# The impact of speculation upon volatility and market efficiency: The *badla* experience on the BSE

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**Abstract**

On 12 March 1994, SEBI imposed new norms on trading in the Bombay Stock Exchange, and the effective consequence of this has been an elimination of *badla*, a form of forward trading. Without badla, the role of speculative traders on the BSE is diminished.

This paper sets out to measure the impact of this elimination of speculative trading upon volatility on the BSE. We explore, and criticise, a variety of different methods of arriving at a conclusion on this question, and present an estimation strategy which exploits the unique opportunity to view this episode as a natural experiment. Our examination of daily unsystematic risk, which takes the value of 3% in our sample on average, reveals that badla diminishes it by roughly 0.25 percentage points. The statistical significance of this estimate is weak, especially in the light of a qualitative argument suggesting that this estimate is biased upwards. Working with weekly returns data, badla seems to have no impact upon unsystematic risk.

On the subject of market efficiency, we find that badla is slightly beneficial for short–horizon market efficiency: the non-forecastability of daily returns of A companies has worsened in the year following 12 March 1994. This effect is concentrated in the short horizon; the degree of forecastability of weekly returns has actually diminished slightly in the year after 12 March 1994.

*This file is http://www.cmie.ernet.in/~ajayshah/PROSE/ARTICLES/badla.ps.gz The estimation strategy used here evolved in email conversations with Venkat Eleswarapu. Mailing address: Centre for Monitoring Indian Economy, 110-120 Kaliandas Udyog Bhavan, Prabhadevi, Bombay 400 025.

# 1 Does speculation stabilise prices?

There is no economic theory suggesting how much price volatility is "optimal" in an economy. The central unifying theoretical principle in finance is the notion that prices reflect information, and as information unfolds, prices fluctuate in response. Market efficiency implies that the signals given out by the price system for resource allocation are constantly on track; the high speed reactions of the price system serve to produces a resource allocation which constantly tracks time–varying information about technology and preferences. This tells us that the "correct" level of price volatility in an economy is hard to define – instead, the only relevant metric in a welfare sense is the degree of market efficiency obtained.

We must hence discuss "excess volatility" in terms of deviations from market efficiency.

On a large scale, we can have speculative bubbles, which are systematic deviations from market efficiency. For example, at the height of the Great Scam of 1992, the price to book ratio of the BSE Sensex portfolio briefly touched 9, as compared with a long-run average between 3 and 4. Alternatively, there can be situations like the UK pound, where a government agency tries to force a price to systematically stray away from the market-clearing level. The presence of rational agents who trade solely to obtain excess returns in the short-run appears crucial to eliminating mispriced assets of these kinds. On the other hand, it could be argued that the Great Scam of 1992 might not have arisen without the presence of a large pool of "speculative traders".

On a smaller scale, we can have markets "over-reacting" to information – when good news for a company appears, markets may bid up its share price by "too much", and when bad news appears, markets may drive down its price by "too much". In this view of the world, markets lurch from one overreaction to the next, and asset prices exhibit mean reversion to fundamental values. The received wisdom of the profession is that over-reaction of this nature would manifest itself as returns predictability of some kind, and arbitrageurs are necessary in a system to eliminate such mispriced assets. The consensus here is not complete; James Tobin, Joseph Stiglitz and Lawrence Summers go so far as to advocate a tax on short-term securities *trading* (not just capital gains).[1]

[1] Umlauf (1993) finds that the imposition of a transactions tax in Sweden reduced volumes while leaving volatility unchanged. This recommendation of a transactions tax has been strongly criticised, for example in Ross (1989).

In India, a 5% tax on brokerage fees was introduced in February 1994, at almost the same time as the restrictions on badla were put in place. One-trip brokerage fees are normally around 1%, so this tax can be interpreted as a transactions tax of five basis points. This appears to be a minor transactions tax, and we will ignore its effects in this

Thus there is reason for believing that both these kinds of excess volatility would be diminished by the presence of speculative traders, but it does not stand unambiguously established. Further, theory does not guide us as to the magnitude of this relationship, and theory does not describe how the microstructure of trading might make a difference to these relationships. We need empirical evidence here to quantify these relationships. The *badla* episode at the Bombay Stock Exchange is a unique opportunity to learn about the volatility implications of speculative trading.

"Speculation" is hard to quantify, and the literature routinely concerns itself with the volatility implications of trading in financial derivatives. There are numerous articles which find that the variance of returns on individual securities decline after trading in options contracts on those securities commences. On the other hand, Stoll & Whaley (1987) find that the volatility of the S&P500 index is increased on expiration dates of index futures, Kocagil (1994) finds that the intensity of futures speculation is not associated with reduced spot price volatility, and Harris (1989) finds that the introduction of derivatives contracts worsens volatility of S&P500 stocks.

## 2 SEBI, BSE and Badla

Badla was a form of forward trading on the Bombay Stock Exchange for the 91 companies in the A group. On 12 March 1994, SEBI announced new norms which would govern badla. These norms were motivated by the desire to improve the reliability of the trading process, and eliminate the periodic breakdowns of trading owing to "payments crises" which used to plague the BSE from time to time. While this article is concerned with measuring the impact of badla, and not with microstructure issues surrounding trading on the BSE floor with or without badla, we may summarise the changes imposed by SEBI as follows: the "squaring off" of long and short positions between brokers was disallowed, and margin requirements were symmetrically applied for both long and short positions.

These requirements were unacceptable to the BSE community, and badla has hence been absent in the period from 12 March 1994 onwards. Thus from 12 March 1994 onwards, beyond the horizon of one fortnightly settlement, trades on the BSE only take place for delivery.

Roughly a year has elapsed since this system was introduced, and it is time to examine the evidence on how it has made a difference. Volumes on the A group have fallen sharply, and many observers have commented on markets being very thin as a consequence of the new trading system.

One reason for studying volatility is that when markets lack depth, the trading activities of market participants are more likely to affect prices sharply

paper.

and generate excess volatility. By studying the volatility of daily returns, we can learn about the depth (or lack thereof) of the underlying markets.

The larger question "Should badla in its old incarnation have been banned, and should it be revived?" is a question in normative economics, and requires a putting together of the *costs* and *benefits* of badla. That larger problem is not addressed here. This paper is an exercise in positive economics, and is exclusively concerned with quantifying the *costs* of eliminating badla.

The issues connected with designing a healthy microstructure of trading, one that is relatively free of the payments crises that have periodically erupted on the BSE, are not considered here; we only focus on the quantifying the impact of eliminating badla. It is hoped that this quantification of the costs of eliminating badla would prove useful in evaluating the larger policy issues at stake.

# 3 Liquidity and value

Did the end of forward trading affect asset prices? Even though liquidity has nothing to do with the expected present value of the cashflow of a company, other things being equal, the equilibrium rate of return on stocks would have to be higher when economic agents perceive that the liquidity of stocks is poor. The existence of this liquidity premium is expected from finance theory, and Eleswarapu & Krishnamurthi (1994) find some empirical evidence of a liquidity premium on the BSE – stocks which trade less frequently offer higher returns.

This implies that if a new trading system came about which improved liquidity, then stock prices would make a one–time upward jump, reflecting the lower required rate of return on stocks. Conversely, to the extent that liquidity in A group securities worsened through the absence of speculative traders, we would expect this to have generated a reduction (other things being equal) in asset values in the A group.

Many observers have implicitly attributed the poor returns on the BSE Sensex over the recent months to the ban on badla. This is inconsistent with our understanding of the liquidity premium. The negative returns of a few percent shortly after 12 March 1994 were partly related to the liquidity premium, but not the 33% decline in the BSE Sensex over the months September 1994 to March 1995.

There are many other reasons why A group securities may have fared poorly in the year after 12 March 1994, and we will make no attempt to decipher these in an attempt to quantify the role played by the liquidity premium.[2]

[2]We cannot use the empirical results of Eleswarapu & Krishnamurthi (1994) to estimate

# 4 Volatility of BSE Sensex

At the simplest, we could measure the volatility of the BSE Sensex for the year preceding 12 March 1994 and the year following 12 March 1994. This gives us the following results:

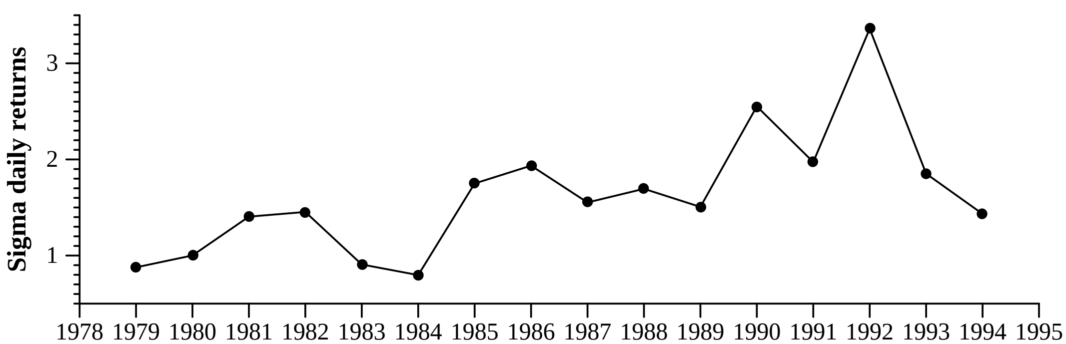
**Table 1** Volatility of BSE Sensex, before and after

| Period | Trading Days | Standard Dev. of Daily Returns |
|---|---|---|
| Before | 217 | 1.95 |
| After | 231 | 1.14 |

These results indicate that the volatility of the BSE Sensex fell, sharply, in the year following 12 March 1994, as compared with the year preceding it. The volatility reduction amounts to roughly 0.7 percentage points per day.

However, this is not conclusive evidence, because it could be the case that the volatility of the BSE Sensex varies over time for reasons unrelated with the new trading system. Hence we take a longer view of the volatility of the BSE Sensex, organised by calendar year.

**Figure 1** Annual standard deviations of daily returns on BSE Sensex




Our objective here is to get a sense of scale about the kind of variability observed in the volatility of the BSE Sensex over any one–year period. In Table 1, we saw volatilities of 1.95% per day and 1.14% per day. Using this long time-series of annual volatilities of the BSE Sensex, we see that the

the magnitude of this effect, since they work in terms of trading frequency as a measure of liquidity, and trading frequency appears to be a poor metric for expressing the loss in liquidity on A group companies in the year after 12 March 1994 – trading frequency in the period after 12 March 1994 is actually slightly higher than in the period before.

volatility of 1.95% per day in the year preceding 12 March 1994 was representative of the post-1985 period, while the volatility in the year following 12 March 1994, at 1.14% per day, classifies as amongst the lowest volatilities in the post-1985 period.

The annual time-series can be summarised in terms of the following four major phases:

**Table 2** Volatility of BSE Sensex: Four Periods

| Period | N | Sigma |
|---|---|---|
| Pre 1986 | 1281 | 1.22915 |
| Post 1986, prescam | 1135 | 1.90769 |
| Scam | 187 | 3.13625 |
| Postscam, pre 12 Mar | 370 | 2.10228 |
| Post 12 Mar 1994 | 231 | 1.14238 |

This shows that the volatility of the BSE Sensex has dropped to one of the lowest levels in the post-1986 period in the 231 trading days which have elapsed after 12 March 1994.

## 5 Volatility at the individual security level

The volatility of the BSE Sensex is not a good measure of the volatility of the stock market in our present context, because returns on the BSE Sensex represent an averaging over the underlying 30 securities which make up the BSE Sensex. It could well be the case that while the individual securities have become jittery, the overall portfolio returns exhibit stability. This would especially be the case with the kind of day-to-day fluctuations caused by thin markets – these would be uncorrelated across securities and the returns on the BSE Sensex portfolio would diversify these fluctuations away.

Also, the market index measures economy-wide news, and a lowered volatility of the BSE Sensex could just suggest that there was less news affecting the macroeconomy in the year following 12/3/1994. One important piece of evidence pointing in this direction is the union budget: there was one union budget in the year before 12/3/1994 but none falling within the year following it. This would tend to generate reduced volatility in the market index.

Hence we need to work at an individual security level. At the simplest, we can just compare the variance of returns on the A group companies in the year before 12 March 1994 as compared with the year following it.

**Table 3** Total risk on A group, before and after

| | The Year Before 12/3/94 | The Year After |
|---|---|---|
| Mean | 3.252 | 2.282 |
| Median | 3.215 | 2.194 |
| Std. Devn. | 0.789 | 0.636 |

Each of the numbers shown in this table are averages over 91 companies. Thus we see that the volatility of daily returns of A group companies has fallen from an average of 3.252% per day to 2.282% per day (a gain of roughly one percentage point per day.

These results are not conclusive because they show the *total* variability of returns on the A group companies. Part of this variability is caused by economy-wide factors, and part of this variability is security-specific. It could just be the case that macroeconomic news over one period generated greater fluctuations in the overall market as compared to the other period. This would contaminate our results.

Hence we focus on daily *unsystematic risk*, or the subcomponent of total variability which is unrelated to fluctuations of the market model. This is based on estimating the market model using daily returns data.

**Table 4** Unsystematic risk on A group, before and after

| | The Year Before 12/3/94 | The Year After |
|---|---|---|
| Mean RMSE | 2.56 | 2.05 |
| Standard deviation | 0.68 | 0.66 |

This shows a small reduction in unsystematic risk over this period, a reduction of 0.5% per company on average.

Eleswarapu & Krishnamurthi (1995) (henceforth EK95) approach the entire question of the impact of badla in the following manner. They create a sample of 74 companies from the A group and 86 companies from the B group, and estimate a model for the unsystematic risk experienced by these 160 companies in calendar 1992. They estimate models of unsystematic risk after controlling for size and trading frequency, and find that even after controlling for size and trading frequency, the unsystematic risk of A group companies is smaller. They attribute this difference to forward trading.

Our experimental design is motivated by the observation that the true model relating unsystematic risk may be related to explanatory variables in a more complex way than the models estimated in EK95, and their result may suffer from omitted variable bias. We will replicate their results, and discuss the difficulties in their interpretation, in Appendix B.

Our experimental design exploits the unique circumstances which we face today: namely the passage of a full year without badla. This allows us to explicitly focus on the impact of badla, on the margin.

# 6 Volatility as compared with control sample

The results above, which compare the unsystematic risk of A group companies before and after 12 March 1994, are not conclusive because it could just be the case that the flow of news at the *security* level was lesser in one period as compared to another. For example, there has been no budget in the period from 12 March 1994 to 12 March 1995, whereas there was one budget in the period from 12 March 1993 to 12 March 1994. To the extent that the budget generates news at the individual company or industry level, it would generate increased unsystematic risk which would make us think that unsystematic risk in the period after 12 March 1994 has been reduced more sharply than was really the case.

To control for this, we will think in terms of a "natural experiment". We will invent a sample of 91 B group companies[3] which is "matched" with the 91 A group companies on two parameters: market capitalisation and trading frequency. Details about this matching algorithm are presented in Appendix A. While the matching is not perfect, because there are not enough large B group companies to match up with the high market capitalisation A group companies, we have attempted to find the "best" sample of 91 B group companies in terms of being like the A group companies on the parameters of market capitalisation and trading frequency.

We can now visualise the "experiment" as follows. For one year (i.e. 12 March 1993 to 12 March 1994) we observed both sets of companies. On 12 March 1994, the trading system was changed for one sample (the A group companies) and left unchanged for the other. Now, we observe both samples for one year. Totally, this gives us four groups of observations of volatility: two samples for a year before 12 March 1994 (one with the old mechanism of forward trading and one without) and two samples for a year after 12 March 1995 (both without badla).

If there were economy-wide factors affecting volatility, such as the lack of a budget in the period from 12 March 1994 to 12 March 1995, they would

[3]We will abuse the term "B group" companies, as is common practice, to mean all companies other than the A group.

affect the control sample (i.e. the B group companies, for whom 12 March 1994 was a non-event) and we would get a benchmark estimate of the change in volatility that would have taken place "in any case".

We would thus learn about the impact of the change in trading system by comparing the reduction in unsystematic risk for the A group companies as compared with the reduction in unsystematic risk for the B group companies.

**Table 5** Unsystematic risk of the two samples, before and after

| | Before 12/3/94 | After 12/3/94 | Change |
|---|---|---|---|
| A companies | 2.559 | 2.046 | -0.513 |
| B companies | | | |
| All B companies | 4.567 | 3.360 | -1.206 |
| After rejecting 3 outliers | 4.191 | 3.239 | -0.952 |

We will prefer to work with the version after outlier rejection, which leaves us with a sample of 88 companies out of the original matched sample of 91 B group companies. It says that the economy–wide flow of news in the period after 12 March 1994 was slower, for the unsystematic risk on B group companies (for whom nothing changed on 12/3/94) dropped by 0.952% per day on average in the year after 12/3/94 as compared with the previous year. If the A group companies had experienced a similar reduction in unsystematic risk, they would have gone to a level like 1.607, instead of which they actually reached 2.046. The gap between the two reductions (0.95 - 0.51, or 0.44% per day on average) is the part that might roughly be attributed to the event of 12 March 1994; i.e., we can think that the event of 12 March 1994 increased daily volatility by 0.44%. This would be a rather robust answer to our question if our sample of B group companies was truly a good matched sample.

An increased daily unsystematic risk of 0.44 percentage points sounds small. However, when returns are white noise, the standard deviations of returns blows up with the interval of measurement as $\sqrt{T}$. For example, if we consider annual returns, and assume that there are roughly 225 trading days in a year, then an increase of daily volatility of 0.44 percentage points translates to an additional annual standard deviation of 6.6 percentage points.

Is this increased unsystematic risk caused by thin markets? If so, it could be the case that the additional jitter is of a relatively mean-reverting variety – where big orders move prices up and down each day, but prices revert to underlying means over the following days. In that case, the impact of additional daily volatility of 0.44 precentage points would work out to an increase in annual standard deviation of less than 6.6 percentage points.

## 6.1 One difficulty in interpretation

We should attenuate these results with a difficulty, one that is easiest to understand in terms of this simple presentation of sample means, though it applies equally to the regression models presented ahead. The period after 12 March 1994 may have been a non-event for the B group companies in terms of the microstructure of trading, but it did mark the starting point of a enormous rise in trading volumes on the B group. Some of the reduction in B group volatility seen here is hence the impact of stabilising speculation, and some of it reflects the slower rate of flow of news.

To the extent that this is the case, our estimate of the impact of badla (increased daily unsystematic risk of 0.44%) is an overestimate. We should keep this in mind when interpreting the regression results ahead also, for the same bias will be present in those results as well.

# 7 Controlling for size and trading frequency

The difficulty with the above results derives from two difficulties with our matched sample:

- Our matching procedure worked with the assumption that market capitalisation and trading frequency are the major factors underlying unsystematic risk. This assumption could well be wrong, in which case the matched sample would be a poor one.
- Even in terms of the metric of closeness defined for our matching process, i.e. in terms of market capitalisation and trading frequency, our "matched sample" of B group companies is not a true matched sample, because B group companies which are closely like the A group companies do not quite exist. The matched sample contains companies which are typically smaller than the A group companies, and which do slightly worse on trading frequency.

As proof that some difficulties of this sort lurk in our matched sample, observe that in the period after 12 March 1994, when the microstructure of trading for both A and B group companies was relatively similar, the unsystematic risk seen for the two groups is quite different. Part of the difference in volatility seen above could just be due to the fact that our B group companies are smaller and less diversified than the A group companies, and trade less frequently.[4] But a significant part of this difference appears to be unexplained: A group companies seem to have lower volatility even after we control for size and trading frequency.

[4]We explored the role of "floating stock", or the percentage shareholding and absolute market capitalisation controlled by agents other than promoters, group companies and financial institutions. This parameter seems to have no effect on unsystematic risk.

## 7.1 Experimental Design

We create a dataset with two observations each (one for the year before 12 March 1994 and another for the year after) for each of the 91 A group companies and each company in the matched sample of B group companies, thus giving us 364 observations in all. Some of these observations are influential, and we symmetrically trim six observations: three with unusually high and three with unusually low volatility, thus leaving us with an estimation sample of 358 observations. For each observation, we create the following variables:

1. `agrp`, a dummy variable which is true if the company belongs to the A group,
2. `tfreq`, trading frequency in the year
3. `ls`, log of the mean market capitalisation in the year,
4. `rmse`, the standard deviation of unsystematic risk in the year,
5. `undiv`, a measure of the extent to which a company is undiversified, defined as the herfindahl index calculated off the shares of the two digit product codes in the sales of the company. High values of undiv correspond to companies where a small number of two-digit product codes account for a large fraction of the sales of the company.
6. `period2`, a dummy variable which is true in the second year (i.e. the period after 12 March 1994).
7. `badla`, a dummy variable which is true for A group companies in the first period.
8. `vpbdit`, the volatility of growth in profit before depreciation, interest and taxes. This volatility is derived from the **CIMM** database produced by CMIE.[5]

Summary statistics for these variables are displayed here:

[5]There were 40 companies where this volatility was not observed. Missing data here is very likely to have economic significance; the volatility of PBDIT growth in the **CIMM** database is not available when the company is observed for too few years, or when even one of the PBDIT observations is negative. The first of these possibilities reflects estimation risk as faced by agents, and the second of them is associated with downside risk. Both these reasons for `vpbdit` being missing are hence likely to generate excess unsystematic risk. Hence, while we attempt imputation of `vpbdit`, we also create a dummy variable `impv` to keep track of every imputation of this sort. This dummy variable appears in our finished model (Model M6 ahead) with the correct sign and strong statistical significance.

Imputation for missing values of `vpbdit` was doing using predictions from a regression of `vpbdit` on log size and membership in the A group. The model used was vpbdit = 0.49 - 0.06 log size + 0.12 Agroup, which has a R2 of 10%. Some of these predictions were negative, which is normally impossible, but they were not modified further.

**Table 6** Summary Statistics about Sample

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| agrp | 358 | .5027933 | .500692 | 0 | 1 |
| tfreq | 358 | 98.34165 | 1.817265 | 84.7926 | 100 |
| rmse | 358 | 3.009705 | 1.182801 | 1.0327 | 8.1941 |
| mktcap | 358 | 873.9453 | 1541.48 | 34.0708 | 15511.8 |
| undiv | 358 | .8355616 | .2002397 | .2893194 | 1 |
| vpbdit | 358 | .1784499 | .2031226 | -.0429258 | .9524 |
| period2 | 358 | .5 | .5006998 | 0 | 1 |
| ls | 358 | 6.108639 | 1.067827 | 3.528441 | 9.649356 |
| negpat | 358 | .1536313 | .3610996 | 0 | 1 |
| badla | 358 | .2541899 | .4360143 | 0 | 1 |

Two such datasets were constructed, using the RMSE of unsystematic risk of both daily returns and weekly returns.

## 7.2 Measuring the impact of badla

At a heuristic level, our approach may be thought of as follows. We know that the model for RMSE in terms of log size and trading frequency is misspecified, because the noninformative dummy variable `Agroup` is strongly significant even after our best attempts to control for exogenous variables. This renders infeasible the purely cross-sectional attempt to learn the impact of badla. We will hence work with regressions using our $2 \times 2 \times 91$ sample, which pools observations of four kinds: the 91 A group companies before and after 12 March, and the matched group of 91 B group companies before and after 12 March.

**Table 7** Models of `rmse` using daily returns

| | Model M5 | Model M6 |
|---|---|---|
| Intercept | 4.2065 | 12.9581 |
| | (0.093) | (2.372) |
| A group | -1.1537 | -0.857 |
| | (0.131) | (0.118) |
| Period 2 | -0.9826 | -0.7731 |
| | (0.131) | (0.117) |
| badla | -0.4935 | -0.2496 |
| | (0.185) | (0.159) |
| Log size < median | | -0.5895 |
| | | (0.093) |
| Log size > median | | -0.2618 |
| | | (0.065) |
| T. freq | | -0.058 |
| | | (0.023) |
| Undiv < median | | -0.1489 |
| | | (0.297) |
| Undiv > median | | 3.2456 |
| | | (1.626) |
| Vpbdit | | 0.3725 |
| | | (0.208) |
| impv | | 0.3176 |
| | | (0.143) |
| $R^2$ | 0.4549 | 0.6205 |
| Adj. $R^2$ | 0.4502 | 0.6095 |
| N | 358 | 358 |

Model M5 is conceptually equivalent to our sample means of Table 5. It is tantamount to saying that A group volatilities are lower (even though we may not know why), that volatility in the period after 12 March 1994 was lower (even though we may not know why), and the marginal impact of badla is estimated at -0.49% per day. This coefficient differs slightly from our estimate of 0.44% based on Table 5 because of slight differences in the samples. This regression also gives us statistical inference on the coefficient of `badla`, and here we find that it is statistically significant.[6]

The picture is considerably altered in Model M6, our best effort at explaining inter-company heterogeneity in daily unsystematic risk.[7] We find

[6] If we estimate a model using the regressors of EK95 (not shown here), the coefficient of badla is -0.277, with a $t$ statistic of 1.7.

[7] The coefficient on `badla` is drastically diminished in statistical and economic signifi-

that the impact of size shows diminishing returns to scale: the coefficient of log size is much sharper below median size as compared with above median size. The coefficient of the diversification measure is essentially zero below its median, and significant above the median.[8] Finally, higher volatility of PBDIT growth is associated with increased unsystematic risk, and the companies where the **CIMM** database was unable to provide a VPBDIT number are associated with significantly higher unsystematic risk.

Overall, Model M6 describes the data much better than Model M5, but it still contains statistically significant dummy variables `Agroup` and `Period2`, both of which reflect our ignorance of the true data generating process underlying unsystematic risk.

Our estimate of `badla`, in this experimental design, is relatively robust to the difficulties in knowing the true model, and we find that the effect of badla is to diminish daily unsystematic risk by 0.25%, and that this coefficient is not very statistically significant. A 95% confidence interval for the impact of badla would run from a reduction in daily unsystematic risk of 0.56% to an increase in unsystematic risk of 0.06%. For the reasons mentioned in Section 6.1, this estimate of the impact of badla upon volatility is likely to be an overestimate.

We will repeat the specifications of models M5 and M6 using weekly returns data.[9]

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cance the moment `ls` is introduced into M5, and stays that way across all the specifications explored. This suggests that the major factor underlying the statistical and economic significance of the `badla` coefficient in Model M5 is the inability of the matching process to truly replicate the size of the A group companies in the matched sample.

[8]A test of the hypothesis that the two slopes in log size are equal is rejected with a prob value of 0.012. A test of the hypothesis that the two slopes in `undiv` are equal is rejected with a prob value of 0.0647.

[9]If we estimate a model using the regressors of EK95, (not shown here) the coefficient of badla is -0.145, with a $t$ statistic of 0.477.

**Table 8** Models of `rmse` using weekly returns

| | Model M7 | Model M8 |
|---|---|---|
| Intercept | 7.683 | 11.5997 |
| | (0.165) | (4.445) |
| A group | -1.9941 | -1.4938 |
| | (0.233) | (0.222) |
| Period 2 | -1.5383 | -1.401 |
| | (0.233) | (0.22) |
| badla | -0.3553 | -0.1253 |
| | (0.328) | (0.298) |
| Log size < median | | -0.6736 |
| | | (0.173) |
| Log size > median | | -0.4381 |
| | | (0.12) |
| T. freq | | 0.0044 |
| | | (0.044) |
| Undiv < median | | -0.3385 |
| | | (0.554) |
| Undiv > median | | 5.7104 |
| | | (3.015) |
| Vpbdit | | 0.8309 |
| | | (0.39) |
| impv | | 0.8898 |
| | | (0.267) |
| $R^2$ | 0.4062 | 0.537 |
| Adj. $R^2$ | 0.4012 | 0.5237 |
| N | 359 | 359 |

Trading frequency appears to be unimportant on a horizon like a week. The volatility of PBDIT growth and above-median undiversification are now strongly significant. Our inability to find a good model for unsystematic risk stands, with strong coefficients for the noninformative dummy variable `Agroup`. The coefficient of badla is now numerically and statistically close to 0. For the reasons mentioned in Section 6.1, this estimate of the impact of badla upon volatility is likely to be an overestimate.

Thus the excess daily unsystematic risk of the order of 0.25% seen in Model M6 does not blow up by a factor of roughly $\sqrt{5}$ (for five days in a week), but is instead mostly diminished over a horizon of a week. This suggests that the *incremental* volatility introduced by the elimination of badla is of a strongly mean-reverting variety, over a horizon of a few days.

This suggests that the elimination of badla is associated with short-run deviations from market efficiency, on a horizon of a few days. We will now explore the question of market efficiency.

# 8 Impact upon market efficiency

At the outset of this paper, we emphasised that economic theory does not guide us on the question of how much volatility is optimal. Instead, the primary metric we have in a welfare economics sense is market efficiency. Even if market efficiency were ensured, reductions in volatility are only welfare-improving at the level of individual agents when we think in terms of the Sharpe's ratio of the full *portfolio* held by a given economic agent; considerations in terms of the unsystematic risk of individual securities, as have been conducted here, are simply not relevant.[10]

In the case of the event of 12 March 1994, for reasons not entirely unconnected with the end of forward trading in A group companies, there was a massive increase in trading volume on the B group. To the extent that nonsynchronous trading and poor trading volume is associated with market inefficiency, we would expect a reduction in violations of market efficiency for the B group companies.

Thomas (1995) studies market efficiency on the BSE from the viewpoint of returns predictability and weak-form efficiency, and finds that many deviations from market efficiency can be identified in a *statistical* sense, but these are often not violations of market efficiency in an economic sense because the transactions costs of trading on the BSE are high enough to preclude arbitrage. This same caveat applies in interpreting the following results. To the extent that trading costs may have stayed roughly constant across the transition, however, we would be able to attribute the *change* in market efficiency to the elimination of badla. Thomas (1995) also finds that deviations from non-forecastability of the BSE Sensex are the most pronounced in the post-scam period (i.e. after 29 May 1992) as compared with the preceding history (i.e. 1 April 1979 to 28 May 1992). It will be interesting for us to decompose the post-scam period and examine the extent of breakdowns from market efficiency before and after 12 March 1994.

We will focus on the autocorrelation function calculated off the year–long time–series of daily and weekly returns. Under market efficiency, all the autocorrelations should be statistically insignificantly different from 0. We will count the number of rejections at the 90%, 95% and 99% level of

[10] There may exist investors who hold portfolios composed of very few securities: for them unsystematic risk of individual securities which makeup their portfolio may directly affect their portfolio risk. In this case, volatility reductions in the sense of unsystematic risk might improve their Sharpe's ratio.

significance[11] for the autocorrelations.

Some amount of spurious rejections, i.e. type I errors, are inevitable. For example, in the first block of results, which use the first 20 autocorrelations, we are doing tests on 91*20 or 1820 numbers. At the 99% level of significance, we would expect 18 or so rejections even if the null hypothesis were true. Totally, we would expect 182 rejections at a 90% or higher level of significance even if the null hypothesis (that all $\rho$s are 0) were true.

## 8.1 Daily returns

In the following table, the entry for "Rejections at 90%" shows the number of $\rho$s where $H_0 : \rho = 0$ was rejected at the 90% level of significance but not at the 95% or 99% levels.

**Table 9** Daily autocorrelations: Frequencies of rejection of $H_0 : \rho_k = 0$

| | Expected | A group | | B group | |
|---|---|---|---|---|---|
| | under $H_0 : \rho_k = 0$ | Before | After | Before | After |
| First 20 lags | | | | | |
| No rejection | 1638 | 1613 | 1584 | 1536 | 1585 |
| Rejections at 90% | 91 | 86 | 91 | 119 | 102 |
| Rejections at 95% | 73 | 80 | 98 | 112 | 86 |
| Rejections at 99% | 18 | 41 | 47 | 53 | 47 |
| First 10 lags | | | | | |
| No rejection | 819 | 782 | 753 | 740 | 772 |
| Rejections at 90% | 45 | 53 | 54 | 65 | 55 |
| Rejections at 95% | 36 | 43 | 63 | 62 | 44 |
| Rejections at 99% | 9 | 32 | 40 | 43 | 39 |

Let us study the block of results for daily returns with 20 lags. In the ideal efficient market, we would expect 182 rejections at the 90% or greater level of significance through type I errors alone, this should give 1638 coefficients with no rejection. In the year before 12 March 1994, the A group companies come quite close to this, with 1613 coefficients where $H_0$ could not be rejected. This has worsened to 1584 coefficients in the period after. The situation for

[11] Our inference procedures for the ACF use a quasi-bootstrap procedure, where the distribution of the test statistic under the null hypothesis of market efficiency is obtained by scrambling the order of the time series $10^4$ times and calculating the test statistic for each generated sample. This gives us superior inference as compared with either assuming normality of the data generating process underlying returns, or falling back upon asymptotics.

B group companies has improved from only 1536 coefficients where $H_0$ could not be rejected in the year before to 1585 coefficients in the year after.

The most striking observation from these tables is the similarity between A and B group companies in the period after 12 March 1994, as opposed with the differences observed in the preceding year. There were 1584 $\rho$s with no rejection in the A group and 1585 in the B group with no rejection. If we consider the most stringent rejection, at the 99% level of significance, both groups have 47 rejections (a number which is quite different from the 18 type I errors that we would have expected under the null).

This suggests that in the case of market efficiency, our matching strategy has indeed been able to produce a sample such that under identical microstructure, both the A group companies and the B group companies have similar market efficiency. In this case, we can confidently interpret the *changes* in market efficiency in each category as having been caused by badla. In the A group, we see more rejections of the null.

The bulk of these rejections, and much of the change in rejection frequency, is in the short–horizon, as seen in the results for the first 10 lags. In the A group, rejections at 99% among the first 20 lags worsened slightly from 41 to 47, a difference that is more than accounted for by the worsening seen in the first 10 lags, where the rejection frequency went from 32 to 40.

## 8.2 Weekly returns

**Table 10** Weekly autocorrelations: Frequencies of rejection of $H_0 : \rho_k = 0$

| | Expected | A group | | B group | |
|---|---|---|---|---|---|
| | under $H_0 : \rho_k = 0$ | Before | After | Before | After |
| First 5 lags | | | | | |
| No rejection | 410 | 398 | 404 | 379 | 402 |
| Rejections at 90% | 23 | 34 | 27 | 36 | 27 |
| Rejections at 95% | 18 | 19 | 21 | 33 | 20 |
| Rejections at 99% | 5 | 4 | 3 | 7 | 6 |

The situation is quite different when we work with weekly returns data, where *both* groups experience fewer rejections of the null. Under $H_0$, i.e. perfect market efficiency, we would have expected 410 coefficients where there was no rejection. In practise, the no-rejection frequency in the period after 12 March 1994 was 404 for the A group and 402 for the B group. In the case of weekly returns data, there has been a major reduction in the rejection frequency for the B group; this is likely to be a reflection of the increased trading volume in the B group in the year after 12 March 1994.

The simple hypothesis "Market efficiency is purely a product of trading volume" is not supported by these results. In the case of A companies, where trading volume dropped sharply and speculative trading has been diminished, market efficiency in daily data has worsened and market efficiency in weekly data has improved slightly. In the case of B companies, where market microstructure has not changed but trading volume has risen sharply, market efficiency in both daily and weekly data has improved sharply. This suggests that both trading volume and market microstructure play a role in determining market efficiency.

Thus badla appears to be somewhat beneficial for market efficiency on a short horizon like a few days – without badla, both samples had similar frequencies of rejection of the null (even though B group companies had experienced a massive increase in trading volume) and with badla, A group companies used to have substantially fewer rejections of the null. The worsening of market efficiency associated with the end of badla is concentrated in short-horizon autocorrelations.

These results are completely consistent with our earlier results, based on comparing Model M6 and Model M8, that increased unsystematic risk is weakly associated with the end of badla in daily returns but absent in weekly returns.

# 9 Conclusion

We have approached the question of volatility on the BSE from many angles, the most important of which was the strategy of comparing the volatility reduction of the A group companies against a matched control sample.

We avoid working with the market index since it may diversify away firm-specific fluctuations introduced through thin trading. A simple comparison of volatility before and after 12/3/1994 is misleading because the flow of news after 12/3/1994 seems to have been significantly lesser, this gives the misleading impression that volatility has dropped sharply after 12/3/1994 as a *consequence* of banning badla, in fact volatility of B group companies (which were unaffected by the ban) has dropped even more sharply in the period following 12/3/1994. A cross-sectional view obtained using data before badla was banned is clouded by the fact that A group companies seem to have systematically lower volatility, even after controlling for all known independant variables.

Hence our experimental design uses a matched sample of A and B group companies, for a year before and after badla, in order to measure the impact of badla.

We found that the ban of badla has introduced an small incremental daily unsystematic risk of roughly 0.25 percentage points, and essentially had no impact upon the weekly unsystematic risk. The statistical significance of this estimate is weak, especially in the light of the argument suggesting that this estimate is biased upwards. We found that badla is beneficial for short–horizon market efficiency: the non-forecastability of daily returns of A companies has worsened in the year following 12 March 1994. This effect is restricted to the short horizon: there is no serious change in the degree of non-forecastability of weekly returns.

# Appendix A: Creation of the Matched Sample

We face a universe of 4193 securities, of which 91 are A group companies. We would like to identify 91 of the B group companies which would form a "matched sample" to the A group companies, to the best extent possible.

We will focus on the parameters of size (market capitalisation) and trading frequency since these have the most impact upon the depth of markets. If, in the ideal case, we are able to obtain a sample of B group companies which exactly mimics the A group companies on both these parameters, then it would constitute an ideal control sample. Not all B group companies are eligible here, and the sample selection works as follows:

**Table 11** Sample Attrition of B Companies

| Reason | Dropped | Survived |
|---|---|---|
| Starting point (all companies) | | 4102 |
| Require listing atleast 500 days ago | 2082 | 2020 |
| Require atleast 200 trading days | 562 | 1458 |
| Dropped since market. cap. unknown | 30 | 1428 |

Thus we are left with a space of 1428 B group companies within which we search for the matched sample. We will now choose to work with log size rather than size because log size is normally distributed. We start by creating two variables ZLS and ZTF which are standardised log size and standardised trading frequency. Both variables are thus measured in standard deviations. The sample moments required for standardisation are calculated over both A and B group companies.[12] Given any two companies $A$ and $B$, we define a metric which gives equal importance to both size and trading frequency: the Euclidian distance from $(\mathrm{ZLS}_a, \mathrm{ZTF}_a)$ and $(\mathrm{ZLS}_b, \mathrm{ZTF}_b)$.

The matching algorithm now proceeds as follows. We sort the A group companies by size, and start from the largest A company (Reliance). We search the universe of eligible B group companies, looking for that B group company which is the "closest" to Reliance by this metric. The answer happens to be SBI. Reliance is the point $(3.23, 0.91)$ in standardised log size – standardised trading frequency space, SBI is the point $(3.17, 0.78)$, and SBI is the closest of all B group companies to Reliance. In similar fashion, we travel down the list of A group companies, searching for the "closest" B group company for each of the A group companies. The results of this matching process are shown in the next two pages.

Broadly speaking, the matched sample is a good control sample in the dimension of trading frequency, and a relatively poor control sample in the dimension of size. Hence, we cannot assume that we have controlled for the effect of size by comparing the A group companies against the matched sample.

[12]Log size is mean 3.719 and standard deviation 1.709, and trading frequency is mean 83.3 and standard deviation 17.2.

The first line here shows that Reliance was matched with SBI. Reliance has a market capitalisation of Rs.$10262 \times 10^7$ and a trading frequency of 99%. The standardised log size is 3.23 and the standardised trading frequency is 0.91. SBI has a standardised log size of 3.17 and a standardised trading frequency of 0.78. The distance between these two companies is 0.146.

This is a reasonably good match – in the case of the next company (Hindustan Lever), the best available match (SAIL) has a distance of 0.37.

| A Company | Size | TF | z_LS | z_TF | B Company | Size | TF | z_LS | z_TF | Distance |
|---|---|---|---|---|---|---|---|---|---|---|
| RELIANCE INDU | 10262 | 99 | 3.23 | 0.91 | STATE BANK OF | 9358 | 96 | 3.17 | 0.78 | 0.146 |
| HINDUSTAN LEV | 8049 | 98 | 3.09 | 0.89 | STEEL AUTHORI | 15146 | 98 | 3.46 | 0.89 | 0.370 |
| TATA IRON& S | 8031 | 99 | 3.08 | 0.92 | INDIAN PETROC | 4034 | 97 | 2.68 | 0.82 | 0.415 |
| I.T.C. LTD | 7221 | 99 | 3.02 | 0.93 | RANBAXY LABOR | 2741 | 98 | 2.46 | 0.86 | 0.572 |
| TATA ENGINEER | 6375 | 98 | 2.95 | 0.90 | ASEA BROWN BO | 2050 | 97 | 2.29 | 0.82 | 0.669 |
| LARSEN & TO | 5850 | 99 | 2.90 | 0.93 | MANGALORE REF | 1725 | 99 | 2.18 | 0.93 | 0.715 |
| BAJAJ AUTO LT | 5452 | 98 | 2.86 | 0.89 | RELIANCE CAPI | 1667 | 98 | 2.16 | 0.90 | 0.693 |
| COLGATE-PALMO | 5440 | 98 | 2.86 | 0.91 | SAW PIPES LTD | 1399 | 98 | 2.06 | 0.89 | 0.795 |
| GRASIM INDUST | 4664 | 98 | 2.77 | 0.89 | PRAKASH INDUS | 1392 | 98 | 2.06 | 0.89 | 0.707 |
| HINDALCO INDU | 4524 | 98 | 2.75 | 0.88 | INGERSOLL-RAN | 1294 | 98 | 2.02 | 0.88 | 0.732 |
| TATA CHEMICAL | 4264 | 99 | 2.71 | 0.91 | ARVIND MILLS | 1369 | 93 | 2.05 | 0.62 | 0.726 |
| BROOKE BOND L | 3976 | 98 | 2.67 | 0.90 | C I P L A LTD | 1229 | 97 | 1.99 | 0.82 | 0.693 |
| INDUSTRIAL CR | 3646 | 99 | 2.62 | 0.92 | USHA ISPAT LT | 1202 | 98 | 1.97 | 0.88 | 0.651 |
| ASSOCIATED CE | 3598 | 99 | 2.61 | 0.92 | NAGARJUNA FER | 1149 | 98 | 1.95 | 0.89 | 0.669 |
| CASTROL INDIA | 3338 | 98 | 2.57 | 0.89 | BALLARPUR IND | 1189 | 96 | 1.97 | 0.75 | 0.621 |
| CENTURY TEXTI | 2722 | 98 | 2.45 | 0.86 | JINDAL IRON | 1024 | 98 | 1.88 | 0.87 | 0.572 |
| ESSAR GUJARAT | 2462 | 99 | 2.39 | 0.94 | JINDAL STRIPS | 1021 | 98 | 1.88 | 0.91 | 0.516 |
| NESTLE INDIA | 2443 | 98 | 2.39 | 0.88 | UNITED PHOSPH | 1008 | 98 | 1.87 | 0.87 | 0.518 |
| INDIAN HOTELS | 2395 | 98 | 2.38 | 0.90 | DR. REDDY'S L | 918 | 98 | 1.82 | 0.91 | 0.561 |
| HOUSING DEVEL | 2303 | 98 | 2.35 | 0.89 | MADRAS CEMENT | 1149 | 91 | 1.95 | 0.51 | 0.556 |
| MOTOR INDUSTR | 2283 | 98 | 2.35 | 0.86 | KOTAK MAHINDR | 882 | 99 | 1.79 | 0.92 | 0.561 |
| SMITHKLINE BE | 2014 | 97 | 2.28 | 0.81 | CORE HEALTHCA | 876 | 96 | 1.79 | 0.75 | 0.490 |
| B S E S LTD | 1929 | 98 | 2.25 | 0.89 | ISIBARS LTD | 850 | 98 | 1.77 | 0.90 | 0.480 |
| INDIAN RAYON | 1785 | 98 | 2.20 | 0.88 | SESA GOA LTD | 804 | 98 | 1.74 | 0.86 | 0.467 |
| TATA TEA LTD | 1751 | 98 | 2.19 | 0.89 | NICHOLAS PIRA | 765 | 97 | 1.71 | 0.82 | 0.491 |
| MAHINDRA& MA | 1750 | 98 | 2.19 | 0.90 | PROCTER & GA | 721 | 98 | 1.67 | 0.86 | 0.521 |
| COCHIN REFINE | 1689 | 98 | 2.17 | 0.91 | CROMPTON GREA | 720 | 97 | 1.67 | 0.80 | 0.513 |
| STERLITE INDU | 1660 | 98 | 2.16 | 0.89 | FINOLEX CABLE | 683 | 98 | 1.64 | 0.90 | 0.520 |
| GUJARAT AMBUJ | 1646 | 98 | 2.16 | 0.89 | NAHAR SPINNIN | 683 | 98 | 1.64 | 0.86 | 0.515 |
| GREAT EASTERN | 1616 | 99 | 2.15 | 0.93 | SANDOZ (INDIA | 656 | 98 | 1.62 | 0.86 | 0.533 |
| SIEMENS LTD | 1477 | 98 | 2.09 | 0.90 | TITAN INDUSTR | 634 | 98 | 1.60 | 0.89 | 0.495 |
| INDIAN ALUMIN | 1470 | 97 | 2.09 | 0.81 | ALFA-LAVAL (I | 608 | 97 | 1.57 | 0.85 | 0.517 |
| POND'S (INDIA | 1456 | 97 | 2.09 | 0.84 | NIPPON DENRO | 603 | 98 | 1.57 | 0.91 | 0.522 |
| ASHOK LEYLAND | 1386 | 98 | 2.06 | 0.89 | ANDHRA VALLEY | 592 | 98 | 1.56 | 0.88 | 0.498 |
| INDO GULF FER | 1385 | 98 | 2.06 | 0.89 | MARDIA CHEMIC | 559 | 98 | 1.52 | 0.87 | 0.532 |
| EAST INDIA HO | 1352 | 96 | 2.04 | 0.74 | LAKSHMI MACHI | 671 | 92 | 1.63 | 0.53 | 0.463 |
| GLAXO INDIA L | 1345 | 98 | 2.04 | 0.89 | S I V INDUSTR | 587 | 95 | 1.55 | 0.71 | 0.515 |
| TATA POWER CO | 1319 | 98 | 2.03 | 0.90 | L M L LTD | 528 | 98 | 1.49 | 0.91 | 0.535 |
| PHILIPS INDIA | 1275 | 97 | 2.01 | 0.85 | I T C CLASSIC | 630 | 92 | 1.60 | 0.56 | 0.499 |
| KIRLOSKAR CUM | 1267 | 97 | 2.00 | 0.83 | J C T LTD | 525 | 96 | 1.49 | 0.75 | 0.521 |
| BOMBAY DYEING | 1200 | 98 | 1.97 | 0.89 | K E C INTERNA | 518 | 98 | 1.48 | 0.90 | 0.492 |
| GUJARAT STATE | 1197 | 97 | 1.97 | 0.82 | LLOYDS STEEL | 516 | 99 | 1.48 | 0.92 | 0.504 |

| A Company | Size | TF | z_LS | z_TF | B Company | Size | TF | z_LS | z_TF | Distance |
|---|---|---|---|---|---|---|---|---|---|---|
| JAIPRAKASH IN | 1087 | 98 | 1.91 | 0.89 | TVS-SUZUKI LT | 502 | 99 | 1.46 | 0.93 | 0.454 |
| J K CORP LTD | 1048 | 98 | 1.89 | 0.89 | MCLEOD RUSSEL | 480 | 98 | 1.44 | 0.88 | 0.456 |
| RECKITT& COL | 1037 | 98 | 1.89 | 0.86 | COLOUR-CHEM L | 501 | 95 | 1.46 | 0.73 | 0.444 |
| I T C BHADRAC | 1017 | 91 | 1.88 | 0.50 | M R F LTD | 954 | 88 | 1.84 | 0.29 | 0.207 |
| S C I C I LTD | 1012 | 99 | 1.87 | 0.91 | HERO HONDA MO | 479 | 97 | 1.44 | 0.80 | 0.452 |
| ASIAN PAINTS | 996 | 98 | 1.86 | 0.88 | NEPC-MICON LT | 463 | 99 | 1.41 | 0.92 | 0.451 |
| RAYMOND LTD | 975 | 96 | 1.85 | 0.78 | FORBES GOKAK | 511 | 93 | 1.47 | 0.60 | 0.417 |
| ESSAR SHIPPIN | 929 | 98 | 1.82 | 0.87 | MORARJEE GOCU | 471 | 96 | 1.42 | 0.76 | 0.411 |
| GUJARAT NARMA | 908 | 98 | 1.81 | 0.89 | HOTEL LEELAVE | 458 | 99 | 1.41 | 0.93 | 0.402 |
| INDIA CEMENTS | 813 | 95 | 1.74 | 0.70 | SUNDRAM FASTE | 524 | 92 | 1.49 | 0.54 | 0.305 |
| HINDUSTAN CIB | 810 | 98 | 1.74 | 0.88 | MIDEAST (INDI | 454 | 97 | 1.40 | 0.85 | 0.341 |
| S K F BEARING | 803 | 98 | 1.74 | 0.87 | HINDUSTHAN DE | 435 | 98 | 1.38 | 0.87 | 0.358 |
| MUKAND LTD | 771 | 98 | 1.71 | 0.86 | VST INDUSTRIE | 479 | 94 | 1.43 | 0.66 | 0.340 |
| BIRLA JUTE& | 756 | 95 | 1.70 | 0.69 | BAYER (INDIA) | 507 | 91 | 1.47 | 0.51 | 0.298 |
| CENTURY ENKA | 756 | 96 | 1.70 | 0.78 | BOOTS PHARMAC | 445 | 96 | 1.39 | 0.74 | 0.312 |
| FINOLEX INDUS | 701 | 98 | 1.66 | 0.91 | TATA HYDRO-EL | 422 | 98 | 1.36 | 0.89 | 0.297 |
| I C I INDIA L | 666 | 98 | 1.63 | 0.89 | THOMAS COOK ( | 422 | 96 | 1.36 | 0.76 | 0.295 |
| VIDEOCON INTE | 609 | 98 | 1.58 | 0.89 | PUNJAB TRACTO | 395 | 98 | 1.32 | 0.86 | 0.256 |
| SOUTHERN PETR | 583 | 98 | 1.55 | 0.89 | WESTERN PAQUE | 392 | 99 | 1.32 | 0.94 | 0.238 |
| NATIONAL ORGA | 576 | 98 | 1.54 | 0.91 | USHA (INDIA) | 374 | 97 | 1.29 | 0.85 | 0.262 |
| BRITANNIA IND | 548 | 96 | 1.51 | 0.79 | ITW SIGNODE I | 367 | 96 | 1.28 | 0.75 | 0.238 |
| GUJARAT ALKAL | 533 | 98 | 1.50 | 0.88 | LLOYDS FINANC | 367 | 98 | 1.28 | 0.88 | 0.218 |
| EXCEL INDUSTR | 516 | 98 | 1.48 | 0.86 | D C M DAEWOO | 360 | 96 | 1.27 | 0.76 | 0.232 |
| CADBURY INDIA | 459 | 97 | 1.41 | 0.83 | TATA TIMKEN L | 349 | 97 | 1.25 | 0.81 | 0.161 |
| ZUARI AGRO CH | 454 | 97 | 1.40 | 0.85 | KALYANI STEEL | 347 | 97 | 1.25 | 0.85 | 0.157 |
| BHARAT FORGE | 440 | 97 | 1.38 | 0.82 | HIMACHAL FUTU | 346 | 98 | 1.24 | 0.86 | 0.146 |
| PFIZER LTD | 434 | 98 | 1.38 | 0.90 | E. MERCK (IND | 346 | 98 | 1.24 | 0.89 | 0.134 |
| ESCORTS LTD | 424 | 98 | 1.36 | 0.88 | GUJARAT LEASE | 337 | 97 | 1.23 | 0.83 | 0.142 |
| SMITHKLINE BE | 397 | 95 | 1.32 | 0.73 | ASSAM CO. LTD | 403 | 93 | 1.33 | 0.61 | 0.117 |
| J.K. INDUSTRI | 388 | 97 | 1.31 | 0.83 | APPLE INDS. L | 329 | 98 | 1.22 | 0.89 | 0.112 |
| HINDUSTAN MOT | 376 | 98 | 1.29 | 0.88 | HAMCO MINING | 321 | 98 | 1.20 | 0.88 | 0.093 |
| APOLLO TYRES | 362 | 98 | 1.27 | 0.86 | SUPREME INDUS | 319 | 98 | 1.20 | 0.87 | 0.075 |
| TAMILNADU PET | 346 | 96 | 1.24 | 0.75 | ESSEL PACKAGI | 324 | 96 | 1.21 | 0.74 | 0.039 |
| CEAT LTD | 335 | 98 | 1.23 | 0.86 | AHMEDABAD ELE | 316 | 97 | 1.19 | 0.83 | 0.044 |
| VOLTAS LTD | 334 | 98 | 1.22 | 0.89 | SANGHI POLYES | 312 | 99 | 1.18 | 0.93 | 0.063 |
| GARWARE POLYE | 319 | 98 | 1.20 | 0.89 | I.G. PETROCHE | 289 | 98 | 1.14 | 0.86 | 0.064 |
| BARODA RAYON | 304 | 98 | 1.17 | 0.89 | CARRIER AIRCO | 281 | 98 | 1.12 | 0.90 | 0.050 |
| PARKE-DAVIS ( | 283 | 98 | 1.13 | 0.87 | INDO RAMA SYN | 281 | 97 | 1.12 | 0.85 | 0.020 |
| VIDEOCON APPL | 275 | 98 | 1.11 | 0.89 | KELVINATOR OF | 278 | 98 | 1.12 | 0.89 | 0.006 |
| ORKAY INDUSTR | 239 | 99 | 1.03 | 0.93 | DIGITAL EQUIP | 237 | 98 | 1.02 | 0.91 | 0.020 |
| J.K. SYNTHETI | 236 | 98 | 1.02 | 0.90 | GARDEN SILK M | 234 | 98 | 1.02 | 0.90 | 0.004 |
| STANDARD INDU | 226 | 93 | 0.99 | 0.60 | GERMAN REMEDI | 239 | 93 | 1.03 | 0.58 | 0.039 |
| VAM ORGANIC C | 194 | 98 | 0.91 | 0.86 | MAHARASHTRA S | 200 | 98 | 0.92 | 0.86 | 0.019 |
| INDIAN ORGANI | 190 | 97 | 0.89 | 0.85 | SHREE CEMENT | 182 | 97 | 0.87 | 0.85 | 0.025 |
| PREMIER AUTOM | 181 | 97 | 0.87 | 0.83 | MAFATLAL INDU | 183 | 97 | 0.87 | 0.81 | 0.020 |
| MODI RUBBER L | 176 | 96 | 0.85 | 0.79 | GUJARAT TELEP | 158 | 97 | 0.79 | 0.80 | 0.063 |
| ATLAS COPCO ( | 170 | 98 | 0.83 | 0.86 | INSILCO LTD | 178 | 98 | 0.85 | 0.86 | 0.025 |
| WIMCO LTD | 125 | 98 | 0.65 | 0.86 | ADVANI-OERLIK | 126 | 98 | 0.65 | 0.86 | 0.003 |
| MANGALORE CHE | 99 | 98 | 0.51 | 0.88 | SYNTHETICS & | 101 | 98 | 0.52 | 0.88 | 0.013 |

# Appendix B: Replicating EK95, and interpreting their results

We will use our dataset to replicate the results of EK95. They used a different matched sample, they used data for 1992 only, and they lacked access to the CMIE database. Hence we should ideally get results which are comparable to theirs in substance, though not in details, if we estimate our model for the pre-12-March period only.[13] Standard errors are shown in brackets.

**Table 12** Replicating Table 3 of EK95, before

| | Model M1 Daily | Model M2 Weekly |
|---|---|---|
| Interc. | -13.1663 | 16.2479 |
| | (3.244) | (5.81) |
| Agroup | -1.0684 | -1.6246 |
| | (0.139) | (0.246) |
| Log size | -0.4972 | -0.6641 |
| | (0.062) | (0.108) |
| T.freq | -0.0636 | -0.0497 |
| | (0.033) | (0.06) |
| $R^2$ | 0.5937 | 0.4722 |
| Adj.$R^2$ | 0.5867 | 0.4632 |
| N | 179 | 180 |

For the reasons mentioned above, these results are numerically different from those of EK95. However, they agree in substance. Log size is clearly negatively related to unsystematic risk, and so is trading frequency (albeit more tenuously).

With both daily and weekly returns, the coefficient of the dummy variable `Agroup` here is negative and statistically significant. EK95 interpret this as being evidence that badla reduces the variance of unsystematic risk. They would infer that badla contributes to a reduction in daily unsystematic risk of the order of 1.07% (Model M1), which is quite far from our estimate of 0.44% per day above. EK95 would interpret Model M2 above as saying that the impact of badla upon weekly unsystematic risk is -1.6%.

The problem here lies in interpreting badla as being synonymous with the A group. It can well be the case that A group securities have lower volatility for reasons unconnected with badla. This is despite our efforts at creating a matched B group sample: our matching could be simply based on the wrong explanatory variables (we used log size and trading frequency, but there could be wholly different reasons why A group volatility is different from B group volatility), and our matching is imperfect in the sense that B group companies which would have size comparable with A group companies do not exist.

This criticism of EK95 is clearly illustrated by estimating their model for the period after 12 March 1995, when badla did not exist.

[13] They also use closing price as an explanatory variable, but it proves to not be statistically significant and we ignore it here. They use market capitalisation as a measure of size, but we find that their models work much better using log market capitalisation. For example, M1 has a R2 of 0.47 using market capitalisation and an R2 of 0.59 using log market capitalisation.

**Table 13** Replicating Table 3 of EK95, after

| | Model M3 Daily | Model M4 Weekly |
|---|---|---|
| Interc. | 7.3990 | -0.4306 |
| | (3.272) | (6.514) |
| Agroup | -0.9065 | -1.5639 |
| | (0.112) | (0.224) |
| Log size | -0.3757 | -0.6033 |
| | (0.056) | (0.11) |
| T.freq | -0.0202 | 0.1017 |
| | (0.033) | (0.067) |
| $R^2$ | 0.4899 | 0.4088 |
| Adj.$R^2$ | 0.4812 | 0.3987 |
| N | 179 | 179 |

If the coefficient of `Agroup` was to be interpreted as being the impact of badla, then it should have been zero in Model M3 and Model M4, which are estimated off the year in which there was no badla. Instead, it is negative and statistically significant in both these models – even after controlling for log size and trading frequency, under conditions of similar market microstructure, membership in the A group is significantly correlated with reduced unsystematic risk. Hence the statistical significance of `Agroup` in Model M1 and Model M2 reflects misspecifications of the model – the coefficient of `Agroup` seen there should not be interpreted as evidence about badla.

We know of no superior, alternative model which would fully explain the cross-sectional variation of the standard deviation of unsystematic risk and reduce the `Agroup` dummy variable in the post-badla period to statistical insignificance – our best effort ahead (Model M6) still uses a `Agroup` dummy variable, which reflects our inability to fully understand *why* the unsystematic risk of A group companies is lower.

# References

Eleswarapu, V. R. & Krishnamurthi, C. (1994), Liquidity, stock returns and ownership structure: an empirical study of the BSE, Technical report, Indian Institute of Management, Bangalore and Indian Institute of Science, Bangalore.

Eleswarapu, V. R. & Krishnamurthi, C. (1995), Do “speculative traders” increase stock price volatility? Empirical evidence from the Bombay Stock Exchange, Technical report, University of Auckland, New Zealand and Indian Institute of Science, Bangalore.

Harris, L. (1989), 'S&P 500 cash stock price volatilities', *Journal of Finance* **44**, 1155–1175.

Kocagil, A. E. (1994), Does futures speculation stabilize spot prices? Evidence from metals markets, Technical report, Pennsylvania State University.

Ross, S. A. (1989), 'Commentary: Using tax policy to curb speculative short-term trading', *Journal of Financial Services Research* **3**, 119.

Stoll, H. R. & Whaley, R. E. (1987), 'Expiration day effects of index options and futures', *Financial Analysts Journal* **43**, 16–28.

Thomas, S. (1995), An empirical characterisation of the Bombay stock exchange, PhD thesis, University of Southern California, Los Angeles, California 90089.

Umlauf, S. R. (1993), 'Transaction taxes and the behaviour of the Swedish stock market', *Journal of Financial Economics* **33**, 227–240.