics for alpha and beta across the market model regressions, but, a more precise evaluation of the significance of the coefficients can be achieved by testing the null that the t-statistics exceed their (5%) critical value. This is done in two ways: first by a (cross-sectional) t test on the absolute values of the t-statistics themselves; and second by using the cumulative binomial distribution to calculate the probability that the absolute value of any t statistic is at-or-above the critical value, the alternative being that it is less than the critical value. These tests, reported in table 3, show that the population mean of the alpha t-statistics (absolute value) is below the critical value, confirming that the alphas are not significantly different from zero. Conversely, the mean of the beta t-statistics is well above the critical value. The binomial probabilities associated with the number of t-statistics lying below or at-or-above the critical t value confirm these results. Overall, these results give us confidence in the choice of sample and of the market index.

In both samples, the mean of the F-statistics (for zero slope coefficients) is high enough to conclude that the true mean value of the F-statistic lies above the 5% critical value. This conclusion is reinforced by the binomial probabilities associated with the number of F-statistics that lie below or at-or-above the critical value. The significance of the F statistics, including as they do the 56 event dummies, is important preliminary evidence that there were significant abnormal returns in the event window associated with the introduction of the BOLT.

Table 3 about here

Figures 1 and 2 show the average CARs obtained from the market models of table 3 and equation (8) for samples A and B respectively. Overall, A and B shares both reacted positively to the introduction of the new trading system, but the average impact on the less liquid B shares was about twice as large as on the A shares.

Figures 1-2 about here

On the first day of trading on the BOLT (day zero), there was an average negative abnormal return on both A shares and B shares. This is not necessarily unexpected, as the change in trading systems from open-outcry to electronic was dramatic, particularly for such a large number of shares simultaneously, and it is likely that there was some uncertainty on the first day of trading, particularly about the possibility of technical failures associated with the new system. On the first day after the event day (day one), the average A share recorded an abnormal return of 1.7%²³. This took the CAR for the period from 5 days before the introduction of BOLT through the end of day one to 2.3%. The average CAR for the whole of the event window is 5%. The price increase appears to have been permanent as the average CAR in the last ten days of the event period (day 41 to 50) is 4.4%. The average B share

gained an abnormal return of 1.9% on the first day after the event day²⁴. This rise took the CAR through the end of day one to 4.1%. The average CAR for the whole of the event window for the B shares is more than twice that on the A shares at 10.8%. Moreover, the effect on the B shares appears to have built up steadily over time, as the average CAR in the last ten days of the event period is 13.8%, or more than 3 times the corresponding statistic for A shares.

These are dramatic figures. For A shares they imply that the BOLT created a permanent price increase of about 4.5%, but for B shares the increase is around 10%. Of course the B shares are a substantially lower proportion of the total market value of the BSE than the A shares. However, if we take the lower figure of 4.5% for all shares and apply this to the total market value of quoted securities on the BSE as of March 1995 (Rs4355bn), this implies a permanent increase in value of some Rs196bn or about 2% of India's 1994-95 current GDP at factor cost (Rs9434bn). However rough this estimate may be, on any reckoning, it represents a substantial increase in value²⁵.

To evaluate more rigorously the importance of the CARs, we extend the approach of Amihud, Mendelson and Lauterbach (1997) and study the event window in segments. Table 4 shows the results of tests on the cross-sectional significance of the CARs at 10 day intervals from days zero through 50. We test significance by computing the t tests for the null hypothesis that the population mean of each CAR is zero. We also check for a positive abnormal return by comparing positive and negative CARs using the cumulative binomial²⁶. For the A shares, all but one of the CARs are statistically significant. Likewise, with one exception, the fraction of positive incidents of CARs in the A shares is sufficiently high so that the null of equally probable positive and negative CARs is decisively rejected. In all cases the proportion of positive CARs (0.58) is in excess of one-half. For the B shares, all the CARs, t-statistics, and fractions of positive CARs are uniformly higher than they are for A shares. These results provide solid evidence that the introduction of the BOLT had a significant positive and permanent effect on share values, and that the effect was particularly marked for the less liquid B shares.

Table 4 about here

The event-dummy approach permits the use of F tests on the estimated $\gamma_{k,h}$ to help determine if groups of days at different points in the event window (particularly towards the end) should be excluded from the window. The null hypothesis for the F-tests on each security is that the dummies are jointly not significantly different from zero. We then compare the F-test results in each cross-section with the relevant critical F value, using t tests and the cumulative binomial. The results are shown in table 5.

Beginning with the A sample, the first row of table 5 shows the results of testing the joint significance of all 56 event dummies. The mean F-statistic at 1.279 is smaller than the relevant critical value, but the difference is not large enough to reject the null that the population mean is equal to the critical value at which the null hypothesis of the F-test can be rejected. We then tested the 49, 40, 30 and 20 dummies most distant from the event day. In all but one case (the case of the twenty dummies from day 31 to day 50), the mean F statistic is lower than the critical F value, but the difference is never large enough to reject the null of the t-test that they are equal. We next tested the joint significance of each group of ten dummies separately (i.e. the dummies for days: 41 to 50; 31 to 40; 21 to 30; 11 to 20 and; 1 to 10). Excluding the most distant dummies (days 41 to 50), the t-tests indicate that the mean F statistics are significantly less than the relevant 5% critical values, implying that the effect within each 10-day period alone was relatively small. Put together, these results reinforce the conclusion that the overall impact of the BOLT on A shares was significant, but that the impact built up slowly over an extended period, with the daily abnormal returns often being individually insignificant.

Table 5 about here

Panel 2 of table 5 summarises the results for sample B. Excluding four cases, for each block of dummies the mean F-statistic is generally above the critical value, implying rejection of the null that the dummies are insignificant. In three of the remaining four cases the difference between the mean F statistic and the critical value is significant, implying rejection of the null of significance. However, these three cases consist of the two blocks of 10 dummies furthest from the event day and the joint test of these 20 dummies. Consequently, these results would suggest that the impact of the BOLT on the B shares was significant overall, and that the most significant impact on the B shares occurred during the first 30 days of its introduction.

Therefore, it appears that the BOLT generated positive and significant abnormal returns, particularly for the less liquid B shares. Moreover, the impact on the B shares built up and was completed more rapidly than that on the A shares. A positive price reaction would be justified if the move to electronic trading created improvements in at least one of the fundamental market attributes, such as liquidity, efficiency or price volatility (Glen, 1994). Likewise, the differential reaction of A and B shares could be explainable by differential changes in any of these attributes. The ways in which electronic trading may be expected to affect market attributes is discussed particularly in Harris (2003) and Allen, Hawkins and Sato, (2001) In the next three sections we examine the changes in liquidity, efficiency, and volatility following the introduction of the BOLT.

5. Liquidity on the BSE

Since B shares are less liquid than A shares, we begin by examining whether their stronger reaction could be explained by a greater improvement in liquidity following the introduction of BOLT. Electronic trading can contribute to market liquidity through its impact on fairness, speed of execution, access and costs (Harris, 2003). Electronic trading enhances fairness and execution speed because the matching and trading rules are implemented objectively and transparently by the system. Manual floor trading may be subject to variations in the interpretation of rules, and outright cheating. Electronic trading also removes the physical constraints to which floor trading is subject and gives equal access to all traders (Allen,

Hawkins and Sato, 2001). According to Shah and Thomas (1997), pre-BOLT access to the BSE trading floor by investors outside Mumbai was severely compromised by the need for additional intermediaries, poor communications, and higher transactions costs. Following the introduction of BOLT, members of the exchange were permitted to open trading terminals within Mumbai and later also in other cities.

Table 6 compares the average trading frequency for the sample of A shares and B shares in the 18 months prior to the introduction of BOLT (340 trading days) with the trading frequency in the first 18 months of electronic trading (351 trading days). The pre-BOLT period ends 6 trading days before the introduction of BOLT; the post-BOLT period begins after the 50 trading days during which the transfer of shares to the BOLT took place. (See panel 2 of appendix table 1A.) Trading frequency for a given firm is defined as the percentage of days on which the share traded on the BSE as a fraction of the total days that the exchange was open during the period. It is taken as a proxy for liquidity because trading volumes are not available prior to 1995.

Table 6 about here

The average trading frequency for A shares amounts to 75% in the pre-BOLT period and 80% in the post-BOLT period, a statistically significant increase. Positive changes in trading frequency dominate negative changes at 49 to 14, and give a rejection of the null that negative and positive changes are equally likely. The average trading frequency of B shares increases from 65% in the pre-BOLT period to 68% in the post-BOLT period. Although this difference is statistically significant, it is not as high or as strongly significant as in the case of A shares. Given the stronger reaction to the BOLT that we recorded for B shares compared with A shares, we might have expected that it would be the B shares that would display a greater improvement in liquidity. To check this point more precisely we also tested whether the increase in liquidity is statistically different as between A and B shares. The results of these

tests (panel 3 in table 6) show that the improvement in liquidity for A shares is also larger than for B shares, although the difference between A and B shares is not significant. We also tested for an association between each individual firm's listing flag (A or B) and the magnitude of the change in its share liquidity (the last row of table 6), but we found no evidence of such a link.

The conclusion from the liquidity analysis is that both A and B shares display a significant improvement in liquidity following the transfer to electronic trading. This helps to explain the positive overall price reaction to the new system but it cannot explain the stronger reaction of the less liquid B shares. We therefore turn next to changes in efficiency.

6. Weak-form efficiency on the BSE

An important aspect of electronic trading is that it promotes the rapid dissemination of information, particularly on trades. Improved transparency, information flows and enhanced liquidity should have improved the price discovery process on the BSE in the post-BOLT period. Since B shares are less heavily traded we would expect there to be less information available in the public domain for B shares than for A shares. If the information content of prices improved following the introduction of the BOLT we would therefore expect this to be particularly important for B shares. We test this hypothesis by conducting simple weak-form efficiency tests for A and B shares, before and after the introduction of the BOLT.

We examine weak-form efficiency by testing for autocorrelation in the returns series using the Ljung-Box Q-Statistic given by:

$$Q_{LB} = T(T+2) \sum_{\tau=1}^m (1/(T-\tau)) \hat{\rho}^2(\tau) \quad \dots(8)$$

where: $\hat{\rho}^2(\tau)$ is the sample autocorrelation at lag τ , m is the maximum lag, T is the sample size, and $Q_{LB} \sim \chi_m^2$. See Diebold (1998) for an exposition. The Q statistic is a portmanteau test and therefore has low power against alternatives which involve intermittent spikes in the autocorrelation function. In general, we would not expect to encounter complex high-order autocorrelations in daily share returns series, and we would argue that the test is therefore adequate for the present purpose. However, as a check on the robustness of the test results we

computed the Q statistic for maximum lag lengths of $m = 1, \dots, 5$. This was done for A and B shares for the same pre-BOLT and post-BOLT periods which were used to compare the trading frequency. The results are shown in table 7.

Table 7 about here

For both A and B shares there is a decrease in the mean Q statistics as between the pre-BOLT and post-BOLT eras. The decreases are mostly not significant for A shares but generally significant for the B. However, for both A and B shares, the mean Q values are typically much larger than the medians, suggesting that the means may be driven by a few very large Q statistics. We therefore focus more attention on the results of the binomial tests rather than those of the t tests. The binomial test compares the number of Q values below the relevant 5% critical value with those which are at-or-above it. Regardless of the maximum lag selected, or whether the period is the pre-BOLT or post-BOLT, the results for both A and B shares show that the number of Q values below the critical value is greater than (and mostly significantly greater than) the number which is at-or-above this value. This suggests that, for a majority of our sample shares, the BSE may have been weak-form efficient both before and after the introduction of the BOLT.

This conclusion does not rule out the possibility that efficiency improvements did take place. First, the mean and median changes in the Q values as between the pre-BOLT and post-BOLT periods are negative regardless of the maximum lag, suggesting an improvement in efficiency. Moreover, the magnitudes of the changes are larger for B shares. In addition, the means and medians for the changes in Q are similar to each other suggesting that greater reliance can be placed on t tests. Table 7 gives the results of t tests that the mean of the change in Q is zero, and binomial tests that negative and positive changes in Q are equally likely. These give further evidence of improvement in efficiency for B shares but much less evidence for A shares. In addition, the sample autocorrelations at lag 1 for both A and B shares are

statistically and economically significant in both the pre-BOLT and post-BOLT eras. There is a decline in the autocorrelation coefficient for both A and B shares as between pre-BOLT and post-BOLT, but once again, the decline is larger for B shares.

In general, these results are consistent with the hypothesis that the introduction of the BOLT was associated with increased efficiency on the BSE, particularly, and probably mainly, for the less liquid B shares. Clearly, this finding is more in line with the larger CARs found for the B shares.

7. Volatility on the BSE

The third aspect of the introduction of the BOLT is its implications for return volatility. Electronic trading may be expected to improve the dissemination of information, reduce the preponderance of uninformed investors, and thereby reduce volatility in returns (Admati and Pfleiderer, 1988). However, volatility is also related to other aspects of market microstructure. Easley and O'Hara (1991) showed that, in a pure dealer market, prices are likely to be less volatile than in a market where dealers co-exist with a public order book. As noted in section 2, implementation of the BOLT included the introduction of an order book alongside dealers in the BSE. Thus, price volatility might be expected to increase as a result. In addition, there are theoretical and empirical relationships between volume and volatility. See Karpoff (1987) for a survey of this literature. Perhaps the most well-documented empirical regularity is that of a positive correlation between volume and volatility (for example, Bessembinder and Seguin, 1993). Thus, increased volume, associated with the increased liquidity we have documented following the introduction of the BOLT, might be expected to increase price volatility. In short, even if electronic trading *per se* reduces volatility, other effects of electronic trading may produce a net increase in volatility. Clearly though, if volatility did decrease following the move to the BOLT, given that we have already established that liquidity and efficiency increased, this would be a further and strong indication that it was the move to electronic trading *per se* which reduced volatility.

We base our study of volatility on the beta coefficients and standard deviations of returns on A and B shares. As a measure of volatility, beta has the advantage that, in theory, it represents the systematic part of a firm's risk which is priced by the market. In addition, individual firm betas necessarily share the same unit of measurement and, in a large portfolio have a mean close to unity. The pre-BOLT and post-BOLT periods are defined as for the liquidity and efficiency tests (panel 2 of appendix table 1A). For the pre-BOLT era, we estimated the market model using (7) from September 1 1993 through day T-6 prior to the introduction of the BOLT. Likewise, the post-BOLT estimates are those obtained by applying (7) to the period from day T+51 relative to the introduction of the BOLT through November 29 1996. We then compared pre- and post-BOLT estimates of the mean and variance of the betas. Deviations from unity of the mean of the betas are best regarded as sampling variation, and we compared the means mainly as a check on this point. To assess the change in volatility, we compare the standard deviation of beta before and after the BOLT. Given the evidence that the market model is an incomplete model of security risks (for example, Fama, 1991), we also examined changes in the total risk measured by the standard deviations of share returns over the same periods.

Table 8 about here

We see from table 8 that the standard deviation of the betas for the A shares fell, as we would expect, but it increased for the B shares. Moreover, the median change in the standard deviation was positive for both A and B shares. In contrast, both A and B shares exhibited a significant decrease in mean total risk as between the pre- and post-BOLT eras. Thus, the evidence on volatility is inconclusive; it increased on some measures but decreased on others.

8. Summarising the effects of liquidity, efficiency and volatility improvements

A weakness of the standard event study method, particularly applied to market microstructure reforms, is that we can only identify mean/median liquidity, efficiency and volatility (hereafter:

LEV) improvements and mean/median CARs for the sample of firms as a whole. The evidence that these were the improvements that contributed to the positive CARs is, we believe, persuasive, but nonetheless essentially circumstantial. The attribution of different CARs for A and B shares to differential LEV improvements is likewise circumstantial. In this section, we aim to strengthen the evidence by testing directly the association between the CARs and the estimated changes in LEV. We do this by modelling the CAR for each firm as a function of the (firm-specific) factors which we hypothesize would generate a positive CAR, ie: the changes in our chosen LEV measures. This final test is important in the context of India where several changes in financial markets were occurring over the period within which we conducted our study. However, few microstructure reforms take place in isolation, and we would argue that all event-study based evaluations of microstructure reforms should include a cross-sectional test of this kind.

Specifically, we estimate the cross-section regression:

$$\begin{aligned}
 CAR_k = & \alpha_k + \beta_1 DTF_k + \beta_2 PTF_k + \gamma_1 DQ_i_k + \gamma_2 PQ_i_k \\
 & + \delta_1 DBETA_k + \delta_2 PBETA_k + \theta_1 DSD_k + \theta_2 PSD_k + \varepsilon_k \quad \dots(9)
 \end{aligned}$$

where: CAR_k is the CAR on the k th stock through day 50

TF_k is the trading frequency

Q_i_k is Ljung-Box Q statistic for i lags

$BETA_k$ is the estimated beta coefficient

SD_k is the standard deviation of returns

and ε_k is the regression error.

Variables prefixed by D give the change between the pre-BOLT and post-BOLT era (panel 2, appendix table 1A). If LEV improvements were responsible for the CARs, we would expect the regression coefficients to have the following signs: $\beta_1 > 0$, $\gamma_1 < 0$, $\delta_1 < 0$, $\theta_1 < 0$. Otherwise, the joint occurrence of positive mean CARs and mean LEV improvements would be coincidental, and not related to one another as we believe.

Variables prefixed by P give the level of liquidity, efficiency or volatility in the pre-BOLT era. To understand the rationale for these variables, consider as an example, firms with low liquidity before the introduction of the BOLT. Illiquid shares would not normally be tracked by brokers. Following the introduction of the BOLT, there are two possibilities. The first is that trading increases sufficiently so that brokers now find it worthwhile to track the stocks, and this creates a secondary improvement in liquidity, implying $\beta_2 > 0$. Alternatively, the increase in trading may not be sufficient to induce brokers to track the stocks, and the secondary change in liquidity is therefore small or negative, implying $\beta_2 \leq 0$. In general therefore, the signs of β_2 , γ_2 , δ_2 , and θ_2 will depend on the sizes and signs of these secondary effects in the cross-section. In short, we hypothesize that it is LEV changes which explain the cross-sectional distribution of CARs, but that these changes may be augmented by secondary effects which are related to (and proxied in the regression by) the initial conditions for each firm. The P ___ variables model these initial conditions.

The LEV measures we use are those already reported. For the Ljung-Box statistic we ran separate regressions with the lag length (i) varying from 1 to 5. The results for each (available from the authors) were qualitatively similar and we therefore report only the result using 5 lags ($Q5$). We included two distinct measures of risk, as beta and the standard deviation correspond to two different concepts. Equation (9) was estimated on the entire cross-section including A and B shares. The hypothesis is that differences in the CARs for A and B shares can be explained by different LEV improvements as between individual shares in each class of share, and not by a different marginal response to the same improvements. We test this hypothesis by reporting the standard Chow test, splitting the sample as between A and B shares.

Table 9 about here

The results are given in table 9 and show that a moderate proportion (about 18%) of the cross-sectional variation in the CARs can be attributed to variations in LEV. The F-test results show

that this proportion is nevertheless clearly significant. However, since LEV improvements are the identified sources of the added value in the BOLT, it would seem reasonable to argue that our initial estimate of added value, based on the CARs alone (section 4.2), should be scaled back. Using the correlation coefficient this would put a more conservative value on the BOLT of $0.18 \times \text{Rs}196\text{bn}$ or about 0.4% of India's 1994-95 GDP. Coefficients for the changes in liquidity, efficiency, and beta-volatility all have the correct sign, although efficiency is not significant. The change in total risk is also significant but with a positive sign. This is consistent with our argument (section 7) that trading improvements may be associated with increased volatility. Two of the variables measuring initial conditions are significant, and these too are reasonably signed: for example, higher initial liquidity creates a positive secondary effect.

The regression results show that it may be necessary to distinguish among different types of risk. Most importantly however, they underline the need to examine the cross-sectional relationships among CARs and the variables which are thought to determine them. We saw that positive CARs were accompanied by (broadly) positive median changes in beta and negative median changes in total risk. However, the regression shows that the CARs were inversely related to changes in beta and positively related to changes in total risk. Since the regression identifies the cross-sectional relationships, we regard the regression results as giving the more reliable estimates of the signs of these relationships. Finally, the Chow test decisively rejects the hypothesis that the sample should be split between A and B shares. This provides firm evidence for our hypothesis that variations among the CARs of individual A and B shares are, in part, attributable to corresponding variations in LEV improvements for these shares.

9. Conclusions

The aim of this paper was to assess the improvement in functioning of the Indian capital market following the implementation of new technology and automation of the trading system. We did this by separately comparing its impact on the most liquid and a sample of less liquid

shares. We found that the impact of the BOLT measured by the CARs over a 56-day event window was substantial: the average CAR for the most liquid A shares was about 4.5%-5.0%, while that for the less liquid B shares was about twice as much, at around 10%. The sample comprises a substantial proportion of the market capitalization of the BSE. Taking the conservative figure of 4.5% for the whole market, and using only the explainable part of the CARs, the estimated impact of the BOLT was equivalent to at least 0.4% of India's GDP: a moderate but important gain.

In the second part of the paper, we sought a more detailed explanation for the CARs in terms of improvements in liquidity, efficiency, and volatility (LEV) accompanying the BOLT. We found that the liquidity of A and B shares increased, but the improvement was greater for A shares. There were also efficiency improvements in A and B shares, but here the improvement was substantially greater for the less liquid B shares. For volatility we found a decline in beta-risk but an increase in total risk, a result which is consistent with other literature suggesting the possibility of a positive correlation between volatility and the effects of trading improvements. Regression analysis provided additional evidence that the CARs could be explained by cross-sectional variations in firm-specific LEV improvements. Overall, the results are consistent with the view that the introduction of the BOLT improved the BSE's market microstructure for both A and B shares, with the effect on B shares being somewhat more marked.

Our conclusion is that improvements in trading arrangements can have significant value where the market is established but currently has inadequate trading arrangements. An important topic of further research is to establish if these conclusions carry over into developing countries in which the market is less well-established and a major goal of reform is to increase the number of firms using the market as well as the participation of existing firms.

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Table 1. Data description

	No. of firms	Membership in leading indices ¹				
		BSE500	BSE200	BSE100	SENSEX	
Sample A	69	67 (97%)	58 (84%)	43 (62%)	15 (22%)	
Sample B	83	83 (100%)	12 (14%)	0 (0%)	0 (0%)	
	Year of incorporation			Sales 1995 (crore Indian rupees ²)		
	Oldest	Average	Youngest	Minimum	Average	Maximum
Sample A	1879	1956	1989	21.62	950.51	7019.05
Sample B	1863	1965	1989	0.51	332.78	1266.09
	Industry ¹		Ownership ^{1,3}			
	Manufacturing	Non-financial services	Indian Business Groups		Independent Indian	
Sample A	64 (93%)	5 (7%)	67 (97%)		2 (3%)	
Sample B	74 (89%)	9 (11%)	77 (93%)		6 (7%)	

NOTES:

- (1) The percentages are of the total number of firms in the respective sample.
- (2) Crore=10⁷ (i.e. 10 million)
- (3) Ownership group is based on the PROWESS classification. This classifies a company under the ownership group with which it is most closely associated. See Centre for Monitoring the Indian Economy (1997).

Table 2. Trading on the BSE – September 1993 to August 1996

	1993-4 ¹	1994-5 ¹	1995-6 ¹	1993-4 to 1995-6
Panel 1. Number of weekdays the BSE was open for trading				
Total weekdays	261	261	261	783
Closed days ²	39	32	22	93
Open days (fraction of total weekdays)	222 (0.85)	229 (0.88)	239 (0.92)	690 (0.88)
Panel 2. Descriptive statistics for number of trading days of 69 A stocks ³				
Average (fraction of open days)	171.921 (0.77)	165.471 (0.72)	189.942 (0.79)	529.889 (0.77)
Std Deviation	16.958	24.790	21.148	53.544
Minimum	133	76	121	348
Median	172	167	192	528
Maximum	207	212	227	639
Panel 3. Descriptive statistics for number of trading days of 83 B stocks				
Average (fraction of open days)	149.470 (0.67)	143.349 (0.63)	163.337 (0.68)	456.157 (0.66)
Std Deviation	23.264	31.115	30.376	67.751
Minimum	87	28	61	249
Median	154	153	167	474
Maximum	194	188	209	568

NOTES

- (1) The years run from 1 September to 31 August.
- (2) Closed days include weekdays when the BSE was closed due to holidays, strikes, payment crises, technical breakdowns etc.
- (3) For six A firms no pricing data is available for at least part of the 1993-4 year. For one of those firms no pricing data is available also for the early part of the 1994-5 year. These firms are therefore excluded from the statistics relating to 1993-4, 1994-5 and to the whole period 1993-4 to 1995-6. Hence in Panel 2 the number of observations for 1993-4 and for the full period is 63, while that for 1994-5 is 68.

Table 3. Regression diagnostics for the market model, event dummy method

Parameter	Mean	Median	Std. Dev.	t-test on the mean of t-statistic ¹ : $ \mu = Z_{5\%}$	Binomial: ² ($< z_{5\%} : \geq z_{5\%}$)
Panel 1. Sample of 69 A shares (350 obs)					
$\hat{\alpha}_k$	-0.001	-0.001	0.002		
$t_{\hat{\alpha}}$	-0.661	-0.723	1.424	-7.631***	53:16
$\hat{\beta}_k$	0.892	0.866	0.361		
$t_{\hat{\beta}}$	3.766	3.574	1.722	8.670***	9:60***
R^2	0.364	0.351	0.140		
F	2.838	2.273	2.072	5.963***	12:57***
Panel 2. Sample of 83 B shares (350 obs)					
$\hat{\alpha}_k$	-0.002	-0.002	0.002		
$t_{\hat{\alpha}}$	-1.455	-1.552	1.040	-4.503***	60:23
$\hat{\beta}_k$	0.915	0.839	0.726		
$t_{\hat{\beta}}$	2.668	2.663	1.223	5.211***	26:57***
R^2	0.308	0.298	0.144		
F	2.207	1.787	1.696	4.602***	32:51**

NOTES

(1) **t-test on the mean of t-statistic:** $|\mu| = Z_{5\%}$ - To construct the cross-section t tests we compare the firm-specific estimates of t_{α} , t_{β} and F from the market model with their respective 5% critical values. The null and alternative hypotheses are: $H_0 : |\mu| = z_{5\%}$, $H_a : |\mu| \neq z_{5\%}$. Interpretation of the alternative hypothesis depends on the tail at which the t statistic falls:

If $t > 0$: implies: $|\mu| > z_{5\%}$ or that the t-test/F-test for insignificance can be rejected at above 5% level

If $t < 0$: implies: $|\mu| < z_{5\%}$ or that the t-test/F-test for insignificance can not be rejected at 5% level

where: μ = mean t_{α} , t_{β} or F value from the market model

$z_{5\%}$ is the relevant 5% critical value of t_{α} , t_{β} or F for the corresponding regression.

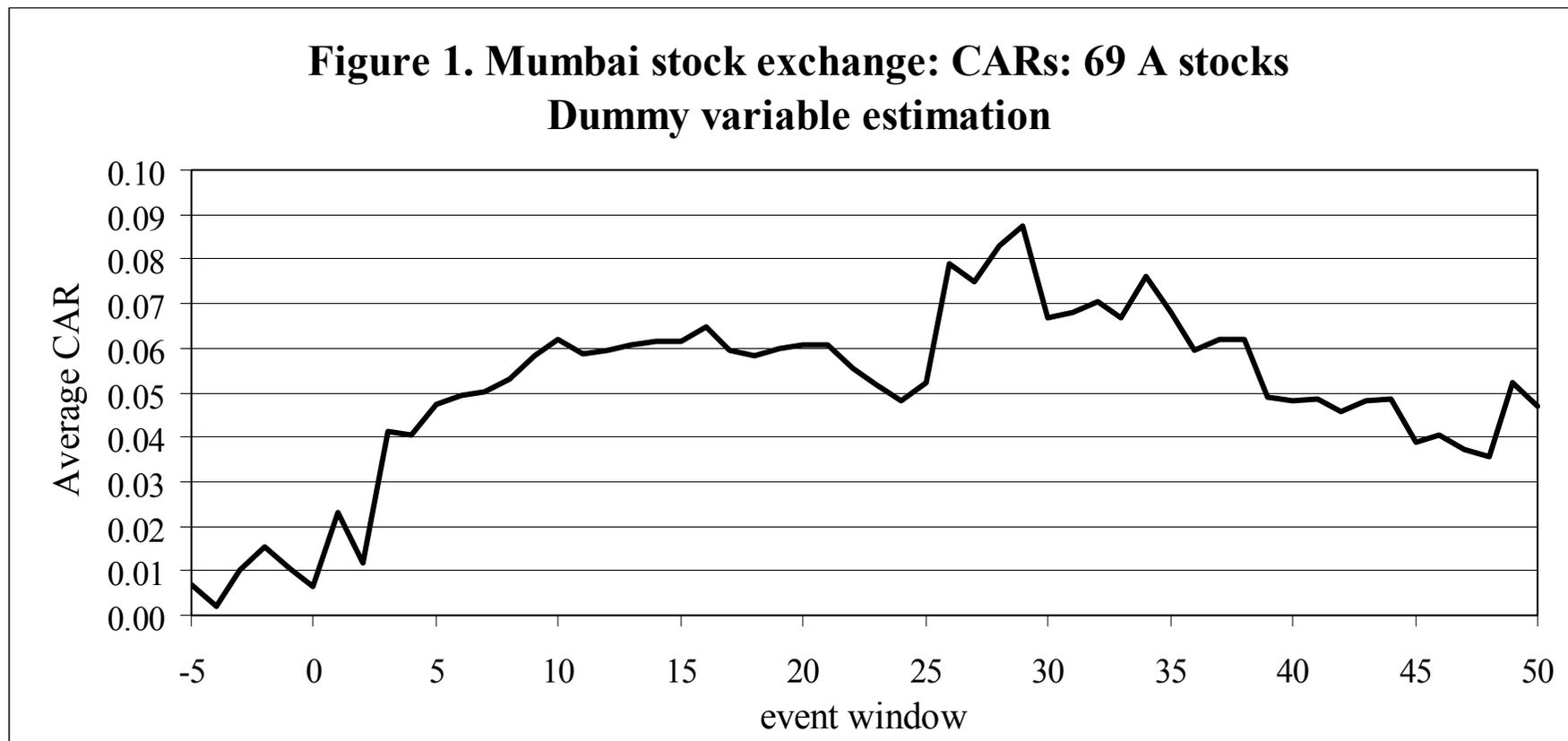
The critical values ($z_{5\%}$) refer to a two-tailed t distribution in the case of α and β , or an F distribution. The critical values against which the means are compared are as follows:

	Degrees of Freedom	Critical value	Area
t	350-68=282	1.9684	2 tail: 0.05
F	DF1=282; DF2=67	1.3498	Upper tail: 0.05

(2) **Binomial:** ($< z_{5\%} : \geq z_{5\%}$) - For the binomial test, (x:y) gives the number of observations for which the absolute value of the t statistic or F statistic is less than (x) or greater than or equal to (y) the relevant critical value given in note 1. The null hypothesis is that $|\mu| < z_{5\%}$ and $|\mu| \geq z_{5\%}$ are equally likely. Based on the cumulative binomial probability (Γ) of observing (x:y), the stars show the significance levels associated with rejecting the null in favour of the hypothesis that observing $|\mu| \geq z_{5\%}$ is significantly greater than 50%.

(3) Significance levels are: *** 1%, ** 5%, * 10%

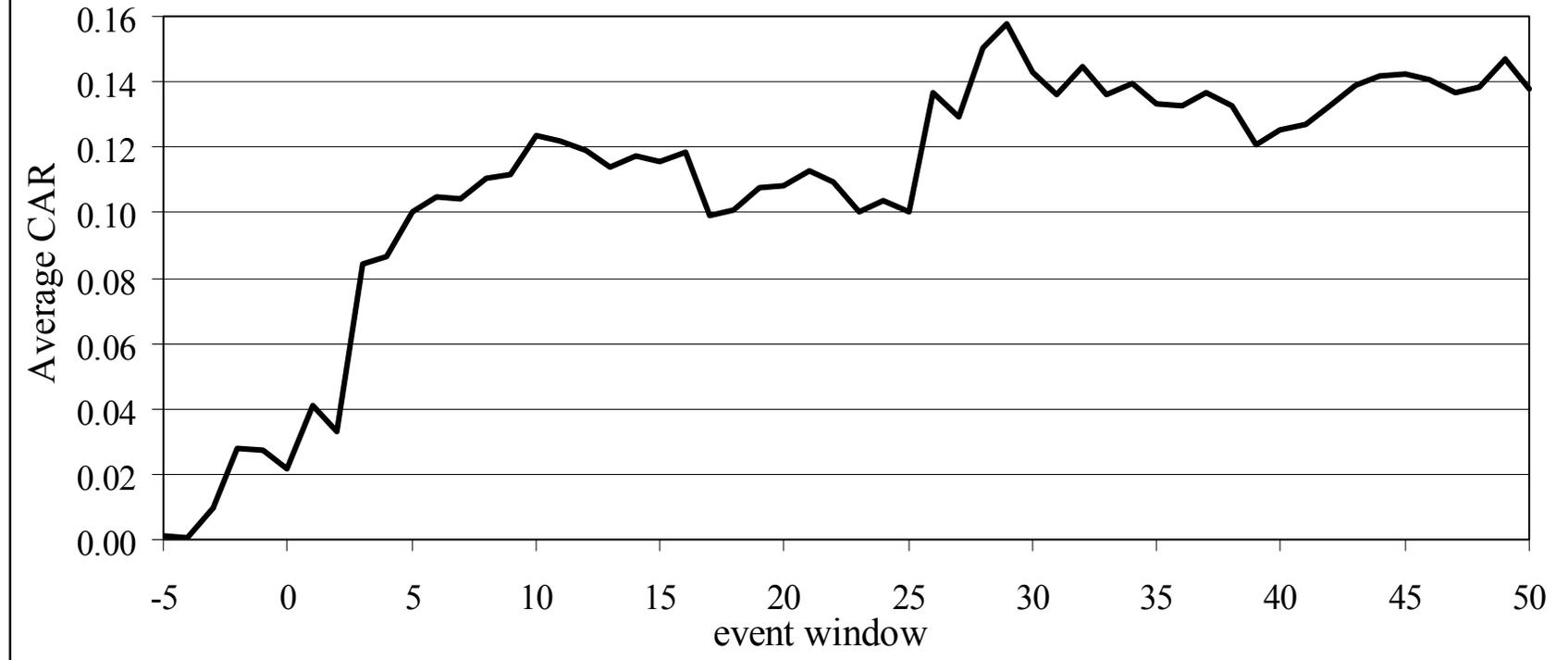
**Figure 1. Mumbai stock exchange: CARs: 69 A stocks
Dummy variable estimation**



NOTES:

- (1) Cumulative abnormal returns for 69 A stocks of non-financial private sector Indian firms that are listed on the BSE. On 14 March 1995 (day 0), these stocks were shifted from open outcry to fully automated trading system, called BOLT.
- (2) The event window is the period from 5 open days (i.e. days when the BSE was open for trading) before the BOLT introduction day, to 50 open days following the introduction. (day -5 to day +50 relative to the event day).
- (3) The market model with 5 leads, 5 lags and 56 event dummies is used to estimate the abnormal returns. 350 daily returns are used for the estimation. These returns are from a period that includes the event period, commencing on day -5 relevant to the event day (7.3.1995) and ending on day +344 (30.8.1996).

**Figure 2. Mumbai stock exchange: CARs: 83 B stocks.
Dummy variable estimation**



NOTES:

- (1) Cumulative abnormal returns for 83 B stocks of non-financial private sector Indian firms that are listed on the BSE. On 14 March 1995 (day 0), these stocks were shifted from open outcry to fully automated trading system, called BOLT.
- (2) The event window is the period from 5 open days (i.e. days when the BSE was open for trading) before the BOLT introduction day, to 50 open days following the introduction. (day -5 to day +50 relative to the event day).
- (3) The market model with 5 leads, 5 lags and 56 event dummies is used to estimate the abnormal returns. 350 daily returns are used for the estimation. These returns are from a period that includes the event period, commencing on day -5 relevant to the event day (7.3.1995) and ending on day +344 (30.8.1996).

Table 4. Tests of the CARs: Event dummy estimation

	Panel 1. 69 A stocks					Panel 2. 83 B stocks				
	Mean	Med.	Std. Dev.	t-test: $\mu = 0$	Binomial: (+ : -)	Mean	Med.	Std. Dev.	t-test: $\mu = 0$	Binomial: (+ : -)
CAR₀	0.006	0.006	0.048	1.086	40:29	0.022	0.018	0.059	3.343***	56:27***
CAR₁₀	0.062	0.060	0.094	5.463***	50:19***	0.124	0.122	0.130	8.646***	76:7***
CAR₂₀	0.061	0.057	0.110	4.589***	48:21***	0.108	0.106	0.141	6.985***	64:19***
CAR₃₀	0.067	0.044	0.131	4.214***	44:25**	0.143	0.128	0.194	6.726***	64:19***
CAR₄₀	0.048	0.048	0.143	2.808***	41:28*	0.126	0.135	0.197	5.801***	58:25***
CAR₅₀	0.047	0.033	0.168	2.319**	42:27*	0.138	0.109	0.216	5.806***	61:22***

NOTES:

- (1) **t test: $\mu = 0$** - t-statistic associated with the mean CAR_u . $t\text{-stat} = E(CAR_u) N^{1/2} / \text{Std Dev} (CAR_u)$. The null and alternative hypotheses are: $H_0 : \mu = 0$, $H_a : \mu \neq 0$, where: $\mu = \text{mean } CAR_u$
- (2) **Binomial: (+ : -)** - For the binomial test, (x:y) gives the number of observations for which $CAR_{k,u}$ is positive (x) or negative (y). The null hypothesis is that positive and negative observations are equally likely. Based on the cumulative binomial probability (Γ) of observing (x:y), the stars show the significance levels associated with rejecting the null in favour of the hypothesis that observing a positive $CAR_{k,u}$ is significantly greater than 50%.
- (3) Significance levels are: *** 1%, ** 5%, * 10%. (For the t-tests these are based on the two-tail area associated with the t-statistic.)

Table 5. Descriptive statistics and tests of the F-statistics for the event dummies.

F-tests Hypothesis	F	F _{5%} ¹	Panel 1. 69 A stocks					Panel 2. 83 B stocks				
			Mean	Med.	Std. Dev.	t-test ² : $\mu = F_{5\%}$	Binomial: ³ < F _{5%} : ≥ F _{5%}	Mean	Med.	Std. Dev.	t-test ² : $\mu = F_{5\%}$	Binomial: ³ < F _{5%} : ≥ F _{5%}
H ₀ : $\gamma_{-5} = \gamma_{-4} = \dots = \gamma_{50} = 0$ all 56 dummies: -5 to 50, insignificant	F _{56,282}	1.377	1.279	1.098	0.791	-1.031	45:24	1.737	1.341	1.682	1.950***	43:40***
H ₀ : $\gamma_2 = \gamma_3 = \dots = \gamma_{50} = 0$ 49 dummies: 2 to 50, insignificant	F _{49,282}	1.400	1.231	1.053	0.840	-1.662	48:21	1.696	1.241	1.568	1.724*	46:37
H ₀ : $\gamma_{11} = \gamma_{12} = \dots = \gamma_{50} = 0$ 40 dummies: 11 to 50, insignificant	F _{40,282}	1.437	1.252	1.009	0.948	-1.628	52:17	1.614	1.230	1.512	1.066	50:33
H ₀ : $\gamma_{21} = \gamma_{22} = \dots = \gamma_{50} = 0$ 30 dummies: 21 to 50, insignificant	F _{30,282}	1.500	1.337	0.976	1.244	-1.086	49:20	1.543	1.048	1.453	0.270	51:32
H ₀ : $\gamma_{31} = \gamma_{32} = \dots = \gamma_{50} = 0$ 20 dummies: 31 to 50, insignificant	F _{20,282}	1.608	1.261	0.874	1.512	-1.908*	57:12	1.328	0.914	1.448	-1.762*	60:23
H ₀ : $\gamma_{41} = \gamma_{42} = \dots = \gamma_{50} = 0$ 10 dummies: 41 to 50, insignificant	F _{10,282}	1.864	1.524	0.866	2.842	-0.995	58:11	1.433	0.681	2.188	-1.796*	67:16
H ₀ : $\gamma_{31} = \gamma_{32} = \dots = \gamma_{40} = 0$ 10 dummies: 31 to 40, insignificant	F _{10,282}	1.864	0.997	0.689	0.933	-7.718***	60:9	1.219	0.829	1.270	-4.627***	68:15
H ₀ : $\gamma_{21} = \gamma_{22} = \dots = \gamma_{30} = 0$ 10 dummies: 21 to 30, insignificant	F _{10,282}	1.864	1.495	1.069	1.414	-2.173**	51:18	1.983	1.072	2.497	0.432	56:27
H ₀ : $\gamma_{11} = \gamma_{12} = \dots = \gamma_{20} = 0$ 10 dummies: 11 to 20, insignificant	F _{10,282}	1.864	0.999	0.626	1.092	-6.582***	58:11	1.825	0.795	3.444	-0.104	58:25
H ₀ : $\gamma_1 = \gamma_2 = \dots = \gamma_{10} = 0$ 10 dummies: 1 to 10, insignificant	F _{10,282}	1.864	1.262	0.776	1.217	-4.111***	52:17	2.122	1.065	3.077	0.764	55:28

NOTES:

- (1) F_{5%} is the critical value of the relevant F statistic at the 5% level.
- (2) **t test:** $\mu = F_{5\%}$ To construct the cross-section t tests we compare the firm-specific estimates of F with their respective 5% critical values. The null and alternative hypotheses are: H₀ : $\mu = z_{5\%}$, H_a : $\mu \neq z_{5\%}$. Interpretation of the alternative hypothesis depends on the tail at which the t statistic falls:
 If $t > 0$: implies: $\mu > z_{5\%}$ or that the F-test that the dummies are jointly insignificant can be rejected at above 5% level
 If $t < 0$: implies: $\mu < z_{5\%}$ or that the F-test that the dummies are jointly insignificant can not be rejected at 5% level
 Where μ is the F value and F(5%) is the relevant 5% critical value of F for the corresponding regression.
- (3) **Binomial:** ($< F_{5\%} : \geq F_{5\%}$) - For the binomial test, (x:y) gives the number of observations for which the F statistic is less than (x) or greater than or equal to (y) the relevant critical value given in column 3. The null hypothesis is that $\mu < z_{5\%}$ and $\mu \geq z_{5\%}$ are equally likely. Based on the cumulative binomial probability of observing (x:y), the stars show the significance levels associated with rejecting the null in favour of the hypothesis that observing $\mu \geq z_{5\%}$ is significantly greater than 50%.
- (4) Significance levels are: ***1%, **5%, *10%. (For the t-tests these are based on the two-tail area associated with the t-statistic.)

Table 6. Trading frequency

	Panel 1. 63 A stocks ⁽¹⁾					Panel 2. 83 B stocks				
	Mean	Median	Std Dev	Min	Max	Mean	Median	Std Dev	Min	Max
Trading days: pre-BOLT ⁽²⁾	253	251	26.918	170	312	220	229	32.722	124	282
Trading frequency: pre-BOLT (TF _{pre}) ⁽³⁾	0.745	0.738	0.079	0.500	0.918	0.647	0.674	0.096	0.365	0.829
Trading days: post-BOLT ⁽²⁾	279	283	31.415	170	330	238	247	45.878	86	304
Trading frequency: post-BOLT (TF _{post}) ⁽³⁾	0.795	0.806	0.090	0.484	0.940	0.677	0.704	0.131	0.245	0.866
Change in trading frequency (DTF) ⁽⁴⁾	0.050	0.057	0.073	-0.160	0.242	0.031	0.052	0.127	-0.352	0.365
t test on mean change ⁽⁵⁾ : $\mu = 0$	5.393***					2.195**				
Binomial on change ⁽⁶⁾ (+ : -)	49:14***					56:27***				
Panel 3. Comparison of the change in trading frequency of A stocks versus B stocks										
Test	Null				Alternative				Test statistics	
F _{(83-1), (63-1)} ⁽⁷⁾	$\sigma_A^2 = \sigma_B^2 = \sigma^2$				$\sigma_A^2 < \sigma_B^2$				3.042***	
T ₍₆₃₊₈₃₋₂₎ ⁽⁸⁾	$\mu_A = \mu_B$ (assuming $\sigma_A^2 = \sigma_B^2$)				$\mu_A < \mu_B$				1.077	
T ₍₁₃₆₎ ⁽⁹⁾	$\mu_A = \mu_B$ (assuming $\sigma_A^2 < \sigma_B^2$)				$\mu_A < \mu_B$				1.155	
$\chi^2_{(2)}$ ⁽¹⁰⁾	Listing flag & size of change are not associated				Listing flag & size of change are associated				0.028	

NOTES:

- (1) Six firms were excluded from sample A due to there being no pricing data in the early part of the pre-BOLT period.
- (2) Trading days for firm k is the number of days in which there was a trade in the firm's shares on the BSE.
- (3) Trading frequency is the number of trading days as a proportion of the number of days that the BSE was open during the period. Pre-BOLT period includes 340 open days, while post-BOLT includes 351 open days. Panel 2 of table 1A in the appendix gives details for each period.
- (4) The change in the trading frequency of firm k, is calculated as the difference between the stock's trading frequency: $DTF_k = TF_{post,k} - TF_{pre,k}$.
- (5) The t test is a test of the null hypothesis that there is no improvement in the trading frequency. The null and alternative hypotheses are: $H_0 : \mu = 0$, $H_a : \mu > 0$, where: $\mu =$ mean DTF. The test is of the form: $t\text{-stat} = E(DTF_k) N^{1/2} / \text{Std Dev} (DTF_k)$. The stars indicate the significance level associated with a one-tailed test.
- (6) For the binomial, (x:y) shows positive (x) and negative (y) changes in trading frequency. The null hypothesis is that positive and negative changes are equally likely. Based on the cumulative binomial, the stars indicate the significance level of rejecting the null in favour of the alternative that the change is positive.
- (7) The F test is of the form: $F\text{-stat} = \sigma_B^2 / \sigma_A^2 \sim F(N_B - 1, N_A - 1)$, where σ_B^2 and σ_A^2 are the respective variances of the A and B samples.
- (8) The t test is of the form: $t_{N_A + N_B - 2} = (\bar{X}_A - \bar{X}_B) / S[(N_A + N_B) / N_A N_B]^{1/2}$. The pooled variance is: $S^2 = [(N_A - 1)S_A^2 + (N_B - 1)S_B^2] / (N_A + N_B - 2)$.
- (9) The t-test is of the form: $t_{D.F.} = (\bar{X}_A - \bar{X}_B) / (S_A^2 / N_A + S_B^2 / N_B)^{1/2}$.
- (10) The χ^2 test is the median test calculated by classifying all scores as being above or at-or-below the median of the combined sample. (These form the contingency table's columns). The table is further classified as belonging to sample A or B. (These form the contingency table's rows). The test takes the following form: $\chi^2 = \sum (O - E)^2 / E$ where O is the observed value and E is the expected value of each cell and is given by its row total times its column total divided by the number of total observations.
- (11) Significance levels are: * 10%; ** 5%; *** 1%.

Table 7.1 Efficiency improvements - Return predictability for A shares before and after the BOLT

Panel 1. 63 A stocks						
	$\chi^2_{5\%}$	Mean	Median	Std Dev	t-test on Q: $\mu = \chi^2_{5\%}$ on change: $\mu = 0$	Binomial Q: ($< \chi^2_{5\%} \geq \chi^2_{5\%}$) change: (- : +)
$ \rho(1) $						
Pre-BOLT		0.105***	0.089	0.069		
Post-BOLT		0.088***	0.073	0.069		
Q_{LB} Max lag =1						
Pre-BOLT	3.841	5.393	2.730	7.039	1.749*	36:27
Post-BOLT	3.841	4.386	1.880	5.965	0.724	42:21***
Change in Q		-1.007	-0.940	8.033	-0.995	40:23**
Q_{LB} Max lag =2						
Pre-BOLT	5.991	6.735	3.980	7.433	0.794	38:25*
Post-BOLT	5.991	6.006	3.640	6.651	0.017	42:21***
Change in Q		-0.729	-0.687	8.730	-0.663	37:26
Q_{LB} Max lag =3						
Pre-BOLT	7.815	7.996	5.460	7.906	0.182	39:24**
Post-BOLT	7.815	6.932	4.430	6.944	-1.009	46:17***
Change in Q		-1.064	-0.930	9.049	-0.933	38:25*
Q_{LB} Max lag =4						
Pre-BOLT	9.488	9.424	7.110	8.534	-0.059	40:23**
Post-BOLT	9.488	8.379	6.290	7.552	-1.165	44:19***
Change in Q		-1.045	-1.110	9.713	-0.854	37:26
Q_{LB} Max lag =5						
Pre-BOLT	11.070	11.108	9.990	9.750	0.030	35:28
Post-BOLT	11.070	9.928	7.730	8.520	-1.064	45:18***
Change in Q		-1.180	-0.700	11.301	-0.828	34:29

NOTES to table 7 follow panel 2

Table 7.2 Efficiency improvements - Return predictability for B shares before and after the BOLT

Panel 2. 83 B stocks						
	$\chi^2_{5\%}$	Mean	Median	Std Dev	t-test on Q: $\mu = \chi^2_{5\%}$ on change: $\mu = 0$	Binomial Q: ($< \chi^2_{5\%} \geq \chi^2_{5\%}$) change: (- : +)
$ \rho(1) $						
Pre-BOLT		0.100***	0.088	0.081		
Post-BOLT		0.074***	0.065	0.050		
Q_{LB} Max lag =1						
Pre-BOLT	3.841	5.642	2.670	8.569	1.914*	50:33**
Post-BOLT	3.841	2.817	1.510	3.444	-2.711***	63:20***
Change in Q		-2.825	-0.149	9.495	-2.711***	44:39
Q_{LB} Max lag =2						
Pre-BOLT	5.991	7.375	4.570	8.752	1.440	50:33**
Post-BOLT	5.991	4.163	2.700	4.308	-3.867***	63:20***
Change in Q		-3.212	-1.188	10.221	-2.863***	52:31**
Q_{LB} Max lag =3						
Pre-BOLT	7.815	8.706	5.540	9.015	0.901	49:34*
Post-BOLT	7.815	5.184	3.890	4.460	-5.374***	62:21***
Change in Q		-3.522	-2.230	10.400	-3.085***	55:28***
Q_{LB} Max lag =4						
Pre-BOLT	9.488	9.917	7.450	9.218	0.425	49:34*
Post-BOLT	9.488	6.518	5.530	5.113	-5.292***	65:18***
Change in Q		-3.399	-2.470	10.881	-2.846***	56:27***
Q_{LB} Max lag =5						
Pre-BOLT	11.070	11.847	9.290	9.470	0.747	47:36
Post-BOLT	11.070	7.813	7.130	5.249	-5.653***	65:18***
Change in Q		-4.034	-3.790	11.071	-3.319***	56:27***

NOTES to table 7 follow this panel

Table 7.3 Efficiency improvements – Notes to table 7

NOTES:

- (1) Six firms were excluded from the sample of 69 A firms. This is due to missing pricing data for part of the first period.
- (2) $|\rho_{(1)}|$ - The absolute value of the autocorrelation at lag 1. The stars indicate significance of the t-test.
- (3) The Pre-BOLT period includes 340 open days, while the post-BOLT includes 351 open days. Panel 2 of table 1A in the appendix gives details for each period.
- (4) **Q_{LB}** - The Ljung-Box Q-statistic defined as: $Q_{LB} = T(T+2) \sum_{\tau=1}^m \rho^2(\tau)/(T-\tau)$; where T is the number of daily returns, $\rho^2(\tau)$ is the autocorrelation at lag τ , and m is the maximum lag. Under the null hypothesis that the time series of returns is white noise, Q_{LB} is distributed as χ^2_m . The change is defined as: $dQ_{LB} = Q_{LB \text{ post-BOLT}} - Q_{LB \text{ pre-BOLT}}$.
- (5) **t-test on Q_{LB}** – The t test on the mean Q_{LB} is defined as : $t = (\mu - \chi^2_{5\%})/(\sigma/\sqrt{T})$ with degrees of freedom 62 (A) or 82 (B). The critical value for the appropriate χ^2 with which the mean Q_{LB} is compared is given in the $\chi^2_{(5\%)}$ column. The null and alternative hypotheses are: $H_0 : \mu = \chi^2_{5\%}$, $H_A : \mu \neq \chi^2_{5\%}$. Interpretation of the alternative hypothesis depends on the tail at which the t statistic falls:
 - If $t > 0$: implies: $\mu > \chi^2_{5\%}$ or that we reject efficiency at above the 5% level
 - If $t < 0$: implies: $\mu < \chi^2_{5\%}$ or that we cannot reject efficiency
- (6) **t-test on the change in Q_{LB}** – The t test is defined as: $t = \mu N^{1/2} / \text{Std Dev}(\mu)$. The null and alternative hypotheses are: $H_0 : \mu = 0$, $H_A : \mu \neq 0$, where: $\mu =$ mean value, and $N =$ number of observations
- (7) **Binomial test on Q_{LB}** - For the binomial test, (x:y) gives the number of observations for which Q_{LB} is less than (x) or greater than or equal to (y) the relevant critical value. The null hypothesis is that $\mu < \chi^2_{5\%}$ and $\mu \geq \chi^2_{5\%}$ are equally likely. Based on the cumulative binomial probability (Γ) of observing (x:y), the stars show the significance levels associated with rejecting the null in favour of the hypothesis that observing $\mu < \chi^2_{5\%}$ is significantly greater than 50%.
- (8) **Binomial the change in Q_{LB}** - the binomial, (x:y) are the negative (x) and negative/zero (y) changes in Q_{LB} . The null hypothesis is that negative or negative/zero changes are equally likely. Based on the cumulative binomial, the stars indicate the significance level of rejecting the null in favour of the alternative that the change is negative.
- (9) Significance levels are: * 10%; ** 5%; *** 1%.

Table 8. Volatility before and after the BOLT

	Panel 1. Systematic risk: beta									
	63 A stocks					83 B stocks				
	Mean	Med	Std Dev	Min	Max	Mean	Med	Std Dev	Min	Max
Pre-BOLT	0.834	0.870	0.333	-0.182	1.476	0.834	0.736	0.401	0.019	2.480
Post-BOLT	0.898	0.938	0.292	0.086	1.513	0.819	0.814	0.547	0.124	4.820
F test for Equality of Variances: A: $F_{62,62} = S_{pre}^2 / S_{post}^2$ B: $F_{82,82} = S_{post}^2 / S_{pre}^2$			1.302					1.866***		
Change (Post – Pre)	0.065	0.069	0.338	-0.668	0.835	-0.014	-0.035	0.548	-1.278	2.966
Binomial on change (+ : -)	34:29					40:43				
	Panel 2. Total risk: std. dev. of returns									
	63 A stocks					83 B stocks				
	Mean	Med	Std Dev	Min	Max	Mean	Med	Std Dev	Min	Max
Pre-BOLT	0.027	0.025	0.010	0.013	0.058	0.035	0.033	0.015	0.014	0.143
Post-BOLT	0.022	0.020	0.006	0.012	0.045	0.028	0.026	0.013	0.015	0.133
Change (Post – Pre)	-0.005	-0.004	0.010	-0.040	0.019	-0.007	-0.008	0.019	-0.105	0.091
t test on mean change: $\mu = 0$	-4.418***					-3.608***				
Binomial on change (+ : -)	15:48***					21:62***				

NOTES to Table 8:

- (1) Six firms were excluded from sample A due to there being no pricing data in the early part of the pre-BOLT period.
- (2) Beta is the beta estimate from the market model with five leads and five lags as specified in equation (3). In the A sample there is one firm with a negative beta estimate. The change in beta is defined as: $BETA_{change} = BETA_{post-BOLT} - BETA_{pre-BOLT}$
- (3) Std. dev. of returns is the standard deviation of daily returns in the period. The change in std. dev. is defined as: $StdDev_{change} = StdDev_{post-BOLT} - StdDev_{pre-BOLT}$
- (4) Pre-BOLT period includes 340 open days, while post-BOLT includes 351 open days. Panel 2 of table 1A in the appendix gives details for each period.
- (5) The F test in panel 1 is a test of the null hypothesis that there is no reduction in volatility as measured by the variance of beta.
- (6) For the binomial, (x:y) shows positive (x) and negative (y) changes in volatility. The null hypothesis is that positive and negative changes are equally likely. Based on the cumulative binomial, the stars indicate the significance level of rejecting the null in favour of the alternative that the change is negative.
- (7) The t test in panel 2 is a test of the null hypothesis that there is no reduction in volatility as measured by total risk. The null and alternative hypotheses are: $H_0 : \mu = 0$, $H_a : \mu \neq 0$, where: $\mu =$ mean change in total risk. The test is of the form: $t\text{-stat} = E(\text{change}) N^{1/2} / \text{Std Dev}(\text{change})$. The stars indicate the significance level associated with a two-tailed test.
- (8) Significance levels are: * 10%; ** 5%; *** 1%.

Table 9. The contributions of liquidity, efficiency and volatility to the price reaction to BOLT

	Coefficient (t-statistic)	Coefficient (t-statistic)
<i>Constant</i>	-0.3011 (2.13)	-0.2913 (2.11)
<i>DTF</i>	0.2664 (1.90)	0.2313 (1.73)
<i>PTF</i>	0.2867 (1.72)	0.2403 (1.59)
<i>DQ5</i>	-0.001465 (0.59)	-0.001171 (0.74)
<i>PQ5</i>	-0.0006577 (0.22)	
<i>DBETA</i>	-0.1066 (1.96)	-0.08689 (2.08)
<i>PBETA</i>	-0.03868 (0.60)	
<i>DSD</i>	9.8505 (3.92)	9.2226 (3.61)
<i>PSD</i>	9.2251 (4.00)	8.5917 (3.67)
<i>R²</i>	0.1825	0.1798
<i>LMHET: $\chi^2_{5\%}(1) = 3.84$</i>	0.1723	0.3482
<i>CHOW</i>	1.4051 F(9,128) = 1.95	1.7634 F(7,132) = 2.08
<i>F (zero slopes)</i>	3.8221*** F(9,137) = 1.95	5.0800*** F(7,139) = 2.08
<i>No. of firms</i>	146	146

Appendix Table 1A. Time periods used in the study

Panel 1. Event period and the estimation periods used for the event study								
Period	First day		Last day		Number of days in period			
	Event day	Date	Event day	Date	Open days	Closed days	Week-days	Total days
12 months period	T-5	7.3.95	T+223	29.2.96	229	29	258	360
18 months period	T-5	7.3.95	T+344	30.8.96	350	39	389	543
Event window period	T-5	7.3.95	T+50	6.6.95	56	10	66	92

Panel 2. Pre-BOLT and post-BOLT periods used for the comparison analysis								
	First day		Last day		Number of days in period			
	Event day	Date	Event day	Date	Open	Closed	Week-days	Total days
Pre-BOLT period	T-345	1.9.93	T-6	6.3.95	340	54	394	552
post-BOLT period	T+51	7.6.95	T+401	29.11.96	351	37	388	544

NOTES:

- (1) Event day = the day relative to the day of the BOLT introduction (T = 14 March 1995)
- (2) Open days = number of weekdays that the BSE was open for trading
- (3) Closed days = number of weekdays that the BSE was closed due to holidays, strikes, payment crises, technical breakdowns etc.
- (4) Weekdays = number of open days + number of closed days.
- (5) Total days = number of weekdays + number of weekend days.
- (6) 30 August, 1996 and 29 November, 1996 both fall on a Friday, hence they are the last trading days of the respective months.

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- ¹ This typically involves a shift from call to continuous and/or automated trading. For example, the Tel Aviv stock exchange gradually shifted from a call auction to continuous trading (Amihud, Mendelson and Lauterbach, 1997); and the Taiwan stock exchange switched from a semi-automated to fully automated trading (Chang et al., 1999; Lang and Lee, 1999).
- ² Roell (1992), Demirguc-Kunt and Levine (1996) and Khambata (2000) note that tight disclosure requirements, auditing and accounting standards create confidence among investors.
- ³ Kim and Singal (2000) find that opening the exchange to foreign investors increased efficiency and reduced exchange rate and inflation volatility in 20 emerging stock markets.
- ⁴ The Mumbai Stock Exchange is usually known by its acronym which uses the former name of the city, Bombay. Hence, "BSE".
- ⁵ We discuss the nature of Badla in more detail in section 2 of the paper.
- ⁶ We thank Ajay Shah and Susan Thomas for supplying this material to us.
- ⁷ The discussion in this section draws heavily on information provided by the Stock Exchange, Mumbai on its web site at *www.bseindia.com*.
- ⁸ See Agarwal (1996) and Singh (1998).
- ⁹ Shah and Thomas (1997) survey the changing role of the Indian financial markets during the 1990's. They examine the rise in the use of financial markets for resource allocation, a role that was traditionally fulfilled by the banking system. They also review the reasons for the lack of efficiency and high transactions costs on the BSE prior to the introduction of the NSE in 1994, and the subsequent modernisation of the BSE.
- ¹⁰ The fraud is usually attributed to Harshad Mehta who was involved in large-scale share-dealings in mainstream and defunct companies using funds obtained from certain public sector banks.
- ¹¹ The NSE was set up by a group of financial institutions with the intention of becoming a model exchange. It began trading in debt securities in June 1994, and in equity shares in November 1994. Equity market trading started with 200 stocks and, by December 1995, 1300 stocks were traded and the NSE had become a more liquid market than the BSE (Shah and Thomas, 2001).
- ¹² Shah and Thomas (1996) describe the BOLT system.
- ¹³ "Jobbers" are dealers.
- ¹⁴ The distinction between A and B shares is explained below.
- ¹⁵ As of November 11, 2002, and following a reclassification exercise by the Exchange.
- ¹⁶ The data were extracted from *DATASTREAM* and matched with that on the *PROWESS* database (CMIE, 1997) to ensure that the sample consisted exclusively of A and B shares of non-financial private sector Indian firms.
- ¹⁷ Non-synchronous trading in the index poses more difficult issues than does thin trading in individual shares (Chan, 1992). We deal with the latter problem in our estimation of the market model; see the discussion in section 4.
- ¹⁸ Amihud, Mendelson, and Lauterbach (1997) constrain their model to just 3 parameters across a 36 day window.
- ¹⁹ Dimson's analysis was concerned with the estimation of the market model using the standard event study methodology (2), but it applies *a fortiori* to the event dummy method (6).
- ²⁰ The probability of a trade in any given trading day can be as low as 0.3. See Dimson (1979).
- ²¹ In the trade-to-trade approach, the market model (1) is expressed in terms of the multi-calendar-day return rather than the per calendar-day return as in (2). More precisely it is written:

$$R_{k,t,n} = \alpha_k n_t + \beta_k M_{t,n} + \sum_{j=1}^n \varepsilon_{k,t-j+1} \quad \dots(2')$$

Here, $R_{k,t,n}$ is the return on stock k between two consecutive trading days, day $t - n$ to day t , and $M_{t,n}$ is the corresponding return on the market index. Since the time interval between closing prices on consecutive trading days will vary depending on the day of the week and holidays, the errors in (2') are heteroskedastic, with a variance of $n_t \sigma_k^2$ (Maynes and Rumsey, 1993). Therefore, (2') can be efficiently estimated by OLS after dividing through by $\sqrt{n_t}$. Since the return being modelled is a multi-calendar-day return, the subsequent adjustment (4) to calculate the ARs is no longer required. Another difference between the Dimson and trade-to-trade method is that with the latter, the number of ARs (and therefore CARs) vary from firm to firm depending on whether the stock was traded on the particular event window day.

²² These include all the shares in our sample.

²³ The highest average daily abnormal return for A sample over the entire event window (3%) occurred on day 3.

²⁴ The highest average daily abnormal return for B sample over the entire event window (5.1%) occurred on day 3.

²⁵ GDP at factor cost is taken from the Reserve Bank of India (1999). The market capitalisation data was obtained from the web site of the Stock Exchange, Mumbai (2001) at www.bseindia.com.

²⁶ None of the CARs is equal to zero.