Journal of Business Finance & Accounting, 29(9) & (10), Nov./Dec. 2002, 0306-686X

The Random Walk Hypothesis in the Emerging Indian Stock Market

Sunil Poshakwale*

1. INTRODUCTION

This paper examines the random walk hypothesis in the emerging Indian stock market. Increasing investor interest in emerging markets has motivated a great deal of research aimed at understanding the return and risk characteristics of stock prices in these markets. In particular, researchers and investors have sought to detect any evidence of informational inefficiency that could be profitably exploited to make large economic gains. Traditionally, analysts and investors assume stock market efficiency because in a competitive market, prices reflect all available information. Fama (1970) classified market efficiency in three categories namely, weak form, semi-strong form, and strong form. A market is considered efficient in the weak form if stock price changes cannot be predicted based on past returns. In statistical terms, this means that changes in stock returns are independent and random. As a consequence, a considerable amount of research has been conducted on testing market efficiency using data from emerging markets. However, most of the research has focused on finding evidence of persistent positive or negative returns using linear equilibrium models and conventional statistical tests such as autocorrelation and spectral

* The author is a Lecturer in the Department of Accounting and Finance of the Business School in the University of Birmingham. He would like to express sincere thanks to an anonymous referee for comments and suggestions on earlier drafts of the paper. The analysis and conclusions of this paper are those of the author and so is the responsibility for any remaining errors. (Paper received January 2001, revised and accepted September 2001)

Address for correspondence: Sunil Poshakwale, Department of Accounting and Finance, Business School, The University of Birmingham, Edgbaston, Birmingham B15 2TT, UK. e-mail: S.Poshakwale@bham.ac.uk

© Blackwell Publishers Ltd. 2002, 108 Cowley Road, Oxford OX4 1JF, UK and 350 Main Street, Malden, MA 02148, USA.

analysis (see, among others, Barnes, 1986; Cheung, Wong and Ho, 1993; Dickinson and Muragu, 1994; and Ayadi and Pyun, 1994).[1] Recent research suggests that the traditional tests of random walk are susceptible to errors because they assume that the time series follows a linear stochastic process. The interaction of noise traders with rational traders can generate non-linear deterministic systems which seemingly show random behaviour in stock prices (see for example, Hsieh, 1989; Scheinkman and LeBaron, 1989; and Brock et al., 1996).

Non-linearity in stock prices has important theoretical and practical implications for asset pricing models and portfolio management techniques. Identification of an appropriate non-linear structure may help in the development of improved asset pricing models which can be used to hedge against the predicted increase in volatility. Although a number of research studies provide evidence of non-linear patterns in equity returns, most of these have used data from mature markets such as the US and the UK (see for example, Willey, 1992; Hsieh, 1991 and 1993; Yadav, Pope and Paudyal, 1999; and Opong et al., 1999). Research on non-linear dynamics in emerging markets is relatively scarce. Sewell et al. (1993) is one of the few studies that provide evidence of non-linear dependence in weekly returns in five Asian stock markets and the US. In yet another study on the Asian markets, Yadav, Paudyal and Pope (1996) report non-linear dynamics in daily returns in Pacific Basin financial markets. Non-linear dependence is also reported in returns from the Warsaw stock exchange by Poshakwale and Wood (1998) who use daily data from two main indices and an equally weighted portfolio of 17 stocks in the emerging Polish market.

Despite the potential benefits of portfolio diversification in emerging markets in general and India in particular, there is a lack of research and relatively much less is known about the characteristics and dynamics of Indian stock returns.[2] The available research on the Indian stock market has primarily focused on testing weak-form efficiency and well known anomalies (see for example, Chan et al., 1996; Wood and Poshakwale, 1997; and Choudhry, 2000). Also, most previous studies have focused on stock indices rather than individual returns. As far as we are aware, this is the first systematic analysis

© Blackwell Publishers Ltd 2002

of stock returns using individual stock prices in the Bombay Stock Exchange.

Established in 1875, Bombay Stock Exchange (BSE) has evolved over the years into its present status as India's premier stock exchange and is generally referred to as the gateway to the capital market in India.[3] The statistics available from BSE for the year to August 2000 show that the total market capitalisation of the exchange has reached Rs7666.43 billion (US$167.83 billion). The total turnover of BSE was Rs6217.49 billion (approx. US$136.11 billion) with an average daily turnover of Rs7.23 billion (approx. US$0.84 billion). In terms of the number of listed companies, the BSE is the second biggest stock exchange in the world with over 5,900 listed companies. The BSE operated an open outcry trading system until 14 March, 1995. This was replaced by a fully automated computerised trading system known as the BOLT (BSE On Line Trading) system. BOLT follows both order and quote driven systems and facilitates efficient processing, automatic order matching and faster execution of trades. Trading on the BOLT is conducted from Monday to Friday between 9:55 a.m. and 3:30 p.m. Transactions in 'A' group stocks (stocks with largest market capitalisation and turnover) can be carried forward from one settlement period to another from the date of original transaction without any restriction as to the number of days. Transfer of ownership of securities is effected through a date stamped transfer-deed, which is signed by the buyer and seller.

Except for a few industries of national strategic importance (e.g., defence), foreign investors are allowed to have a majority stake in Indian companies. Foreign Institutional Investors (FIIs) are required to register with the Securities and Exchange Board of India (SEBI) and Reserve Bank of India (RBI). Investment by a single FII and/or a Non Resident Indian (NRI) in any one company is subject to a ceiling of 10% of the total issued capital. Foreign investments under a financial collaboration agreement are permitted up to a maximum of 51%. By August 2000, there were more than 530 registered FIIs and 35 foreign brokers. The total investments by the FIIs exceeded Rs740 billion (US$16 billion) in the primary and the secondary market.

This paper makes some important contributions. First, the paper employs statistical tests capable of detecting linear as well as

© Blackwell Publishers Ltd 2002

non-linear dependence. This aim is consistent with Granger and Andersen (1978) who suggest that in testing for the random walk hypothesis, the absence of both linear and non-linear dependence should be confirmed since rejection of linear dependence does not imply independence but merely suggests a lack of linear autocorrelation. Second, we analyse an equally weighted portfolio of 100 stocks and a sample comprising of 38 of the most actively traded individual stocks. This disaggregated approach is strongly supported by MacDonald and Power (1993) who recommend investigation of individual stocks' returns because they may reveal specific factors which tend to be hidden when aggregate indexes are analysed. Finally, to the best of our knowledge, this is the first study that provides evidence on the return and risk characteristics of daily stock prices in the Indian stock market using a large set of data and a range of econometric tests.

The statistical evidence in this paper rejects the random walk hypothesis for the emerging Indian stock market. The results suggest that daily returns earned by individual stocks and by an equally weighted portfolio show significant non-linear dependence and persistent volatility effects. The non-linear dependence takes the form of ARCH-type conditional heteroskedasticity and does not appear to be caused by nonstationarity of underlying economic variables. Though conditional volatility is time varying, it does not explain expected returns. The remainder of the paper is organised as follows. The next section explains the data and methodology and reports empirical findings while the last section summarises the main conclusions.

2. THE DATA, METHODOLOGY AND EMPIRICAL RESULTS

(i) The Data

Daily closing prices for the 100 actively traded stocks, from 1 January, 1990 to 30 November, 1998 have been collected from Datastream International. An equally weighted portfolio of 100 actively traded stocks is constructed.[4] The 100 stocks are the ones which are included in the Bombay Stock Exchange National Index (BSEN) and represent actively traded stocks on the five

© Blackwell Publishers Ltd 2002

important stock exchanges in India. Further, we select a sample of 38 individual stocks from these 100 stocks. The selection of individual stocks was based on the criteria that the chosen stock should have traded on at least 70% or more of the total available number of trading days for the period 1990 to 1998. The other selection criterion was that the selected stocks should represent a large number of sectors of the economy (see the Appendix for names of stocks and their Datastream codes). Daily returns are computed as the log difference in the closing stock prices. The closing prices have been adjusted for stock splits and rights issues.

(ii) Descriptive Statistics

Table 1 shows descriptive statistics for the equally weighted portfolio of 100 stocks (EQPORT) and the 38 individual stocks. The highest average returns are obtained in Infosys Technology, a software company floated on the stock market in June 1993. This reflects the performance of technology stocks worldwide and in India in particular due to the high growth in the IT services. Other stocks which show significantly high returns are Indian Tobacco Company (Tobacco), Castrol (Chemical), Hindustan Lever and Ponds India (Consumer), Gujrat Ambuja (Cement), and Glaxo India (Pharmaceutical). The lowest returns are earned by CESC (Power). Some other stocks that have earned negative returns include Baroda Rayon and Century (Textiles), IDBI (Bank), Cochin Refinery and Manglore Refinery (Oil), Telco (Engineering), Hindustan Petroleum Company and Indian Petrochemical Corporation Limited (Petroleum), and Premier Automobiles Ltd. (Automobile). Notably, these stocks also exhibit higher volatility when compared with the volatility of the equally weighted portfolio (EQPORT) and other individual stocks. Most individual stocks show significant kurtosis and skewness and generally this is higher than the EQPORT. The computed Jarque-Bera statistic was high and statistically significant for all stocks and the EQPORT indicating that returns are not normal.

The Ljung-Box statistics shown for lags 1, 5, and 10 are significant at the 5% level for 28 out of the 38 individual stocks.[5] The EQPORT also exhibit significant Ljung-Box Q statistics on all

© Blackwell Publishers Ltd 2002

Table 1

Descriptive Statistics

Company	*Mean*	*Std. Dev.*	*Skew*	*Kurtosis*	*AC(1)*	*AC(5)*	*AC(10)*	*ARCH-LM*	*Observations*
API	0.059	2.286	0.288*	8.919*	−0.101 (23.6*)	0.019 (34.5*)	0.000 (38.5*)	80.95	2325
ASC	0.075	3.098	0.254*	10.017*	0.074 (12.8*)	0.028 (16.0*)	0.039 (29.1*)	39.26	2325
BAJ	0.091	2.206	1.181*	16.557*	0.06 (8.3*)	0.01 (13.4*)	0.03 (23.7*)	22.65	2325
BAR	−0.195	5.933	−17.481*	632.420*	−0.04 (4.5*)	−0.02 (8.2)	−0.03 (13.4)	0.004	2325
BIN	−0.017	3.577	−0.069	10.843*	−0.07 (6.4*)	0.03 (8.0)	0.03 (11.4)	12.99	1267
BOM	−0.032	2.820	0.086	7.596*	−0.10 (22.5*)	0.00 (24.4*)	0.08 (43.5*)	71.00	2325
BSS	0.038	3.766	−1.120*	39.177*	0.05 (7.11*)	0.01 (7.48)	0.05 (18.2)	35.62	2325
CAS	0.144	2.795	1.704*	26.498*	0.04 (5.24*)	−0.08 (24.2*)	0.07 (45.5*)	21.56	2325
CET	−0.141	5.483	−35.500*	1549.135*	0.03 (2.83*)	0.01 (8.91)	0.03 (15.46)	0.002	2325
CES	−0.205	3.490	0.175*	6.237*	0.00 (0.00	0.01 (6.06)	0.05 (14.6)	33.38	1247
COR	−0.065	5.878	−28.003*	1125.017*	0.02 (1.36)	−0.01 (5.48)	0.00 (6.51)	0.005	2325
COP	0.048	2.146	1.654*	22.219*	0.05 (5.50*)	0.01 (6.85)	0.03 (19.9*)	50.86	2325
GXI	0.104	2.743	0.961*	12.551*	0.05 (5.66*)	−0.07 (20.9*)	0.03 (28.6*)	58.06	2325

© Blackwell Publishers Ltd 2002

GSI	0.005	2.078	0.477*	10.621*	0.11	0.04	0.03	49.10	2325
					(27.9*)	(33.3*)	(42.1*)		
GES	0.011	2.936	0.848*	11.274*	0.05	−0.01	0.02	19.03	2325
					(5.9*)	(9.4)	(12.8)		
CEM	0.124	2.812	0.586*	11.688*	0.05	0.02	−0.01	33.37	2325
					(5.19*)	(13.5*)	(16.0)		
HDI	0.066	2.141	1.513*	23.772*	0.08	0.03	0.01	4.27	2325
					(14.7*)	(19.7*)	(31.7*)		
HDL	0.131	1.958	2.457*	35.048*	0.09	−0.06	0.00	104.99	2325
					(19.7*)	(29.7*)	(40.3*)		
HPT	−0.022	2.658	−0.307*	10.369*	−0.06	0.06	0.04	72.51	1621
					(5.7*)	(30.3*)	(37.1*)		
HDF	0.095	2.950	−0.747*	42.566*	−0.03	0.02	0.05	18.87	2324
					(1.65)	(5.87)	(19.5*)		
ICT	0.036	4.074	2.225*	47.014*	0.01	−0.01	0.04	1.01	2324
					(0.11)	(3.52)	(9.80)		
INO	−0.071	2.972	−1.030*	20.246*	0.01	0.01	0.06	73.73	1571
					(0.23)	(3.09)	(11.66)		
IRS	0.017	2.426	0.906*	15.867*	0.06	−0.07	0.07	21.66	2325
					(8.3*)	(25.4*)	(43.6*)		
IDB	−0.114	2.561	1.140*	11.365*	0.06	−0.05	0.04	3.96	1243
					(4.22*)	(9.81)	(18.24)		
INE	0.285	2.670	0.675*	8.499*	0.10	0.01	−0.01	44.21	1425
					(14.4*)	(18.2*)	(22.0*)		
ITC	0.152	2.720	1.136*	19.156*	0.04	−0.02	0.03	32.84	2325
					(4.6*)	(13.3*)	(20.3*)		
LST	0.025	3.076	1.131	25.643*	0.01	0.02	0.05	30.10	2325
					(0.26)	(8.02)	(17.8)		
MTN	0.039	3.095	−0.444*	10.679*	−0.02	0.02	0.08	58.65	1469
					(0.65)	(5.91)	(18.4*)		
MAG	−0.079	2.929	1.019*	17.621*	−0.07	0.03	0.04	9.30	1602
					(8.98*)	(13.4*)	(24.5*)		

© Blackwell Publishers Ltd 2002

Table 1 (Continued)

Company	*Mean*	*Std. Dev.*	*Skew*	*Kurtosis*	*AC(1)*	*AC(5)*	*AC(10)*	*ARCH-LM*	*Observations*
PFZ	0.084	3.133	0.456*	10.992*	0.02	−0.04	0.03	89.94	2325
					(1.27)	(7.19)	(13.25)		
PDS	0.119	2.433	1.990*	25.884*	0.02	−0.00	0.01	8.20	2325
					(1.03)	(4.13)	(15.67)		
PAU	−0.078	4.093	0.364*	7.463*	−0.01	−0.01	0.07	29.17	2325
					(0.39)	(3.88)	(20.8*)		
REL	0.041	3.382	1.504*	21.269*	0.05	0.03	0.04	2.11	2325
					(5.47*)	(10.3)	(21.0*)		
TTC	−0.005	2.994	1.181*	61.189*	0.03	−0.03	0.05	39.34	2325
					(2.79)	(17.6*)	(28.8*)		
TTE	−0.080	5.374	−32.943*	1400.258*	0.03	0.01	0.01	0.28	2325
					(2.07)	(2.40)	(4.06)		
TIS	−0.014	2.880	0.109*	12.460*	0.05	0.01	0.05	33.49	2325
					(5.69*)	(13.8*)	(26.3*)		
TTP	0.047	3.105	−2.461*	51.539*	0.07	0.05	0.05	3.61	2325
					(11.3*)	(18.5*)	(27.1*)		
TEA	0.052	2.599	0.911*	11.603*	0.05	−0.04	0.02	22.54	2325
					(4.83*)	(10.8)	(15.3)		
EQPORT	0.015	1.596	0.555*	16.241*	0.17	0.02	0.07	85.51	2325
					(66.8*)	(86.4*)	(101*)		

Notes:
AC = Autocorrelation coefficients, Ljung-Box Q statistics are given in parentheses. * Significant at the 5% level. ARCH LM test is based on the regression of squared residuals on lagged squared residuals. The statistic is asymptotically distributed as χ^2. NE = not estimated.

© Blackwell Publishers Ltd 2002

selected lags. This result suggests a general trend of serial dependence in returns. Nevertheless, we are not able to reject the null hypothesis of no autocorrelation for Calcutta Electric Supply Company (CES), Cochin Refinery (COR), Indian Petrochemical Corporation (INO), Pfizer (PFZ), Ponds (PDS), Tata Engineering and Locomotive Company (TTE), Larson & Tubro Ltd. (LST), and Industrial Credit and Investment Corporation of India (ICT).

Using the test proposed by Engle (1982), the ARCH LM statistics are computed. The results show that except for a few individual stocks, the null hypothesis of no ARCH is clearly rejected. This result suggests that ARCH type non-linearity may be present and therefore testing for nonlinear dependence is all the more worthwhile.[6]

(iii) Tests for IID hypothesis

Following Hsieh (1991), we use an autoregressive model for removing linear dependence from daily returns before investigating whether a potentially forecastable non-linear structure, nonstationarity or other hidden patterns are present in linearly filtered returns. This adjustment is required because the BDS test is capable of easily detecting any linear dependence in the data. The BDS test developed by Brock, Dechert, and Schienkman (1996) is based on a null hypothesis of independent and identical distribution (IID) and is widely used as a means of examining non-linear dependence and the adequacy of a variety of time series models (see for example, Brock and Sayers, 1988; Frank and Stengos, 1989; Scheinkman and LeBaron, 1989; Hsieh, 1989; and Brock et al., 1991).

The BDS test uses the concept of correlation dimensions (CD) proposed by Grassberger and Procaccia (1983). The CD technique is designed to reveal evidence of a non-linear structure in data embedded in phase space. This technique involves embedding overlapping sub-sequences of length (l) of a data series in *m*-dimensional space for various embedding dimensions *m*. Truly random data will create a region of *m* space for any *m*, deterministically generated data will only show geometric structure for sufficiently large *m*. Given a time series $\{Z_t\colon t = 1, \ldots T\}$ of D dimensional vectors, the correlation

© Blackwell Publishers Ltd 2002

integral $C(l)$ is defined as:

$$C(l) = \lim_{T\to\infty} \frac{2}{T(T-1)} \sum_{i<j} I_l(Z_i, Z_j). \tag{1}$$

Where $I_l(x, y)$ is an indicator function that equals one if $||x - y|| < l$, and zero otherwise, where $|| \ ||$ is the sup-norm. The correlation integral measures the fraction of pairs of points of $\{Z_t\}$ that are within a distance of l, from each other. The CD of $\{Z_t\}$ is thus defined as:

$$\nu = \lim_{l\to 0} \left[\frac{\log C(l)}{\operatorname{Log} l}\right], \quad \text{if the limit exists.} \tag{2}$$

If $\{Z_t\}$ were independently and identically distributed (IID), then the BDS tests the null hypothesis that $C_m(l) = C_1(l)^m$. Brock et al. (1991) show that the test statistic is asymptotically a standard normal distribution and that the asymptotic distribution is a good approximation of the finite sample distribution when there are more than 500 observations. Further, they recommend that l should be between one-half to two times the standard deviation and that the accuracy of the asymptotic distribution deteriorates for high embedding dimensions of 10 or above. The BDS is used in testing the hypothesis whether returns are independently and identically distributed. Rejection of IID would indicate that returns are non-linear.

The average of the BDS statistics for the linearly filtered time series for epsilon values ranging from half to two times the standard deviation and for dimensions 2 to 10 are reported in Table 2. The results confirm the presence of significant non-linear dependence in returns. The BDS statistics are significant at the 10% or 5% level for 22 out of the 38 individual stocks as well as for the EQPORT. Following Brock and Sayers (1988), rejection of IID is *prime facie* evidence of non-linear dependence in the data. While we are able to reject the null hypothesis of IID for a majority of the stocks in our sample, there are 16 stocks which pass the BDS test. However, it is not enough to merely identify non-linear dependence. Previous research has shown that often the non-linear dependence can be successfully described by an ARCH process.[7] Further examination of causes of acceptance/ rejection of non-IID behaviour could facilitate development of

© Blackwell Publishers Ltd 2002

Table 2

Average of the BDS Statistics for the OSL Residuals

m	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
API	1.02	1.76*	2.37*	2.76**	2.99**	3.07**	3.10**	3.06**	2.97**
ASC	0.55	1.01	1.34	1.58	1.75*	1.90*	2.02**	2.08**	2.11**
BAJ	0.55	0.91	1.22	1.40	1.56	1.66*	1.71*	1.76*	1.76*
BAR	0.55	1.07	1.50	1.81*	2.19**	1.50**	2.78**	3.01**	3.19**
BIN	0.49	0.85	1.06	1.19	1.24	1.26	1.23	1.18	1.13
BOM	0.70	1.22	1.61	1.81*	1.90*	1.94*	1.93*	1.89*	1.83*
BSS	0.72	1.24	1.69*	2.00**	2.27**	2.44**	2.60**	2.68**	2.73**
CAS	0.72	1.31	1.80*	2.07**	2.27**	2.41**	2.48**	2.51**	2.49**
CET	0.61	1.20	1.72*	2.13**	2.49**	2.77**	2.97**	3.14**	3.28**
CES	0.35	0.70	0.91	1.02	1.06	1.06	1.01	0.96	0.91
COR	0.54	1.10	1.55	1.96*	2.30*	2.63**	2.89**	3.09**	3.25**
COP	0.44	0.66	0.69	0.67	0.64	0.61	0.61	0.59	0.55
GXI	0.32	0.57	0.63	0.66	0.67	0.65	0.63	0.60	0.59
GSI	0.32	0.42	0.47	0.51	0.52	0.50	0.48	0.44	0.40
GES	0.33	0.51	0.54	0.49	0.43	0.37	0.33	0.29	0.26
CEM	0.38	0.53	0.62	0.66	0.66	0.62	0.54	0.46	0.42
HDI	0.26	0.43	0.47	0.48	0.43	0.41	0.38	0.32	0.25
HDL	0.31	0.50	0.60	0.67	0.68	0.66	0.63	0.56	0.50
HPT	0.32	0.48	0.55	0.51	0.51	0.48	0.43	0.39	0.34
HDF	0.65	1.05	1.36	1.47	1.53	1.55	1.61	1.61	1.61
ICT	0.42	0.77	0.94	1.03	1.07	1.04	1.01	0.96	0.93
INO	0.23	0.37	0.48	0.50	0.55	0.57	0.59	0.62	0.63
IRS	0.31	0.47	0.54	0.51	0.49	0.48	0.44	0.39	0.34
IDB	0.14	0.27	0.25	0.24	0.23	0.20	0.128	0.18	0.16
INE	0.19	0.32	0.35	0.33	0.35	0.35	0.34	0.37	0.39

© Blackwell Publishers Ltd 2002

Table 2 (Continued)

m	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
ITC	0.25	0.35	0.33	0.30	0.27	0.24	0.21	0.17	0.12
LST	0.49	0.94	1.22	1.41	1.63	1.78*	1.90*	1.98*	2.01**
MTN	0.57	1.14	1.58	1.82*	1.98**	2.05**	2.10**	2.15**	2.18**
MAG	0.68	1.22	1.54	1.70*	1.77*	1.83*	1.86*	1.86*	1.83*
PFZ	0.46	0.84	1.08	1.27	1.39	1.45	1.48	1.47	1.45
PDS	0.93	1.62	2.00**	2.22**	2.35*	2.45**	2.48**	2.47**	2.44**
PAU	0.34	0.65	0.87	1.03	1.15	1.22	1.30	1.33	1.35
REL	0.60	1.02	1.33	1.62	1.85*	2.04**	2.11**	2.12**	1.40
TTC	0.79	1.46	1.92*	2.28**	2.53*	2.73**	2.89**	2.99**	3.04**
TTE	0.29	0.55	0.84	1.13	0.96	1.02	1.08	1.13	1.17
TIS	0.29	0.58	0.82	0.98	1.11	1.24	1.31	1.37	1.39
TTP	0.61	1.16	1.52	1.76*	1.94*	2.07**	2.17**	2.24**	2.26**
TEA	0.60	1.11	1.38	1.59	1.73*	1.83*	1.87*	1.88*	1.85*
EQPORT	0.64	1.10	1.48	1.73*	1.91*	2.02**	2.10**	2.14**	2.15**

Notes:
Critical values are 1.645 and 1.96 at * 10% and ** 5% significance levels respectively.

© Blackwell Publishers Ltd 2002

appropriate models. We therefore investigate whether the non-linear dependence in the Indian stock returns is caused by predictable conditional volatility.

(iv) Conditional Volatility

Evidence of high kurtosis, variance clustering and significant ARCH-LM statistics reported in Table 1 suggests that an ARCH process and its generalisation due to Bollerslev (1986) may help in explaining non-linear dependence. Research has shown that ARCH models efficiently capture time-varying stock return volatility and fat tailed distributions, while incorporating autocorrelation (Bollerslev, Chou and Kroner, 1992).

We follow McCurdy and Morgan (1988), when testing the martingale hypothesis. Stock price changes from period $t-1$ to period t are modelled as innovations which are orthogonal to the information available at period $t-1$. The model to be estimated is as follows:

$$\Delta P_t = \gamma_0 + \sum_{i=1}^{n} \gamma_i \Delta P_{t-i} + \sum_{j=1}^{m} \delta_j + \varepsilon_t \tag{3}$$

where ΔP_t is the difference in logarithms of daily stock prices. Under the null hypothesis, if changes in daily stock prices are independent of the previously available information, parameters γ_i and δ_j are expected to equal zero, and errors ε_t should be uncorrelated with a zero mean, but may not necessarily be homoskedastic. In the GARCH (p, q) specification, the conditional variance of daily stock return h_t is modelled as a linear function of its own lagged p conditional variances and the lagged q squared residuals where α and β are parameters to be estimated. For $p = 0$, the model becomes the ARCH(q) process, and for $p = q = 0$ the variance of daily stock returns is simply a white noise process. In this linear GARCH (p, q) procedure, shocks to the current volatility of stock returns persist if $\sum \alpha_i + \sum \beta_j = 1$. Engle and Bollerslev (1986) suggest that in such cases, current information remains important in forecasts of the conditional variance for all horizons.

We extend the GARCH (p, q) model to a GARCH in Mean (GARCH-M) model which enables us to examine the relationship between conditional volatility and expected returns. In the

© Blackwell Publishers Ltd 2002

absence of daily data for risk-free returns, the GARCH-M specification is widely used in empirical testing of the hypothesis of a time varying risk premium.[8] For the emerging Indian market, data on nominal risk-free returns is not easily available and hence a GARCH-M model provides a convenient and robust measure to test whether conditional volatility is priced in the Indian stock market. The GARCH model is extended to a GARCH-M specification by including conditional variance $h^{1/2}$ given the available information at time $t-1$:

$$\Delta P_t = \gamma_0 + \sum_{i=1}^{n} \gamma_i \Delta P_{t-i} + \sum_{j=1}^{m} \delta_j D_{tj} + \theta\sqrt{h_t} + \varepsilon_t \tag{4}$$

where, D represents a dummy variable that captures any effects that may have been caused by the regulatory changes. The conditional variance h_t is defined as:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2 t\text{-}1 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{5}$$

During our sample period 1990–1998, a number of regulatory changes were introduced in the Indian stock market (see Poshakwale and Wood, 1997). For example, on 21 May, 1991, with a view to allowing only financially sound and well managed companies to list their shares on the Bombay stock exchange, the Security Exchange Board of India (SEBI) announced stringent criteria for grading prospectus. On 14 September, 1992, the Ministry of Finance announced formal guidelines permitting foreign institutional investors to invest in all securities traded on the primary and the secondary stock markets in India. In a significant move, the Bombay stock exchange banned 'Badla' trading, a forward trading facility for the most liquid stocks on 13 December, 1993. In December 1994, the National Stock Exchange was set up. In another significant move, the BSE introduced an 'electronic book order' system on 14 March, 1995. Detailed guidelines with regard to short selling came into effect from November 1996 and in July 1997, the share transfer system was simplified.

In order to examine whether these events caused any structural breaks in the stock market volatility process, we introduced the

© Blackwell Publishers Ltd 2002

following dummy variables in equation (4) to break the time series into seven segments:[9]

D_t^0 = 1 between 2 January, 1990 and 21 March, 1991, 0 otherwise.
D_t^1 = 1 between 22 March, 1991 and 14 July, 1992, 0 otherwise.
D_t^2 = 1 between 15 July, 1992 and 13 October, 1993, 0 otherwise.
D_t^3 = 1 between 14 October, 1993 and 1 October, 1994, 0 otherwise.
D_t^4 = 1 between 2 October, 1994 and 14 January, 1995, 0 otherwise.
D_t^5 = 1 between 15 January, 1995 and 1 September, 1996, 0 otherwise.
D_t^6 = 1 between 2 September, 1996 and 1 May, 1997, 0 otherwise.

Estimates presented in Table 3 show that significant ARCH and GARCH effects are evident for 32 out of the total 38 individual stocks as well as the EQPORT. Only two stocks, Cochin Refinery (COR) and Indian Petrochemical Corporation (INO), do not exhibit either an ARCH or GARCH effect. Moreover, in most cases the sum of $\alpha_i + \beta_j$ is either equal to one or nearly one. This confirms that integrated GARCH (IGARCH) effects are present and that daily return volatility is persistent in nature. Thus any shock caused to the stock prices in the Indian stock market tends to die out slowly. The estimated coefficients for the dummy variables are significant only in nine individual stocks and only one dummy variable is significant for the EQPORT suggesting that the regulatory changes do not appear to have any statistically significant effect. The adjusted R^2 is very low for all the stocks as well as EQPORT indicating that the model perform poorly. In our GARCH model, we included an autoregressive term (γ_i) to capture any remaining linear dependence in conditional mean particularly for those individual stocks where significant Ljung-Box statistics were reported. The coefficient for autoregression is significant for 22 of the 38 stocks as well as the EQPORT. Thus we conclude that even after modelling the second moment dependencies, the time dependence in daily returns is not fully captured. Overall, the results show that significant autoregressive

© Blackwell Publishers Ltd 2002

Table 3

GARCH-M Estimate

	θ	γ_0	γ_1	D_1	D_2	D_3	D_4	D_5	D_6	*Constant*	α	β	$\bar{R}^2$	*LR*
API	0.12	−0.16	−0.07	−0.03	−0.13	0.05	−0.26	−0.05	−0.09	0.58	0.13	0.76	0.006	−5049.70
	(1.08)	(−0.66)	(−2.86*)	(−0.23)	(−0.68)	(0.24)	(−0.94)	(−0.35)	(−0.74)	(2.30*)	(5.28*)	(13.50*)		
ASC	−0.002	0.52	−0.04	−0.24	−0.68	−0.23	−0.77	−0.53	−0.64	0.04	0.05	0.95	0.004	−5677.36
	(−0.02)	(1.99*)	(−1.59)	(−0.93)	(−1.99*)	(−1.21)	(−3.54*)	(−2.89*)	(−3.30*)	(1.66)	(4.29*)	(79.89*)		
BAJ	0.023	0.20	0.09	−0.12	−0.25	0.15	−0.34	−0.13	−0.30	0.10	0.06	0.92	0.001	−4976.98
	(0.22)	(0.82)	(3.55*)	(−0.67)	(−1.20)	(0.70)	(−1.57)	(−0.82)	(−1.66)	(2.43*)	(3.27*)	(41.80*)		
BAR	1.23	−9.89	−0.08	0.80	0.75	0.97	−0.35	0.44	−0.36	23.04	−0.001	0.60	−0.003	−7551.66
	(1.44)	(−1.34)	(−3.05*)	(2.30*)	(2.62*)	(3.47*)	(−1.28)	(1.87)	(−0.79)	(2.26*)	(−3.13*)	(3.05*)		
BIN	0.15	−1.09	−0.06	−0.84	−0.36	−0.16	−0.28	−0.04	−0.56	2.46	0.34	0.63	0.027	−3351.19
	(1.35)	(−1.14)	(−1.69)	(−2.35*)	(−1.30)	(−1.99*)	(−0.79)	(−0.37)	(−0.76)	(2.02*)	(1.90)	(3.89*)		
BOM	−0.02	0.25	0.12	0.17	−0.45	−0.008	−0.35	−0.35	−0.38	0.42	0.09	0.86	0.008	−5562.87
	(−0.21)	(0.79)	(4.80*)	(0.78)	(−2.10*)	(−0.04)	(−1.45)	(−1.98*)	(−2.03*)	(2.92*)	(4.50*)	(26.40*)		
BSS	−0.13	−0.02	0.02	1.18	0.33	0.63	0.01	0.35	0.29	0.89	0.23	0.75	−0.01	−6002.59
	(−1.03)	(−0.07)	(0.41)	(2.00)	(0.68)	(1.35)	(0.03)	(0.79)	(0.65)	(3.62*)	(3.58*)	(19.77*)		
CAS	−0.07	0.52	0.11	0.36	−0.22	−0.19	−0.47	−0.35	−0.31	0.12	0.06	0.93	−0.003	−5457.39
	(−0.77)	(1.47)	(3.15*)	(1.22)	(−0.87)	(−0.74)	(−1.69)	(−1.45)	(−1.29)	(2.49*)	(3.82*)	(66.09*)		
CET	0.13	−0.18	0.04	0.65	−0.08	−0.06	−0.34	−0.07	−9.40	0.15	0.41	0.76	−0.47	−5895.97
	(1.03)	(−0.76)	(0.62)	(3.10*)	(−0.65)	(−0.42)	(−2.02*)	(−0.58)	(−2.19*)	(2.20*)	(3.18*)	(14.12*)		
CES	0.11	−1.40	NE	−0.68	0.19	−0.74	−0.04	0.04	−0.18	0.97	0.06	0.86	0.001	−3295.00
	(2.62*)	(−2.18*)		(−2.01*)	(0.63)	(−2.66*)	(−0.09)	(0.10)	(−0.50)	(1.76)	(2.86*)	(15.18*)		
COR	−1.04	6.65	NE	0.19	−1.02	−0.06	−0.24	−0.25	−0.13	5.33	−0.00	0.87	−0.002	−7423.85
	(−0.21)	(0.22)		(0.67)	(−1.24)	(−0.24)	(−1.10)	(−1.32)	(−0.64)	(0.19)	(−0.38)	(1.11)		
COP	−0.15	0.88	0.11	−0.33	−0.61	−0.65	−0.78	−0.74	−0.64	0.31	0.14	0.81	−0.01	−4875.93
	(−1.17)	(1.24)	(3.02*)	(−0.59)	(−1.15)	(−1.21)	(−1.40)	(−1.37)	(−1.24)	(1.92)	(3.02*)	(14.29*)		
GXI	−0.09	0.18	0.08	0.78	0.31	0.26	−0.14	0.01	0.18	0.13	0.05	0.93	−0.007	−5429.93
	(−0.42)	(0.39)	(3.05*)	(1.17)	(0.93)	(1.25)	(−0.72)	(0.11)	(1.23)	(1.55)	(4.52*)	(48.05*)		

© Blackwell Publishers Ltd 2002

© Blackwell Publishers Ltd 2002

GSI	0.02	0.11	0.12	0.03	−0.15	0.007	−0.16	−0.27	−0.25	0.07	0.05	0.93	0.01	−4747.04
	(0.22)	(0.44)	(4.94*)	(0.17)	(−0.94)	(0.042)	(−0.85)	(−1.74)	(−1.65)	(1.97*)	(4.66*)	(57.33*)		
GES	0.04	−0.24	0.07	0.90	0.16	0.15	−0.02	0.07	0.004	0.10	0.04	0.94	−0.001	−5655.41
	(0.29)	(−0.67)	(2.42*)	(1.72)	(0.73)	(0.79)	(−0.08)	(0.41)	(0.02)	(2.08*)	(4.42*)	(72.72*)		
CEM	−0.07	0.76	0.08	−0.07	−0.58	−0.30	−0.82	−0.57	−0.63	0.03	0.04	0.96	0.002	−5471.06
	(−0.70)	(1.74)	(3.17*)	(−0.21)	(−2.01*)	(−0.99)	(−2.24*)	(−1.88*)	(−2.31*)	(1.27)	(3.21*)	(71.34*)		
HDI	0.13	−0.13	0.10	−0.07	−0.06	−0.05	−0.25	−0.10	−0.20	0.24	0.09	0.86	0.001	−4925.60
	(1.33)	(−0.50)	(4.27*)	(−0.32)	(−0.29)	(−0.27)	(−1.13)	(−0.53)	(−1.05)	(1.98*)	(3.76*)	(25.30*)		
HDL	0.22	−0.16	0.13	−0.18	−0.24	−0.22	−0.32	−0.07	−0.12	0.22	0.15	0.80	−0.002	−4480.65
	(2.25*)	(−0.91)	(4.87*)	(−1.42)	(−1.65)	(−1.51)	(−1.80)	(−0.63)	(−0.99)	(2.30*)	(4.04*)	(15.99*)		
HPT	−0.009	0.13	−0.02	−0.37	−0.16	0.19	−0.46	−0.10	−0.09	0.05	0.05	0.95	0.000	−3680.69
	(−0.39)	(0.31)	(−0.80)	(−2.24*)	(−0.83)	(0.57)	(−1.13)	(−0.27)	(−0.25)	(1.66)	(4.34*)	(70.40)		
HDF	0.24	−0.45	0.06	0.58	−0.81	−0.06	−0.50	−0.12	−0.19	2.74	0.36	0.42	−0.005	−5617.44
	(2.21*)	(−1.27)	(2.07*)	(1.25)	(−1.31)	(−0.20)	(−1.42)	(−0.39)	(−0.61)	(2.33*)	(1.59)	(2.37*)		
ICT	−0.29	1.63	0.03	0.78	−0.38	−0.65	−1.36	−1.00	−0.84	0.01	0.01	0.99	0.003	−6210.60
	(−1.83)	(1.89)	(1.46)	(1.17)	(−0.89)	(−1.30)	(−2.33*)	(−1.85)	(−1.68)	(0.43)	(3.78*)	(243.2*)		
INO	1.22	−3.72	NE	−0.16	0.13	0.24	−0.02	0.19	0.01	4.99	0.07	0.34	0.014	−3899.04
	(1.33)	(−1.30)		(−0.73)	(0.33)	(0.77)	(−0.07)	(0.81)	(0.06)	(2.35*)	(1.37)	(1.61)		
IRS	0.03	0.03	0.10	0.36	−0.11	0.07	−0.18	−0.13	−0.26	0.06	0.07	0.92	−0.000	−5105.84
	(0.38)	(0.19)	(3.57*)	(1.44)	(−0.69)	(0.47)	(−0.85)	(−0.97)	(−1.95)	(1.97*)	(4.52*)	(57.77*)		
IDB	−0.06	0.26	0.05	−0.74	−0.05	−0.45	−0.11	0.02	0.06	1.59	0.07	0.67	0.000	−2899.51
	(−1.13)	(0.63)	(1.33)	(−3.21*)	(−0.19)	(−2.17*)	(−0.34)	(0.09)	(0.25)	(1.56)	(1.67)	(3.77*)		
INE	0.02	−0.00	0.09	−0.30	−0.12	−0.23	−0.33	−0.03	0.01	0.49	0.11	0.82	0.000	−2878.79
	(0.99)	(−0.02)	(2.60*)	(−1.09)	(−1.26)	(−1.01)	(−1.03)	(−0.15)	(0.05)	(1.32)	(3.46*)	(11.38*)		
ITC	−0.06	0.50	0.08	0.43	−0.31	−0.24	−0.61	−0.41	−0.19	0.07	0.05	0.94	−0.000	−5446.07
	(−0.48)	(0.94)	(2.77*)	(1.10)	(−0.92)	(−0.63)	(−1.49)	(−1.17)	(−0.58)	(2.28*)	(2.58*)	(52.14*)		
LST	−0.08	−0.07	−0.05	0.46	0.11	0.40	0.007	0.25	0.23	0.12	0.08	0.91	−0.003	−5569.21
	(−0.88)	(−0.14)	(−2.80*)	(1.23)	(0.28)	(1.08)	(0.02)	(0.69)	(0.65)	(2.60*)	(3.92*)	(60.55*)		
MTN	0.35	−1.31	−0.04	−0.26	0.08	0.03	0.61	0.57	0.43	0.41	0.11	0.83	0.002	−2877.50
	(2.34*)	(−2.20*)	(−1.20)	(−1.28)	(0.27)	(0.30)	(1.39)	(1.43)	(1.13)	(1.88)	(3.63*)	(14.78*)		
MAG	0.14	−0.38	0.09	−0.13	0.43	0.07	−0.05	−0.15	−0.16	1.42	0.19	0.61	−0.004	−2887.29
	(0.97)	(−0.80*)	(2.48*)	(−0.51)	(1.74)	(0.39)	(−0.17)	(−0.58)	(−0.63)	(2.29*)	(2.75*)	(5.47*)		
PFZ	0.08	−0.29	NE	0.49	0.21	0.34	−0.46	−0.03	0.28	0.53	0.07	0.88	−0.000	−5832.67
	(0.54)	(−0.73)		(1.46)	(0.73)	(1.50)	(−1.78)	(−0.15)	(1.71)	(2.30*)	(3.77*)	(26.06*)		

Table 3 (Continued)

	θ	γ_0	γ_1	D_1	D_2	D_3	D_4	D_5	D_6	*Constant*	α	β	$\bar{R}^2$	*LR*
PDS	−0.05	0.23	NE	0.21	−0.05	0.08	−0.34	−0.16	0.00	0.12	0.03	0.95	−0.002	−5254.98
	(−0.32)	(0.61)		(1.11)	(−0.26)	(0.23)	(−1.17)	(−0.93)	(0.01)	(1.57)	(1.36)	(30.69*)		
PAU	−0.07	0.14	0.08	0.,18	0.12	0.45	−0.20	−0.01	0.15	0.49	0.05	0.92	0.002	−6445.28
	(−0.63)	(0.32)	(3.65*)	(0.67)	(0.36)	(1.41)	(−0.53)	(−0.05)	(0.49)	(3.09*)	(4.35*)	(49.85*)		
REL	−0.004	0.06	0.05	−0.06	0.02	0.09	−0.25	−0.09	−0.000	0.05	0.04	0.96	−0.002	−5918.71
	(−0.05)	(0.12)	(2.12*)	(−0.18)	(0.06)	(0.28)	(−0.64)	(−0.28)	(−0.001)	(1.43)	(3.24*)	(78.13*)		
TTC	0.19	−0.49	−0.000	0.20	0.10	0.09	−0.09	−0.66	−0.16	0.36	0.06	0.90	−0.01	−5559.45
	(0.78)	(−0.76)	(−0.007)	(1.04)	(0.60)	(0.60)	(−0.51)	(−0.97)	(−0.14)	(1.17)	(2.14*)	(19.10*)		
TTE	−0.01	0.10	NE	0.26	−0.23	0.10	−0.32	−0.004	−0.25	0.75	0.12	0.86	−0.004	−5315.63
	(−0.82)	(0.57)		(1.10)	(−0.88)	(0.48)	(−1.36)	(−0.02)	(−1.19)	(1.68)	(5.95*)	(47.40*)		
TIS	−0.04	0.18	0.06	0.20	−0.38	0.13	−0.38	−0.11	−0.19	0.13	0.03	0.95	0.001	−5639.30
	(−0.30)	(0.49)	(2.56*)	(0.89)	(−1.33)	(0.59)	(−1.11)	(−0.61)	(−1.05)	(1.11)	(2.03*)	(33.23*)		
TTP	−0.13	0.94	0.08	−1.02	−0.67	−0.44	−0.78	−0.57	−0.72	0.04	0.05	0.95	−0.006	−5712.79
	(−1.47)	(2.21*)	(2.96*)	(−1.50)	(−2.14*)	(−1.44)	(−2.22)	(−1.87)	(−2.36*)	(0.93)	(2.04*)	(41.67*)		
TEA	0.05	0.07	0.01	−0.15	−0.02	−0.23	−0.39	−0.29	−0.24	0.23	0.07	0.90	−0.002	−5355.64
	(0.51)	(0.27)	(0.62)	(−0.73)	(−0.11)	(−1.31)	(−1.85)	(−1.70)	(−1.43)	(2.27*)	(3.79*)	(33.86*)		
EQ-PORT	−0.009	0.12	0.24	0.06	−0.20	0.02	−0.28	−0.18	−0.22	0.04	0.07	0.91	0.02	−4113.41
	(−0.10)	(0.68)	(8.63*)	(0.42)	(−1.12)	(0.15)	(−2.00*)	(−1.46)	(−1.81)	(2.54*)	(4.79*)	(55.39*)		

Notes:
* Significant at the 5% level. *t*-statistics are in parentheses. LR = Log-likelihood Ratio. NE = Not Estimated.

© Blackwell Publishers Ltd 2002

conditional heteroskedasticity is present, confirming that daily returns do not conform to a random walk model.

The coefficient for risk premium (θ) is significant at the 5% level for only four stocks, Calcutta Electric Supply (CES), Hindustan Lever (HDL), Housing Development Corporation (HDF), and Mahanagar Telephone Ltd (MTN). For the rest of the stocks and the EQPORT, the coefficient (θ) is statistically insignificant. This evidence suggests that there is no relationship between conditional volatility and expected returns. This lack of a relationship may be explained by the presence of significant positive autocorrelation in daily return series. The hypothesis that conditional volatility explains expected returns is rejected for the Indian stock market.[10]

(v) Nonlinearity, Nonstationarity and ARCH

We find that the GARCH procedure does not normalise residuals as in most cases, significant skewness, kurtosis, and Ljung-Box statistics are still reported. In this context, it is interesting to investigate whether the residuals even though not normal, are independently and identically distributed and are free from non-linear dependence. The BDS statistics calculated for residuals from the GARCH-M model (not reported, but available on request) suggest that except for five stocks, the BDS statistics are not significant for 33 individual stocks and the EQPORT.[11] This finding suggests that for most stocks, the non-linear dependence appear to have been caused by the conditional heteroskedasticity.

Previous research has shown that nonstationarity can be one of the possible reasons for rejecting the IID hypothesis because the underlying structural and economic variables which influence the price evolutionary process can be nonstationary. This is particularly relevant in the Indian case where a number of structural changes have been introduced in the process of economic liberalisation initiated by the government of India since 1991. We therefore use Augmented Dickey-Fuller (Said and Dickey, 1984) and Phillips-Perron (1988) tests to eliminate nonstationarity as a possible explanation for the rejection of the null hypothesis of IID. The statistics have been estimated with the Newey-West correction using MacKinnon critical values.[12] Results (not reported, but available from the author on request) strongly

© Blackwell Publishers Ltd 2002

support the absence of unit roots in the return series of all individual stocks and the EQPORT. This confirms that non-linear dependence is not caused by nonstationarity of underlying economic variables. The evidence supports our conclusions that for most individual stocks, the non-linear dependence seems to be attributable to the ARCH effects.

3. CONCLUSIONS

This paper examines the random walk hypothesis in the emerging Indian stock market by investigating daily returns calculated from an equally weighted portfolio of 100 stocks and a sample of 38 most actively traded stocks in the Bombay Stock Exchange. To the best of our knowledge, this is the first study that examines the random walk hypothesis by testing for the non-linear dependence using a large disaggregated daily data from the Indian stock market. The broad conclusions of this study are that daily returns from the Indian market do not conform to a random walk. Daily returns from most individual stocks and the equally weighted portfolio exhibit significant non-linear dependence. Further examination reveals that most of the non-linear dependence is in the form of ARCH type conditional heteroskedasticity. However, in a few cases, the non-linearity is explained by the EGARCH model and in at least one anomalous case, the GARCH process could not explain the non-linear dependence. The unit root tests confirm that non-linear dependence does not appear to be caused by nonstationarity of underlying economic variables. Our results are largely consistent with the previous research that has shown evidence of non-linear dependence in returns from the stock market indexes and individual stocks in the US and the UK. We find that daily return volatility is time varying and persistent in nature but as measured by a GARCH-M model, it does not explain expected returns. Finally, though the statistical evidence in this paper rejects the random walk model of efficient price formation for the Indian market, further research is suggested whereby other plausible models should be analysed to confirm the empirical evidence presented in this paper.

© Blackwell Publishers Ltd 2002

APPENDIX

	Names of Selected Stocks	Datastream Code	Industry Sector
1	Asian Paints Ltd	API	Paints
2	Associated Cement Company Ltd	ASC	Cement
3	Bajaj Auto Ltd	BAJ	Automobiles
4	Baroda Rayon Ltd	BAR	Textiles
5	Bata India Ltd	BIN	Footwear
6	Bombay Dying Ltd	BOM	Textiles
7	Bombay State Electricity Supply Company	BSS	Power
8	Castrol India Ltd	CAS	Chemical
9	Century Textiles Ltd	CET	Textiles
10	Calcutta Electric Supply Company	CES	Power
11	Chochin Refinery Ltd	COR	Oil Refinery
12	Colgate Palmolive Ltd	COP	Consumer products
13	Glaxo (India) Ltd	GXI	Pharmaceutical
14	Grasim Industries	GSI	Textiles
15	Great Eastern Shipping	GES	Shipping
16	Gujrat Ambuja Cements	CEM	Cement
17	Hindalco	HDI	Aluminium
18	Hindustan Lever Ltd	HDL	Consumer products
19	Hindustan Petroleum Corporation	HPT	Petroleum
20	Housing Development and Finance Corporation	HDF	Finance and Banking
21	Industrial Credit and Investment Corporation of India	ICT	Finance and Banking
22	Indian Petrochemical Corporation Limited	INO	Petroleum
23	Indian Rayon Industries	IRS	Textiles
24	Industrial Development Bank of India	IDB	Finance and Banking
25	Infosys Technology Ltd	INE	Software
26	Imperial Tobacco Corporation (India) Ltd	ITC	Tobacco products
27	Larson and Tubro	LST	Engineering
28	Mahanagar Telephone Nigam Limited	MTN	Telecommunication
29	Manglore Refinery	MAG	Oil Refinery
30	Pfizer Ltd	PFZ	Pharmaceutical
31	Ponds India Ltd	PDS	Consumer products
32	Premier Automobiles Ltd	PAU	Automobiles
33	Reliance Industries	REL	Diversified
34	Tata Chemicals	TTC	Chemical
35	Tata Engineering and Locomotive Company	TTE	Engineering and Heavy Vehicles
36	Tata Iron and Steel Company	TIS	Steel
37	Tata Power	TTP	Power
38	Tata Tea Ltd	TEA	Tea

© Blackwell Publishers Ltd 2002

NOTES

1 See Barry and Lockwood (1995) for an excellent summary of literature on research in emerging markets.

2 See Chatrath (1996) for diversification benefits in the Indian market. India is the fifth-largest economy (in purchasing-power parity terms) after the United States, China, Germany and Japan. With a relatively low inflation rate and stable currency, the GDP growth for 2001, is projected to be more than 6%. In the first quarter of 2000, the national index (BSENI-100) recorded a return of 10.4% in dollar terms and was among the top of Asia-Pacific performers. (Source: Bombay stock exchange reports.)

3 Although there are over 17 stock exchanges in India, the Bombay stock exchange is the largest and represents over 70% of the total turnover of equity shares in India. Despite competition, the BSE is considered as the most important and influential stock exchange. Therefore, we consider that analysis of stock prices on the BSE well represents stock trading activity for the Indian stock market.

4 To save space we have not provided the names of all 100 companies whose stocks are included in the equally weighted portfolio. However, this can be made available on request from the author.

5 To save space, the Ljung-Box statistics are not shown for all lags. In fact except for a few stocks, majority of the stocks shows significant autocorrelations on various lags.

6 Standard statistical tests such as the Ljung-Box test cannot distinguish between chaotic and random behaviour. The Ljung-Box statistic tests only for white noise, which is a sequence of uncorrelated random variables with a constant mean and variance. A 'strict white noise process' follows a sequence of independent and identically distributed (IID) random variables. Research suggests that it is important to distinguish 'white noise' from 'strict white noise' since a series generated by a non-linear process may have the white noise property although it may not be independently and identically distributed. This condition is particularly important since identification of a non-linear structure can clearly aid the formulation of improved models.

7 See for example, Hsieh (1993) who finds that non-IID behaviour of daily log price changes of currency futures contracts is caused by predictable conditional variances which could be described by an autoregressive volatility model. In another study, Booth et al. (1994) confirm that a simple GARCH model is able to capture the non-linear dependence in Finnish stock returns.

8 Chou (1988) uses the GARCH-M model in examining the risk premium assumptions, while Bollerslev, Engle and Wooldridge (1988) use a multivariate GARCH-M model to test for time-varying risk premiums. Also, see the seminal work by Engle, Lilien and Robins (1987) and Theodossiou and Lee (1995).

9 Due to investor's anticipation, stock market volatility may have been affected prior to the date of the policy announcements. We allowed two months for such anticipation.

10 This finding is not surprising as in a study of five Pacific Rim markets and the UK and the USA, Fraser and Power (1997) find that the conditional volatility connects to the expected returns in only one market (Malaysia).

11 For the five stocks, Baroda Rayon (BAR), Century Textiles (CET), Cochin

© Blackwell Publishers Ltd 2002

Refinery (COR), Housing Development Finance Corporation (HDF), and Tata Iron and Steel Company (TIS), we generated residuals from EGARCH and GARCH-M models. The results show that for BAR, CET and TIS, the non-linear dependence disappears in EGARCH residuals. However, for COR and HDF, the BDS statistics remain significant. Further analysis with GARCH-M indicates that while for HDF, non-linear dependence is captured by inclusion of conditional mean, the BDS statistics remain significant in residuals for COR. We therefore consider COR as an anomalous case. The results are available on request from the author.

12 Recently, MacKinnon (1991) has implemented a much larger set of simulations than those tabulated by Dickey and Fuller. The MacKinnon procedure can estimate the response surface using the simulation results permitting the calculation of Dickey and Fuller values for any sample size and for any number of right hand variables.

REFERENCES

Ayadi, O. and C. Pyun (1994), 'An Application of Variance Ratio Test to the Korean Securities Market', *Journal of Banking and Finance*, Vol. 18, pp. 643–58.

Barnes, P. (1986), 'Thin Trading and Stock Market Efficiency: The Case of the Kuala-Lumpur Stock Exchange', *Journal of Business Finance & Accounting* (Winter), pp. 609–17.

Barry, C. B. and L. J. Lockwood (1995), 'New Directions in Research on Emerging Capital Markets', *Financial Markets, Institutions and Instruments*, Vol. 4, No. 5, pp. 15–36.

Bollerslev, T. (1986), 'Generalised Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, Vol. 31, pp. 307–27.

________ R.Y. Chou, and K.F. Kroner (1992), 'ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence', *Journal of Econometrics*, Vol. 52, pp. 5–59.

________ R.F. Engle and J.M. Wooldridge (1988), 'A Capital Asset Pricing Model with Time-varying Covariance', *Journal of Political Economy*, Vol. 96, pp. 116–31.

Booth, G., T. Martikainen, S. Sarkar, I. Virtanen and P. Yli-Olli (1994), 'Nonlinear Dependence in Finnish Stock Returns', *European Journal of Operational Research*, Vol. 74, Issue 2 (April), pp. 273–83.

Brock, W. and C. Sayers (1988), 'Is the Business Cycle Characterised by Deterministic Chaos?', *Journal of Monetary Economics*, Vol. 22, pp. 71–90.

________ D. A. Hsieh and B. Le Baron (1991), *Nonlinear Dynamics, Chaos, and Instability: Statistical Theory and Economic Evidence* (MIT Press, Massachusetts and London).

________ W. D. Dechert, J. A. Scheinkman and B. Le Baron (1996), 'A Test For Independence Based on the Correlation Dimension', *Econometric Reviews*, Vol. 15, pp. 197–235.

Chan, M. W. L., A. Khanthavit and T. Hugh (1996), 'Seasonality and Cultural Influences on Four Asian Stock Markets', *Asia Pacific Journal of Management*, Vol. 13, No. 2, pp. 1–24.

Chatrath, A., S. Ramchander and F. Song (1996), 'Benefits From Portofolio Diversification into the Indian Equity Market', *American Business Review*,

© Blackwell Publishers Ltd 2002

Vol. 14, No. 1, pp. 1–10.
Cheung, Y.-L., K.-A. Wong and Y-Ki Ho (1993), 'The Pricing of Risky Assets in Two Emerging Asian Markets – Korea and Taiwan', *Applied Financial Economics*, Vol. 3, No. 4, pp. 315–24.
Chou, R. Y. (1988), 'Volatility Persistence and Stock Valuations: Some Evidence using GARCH', *Journal of Applied Econometrics*, Vol. 3, pp. 279–94.
Choudhry, T. (2000), 'Day of the Week Effect in Emerging Asian Stock Markets: Evidence from the GARCH Model', *Applied Financial Economics*, Vol. 10, pp. 235–42.
Dickinson, J. and K. Muragu (1994), 'Market Efficiency in Developing Countries: A Case Study of the Nairobi Stock Exchange', *Journal of Business Finance & Accounting*, Vol. 21, No. 1, pp. 133–50.
Engle, R. (1982), 'Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of UK Inflation', *Econometrica*, Vol. 50, pp. 987–1007
________ and T. Bollerslev (1986), 'Modelling the Persistence of Conditional Variances', *Econometric Reviews*, Vol. 5, pp. 1–50.
________ D. Lilien and R. Robins (1987), 'Estimating Time Varying Risk Premia in the Term Structure: The ARCH Model, *Econometrica*, Vol. 55, pp. 391–408.
Fama, E.F. (1970), 'Efficient Capital Markets: A Review of Theory and Empirical Work' *Journal of Finance*, Vol. 25, No. 2 (May), pp. 383–417.
Frank, M. and T. Stengos (1989), 'Measuring the Strongness of Gold and Silver Rates of Return', *Review of Economic Studies* (October), pp. 553–67.
Fraser, P. and D. Power (1997), 'Stock Return Volatility and Information: An Empirical Analysis of Pacific Rim, UK and US Equity Markets', *Applied Financial Economics*, Vol. 7, pp. 241–53.
Granger, C. and A.P. Andersen (1978), 'An Introduction to Bilinear Time Series Models' (Vandenhoeck & Ruprecht: Gottingen).
Grassberger, P. and I. Procaccia (1983), 'Characterisation of Strange Attractors,' *Physics Review Letters*, Vol. 50, pp. 346–58.
Hsieh, D.A. (1989), 'Testing for Nonlinear Dependence in Daily Foreign Exchange Rates', *Journal of Business*, Vol. 62, pp. 339–68.
________ (1991), 'Chaos and Nonlinear Dynamics: Application to Financial Markets', *Journal of Finance*, Vol. 46, pp. 1839–877.
________ (1993), 'Implications of Nonlinear Dynamics for Financial Risk Management', *Journal of Financial and Quantitative Analysis*, Vol. 28, pp. 41–64.
MacDonald, R. and D. Power (1993), 'Persistence in UK Share Returns: Some Evidence From Disaggregated Data, *Applied Financial Economics*, Vol. 3, pp. 27–38.
MacKinnon, J. (1991), 'Critical Values for Cointegration Tests, chapter 13 in R.F. Engle and C.W.J. Granger (eds.), *Long-run Economic Relationships: Readings in Cointegration* (Oxford University Press).
McCurdy, T. and I. Morgan (1988), 'Testing the Martingale Hypothesis in Deutsche Mark Futures with Models Specifying the Form of Heteroskedasticity', *Journal of Applied Econometrics*, Vol. 3, pp. 187–202.
Opong, K.K., G. Mulholland, A. Fox and K. Farahmand (1999), 'The Behaviour of Some UK Equity Indices: An Application of Hurst and BDS Tests, *Journal of Empirical Finance*, Vol. 6, pp. 267–82.
Phillips, P. and P. Perron (1988), 'Testing For Unit Root in Time Series Regression', *Biometrika*, Vol. 75, pp. 335–46.
Poshakwale, S. and D. Wood (1997), 'The Impact of Regulatory Changes in the

© Blackwell Publishers Ltd 2002

Indian Stock Market: An Event Study', in V. Titus, S. Sundaram and K. Kulkarni (eds.), *Economic Liberalisation: Its Impact on Indian Economy, Business, and Society* (Association of Indian Economic Studies, Illinois), pp. 86–101.

Poshakwale, S. and D. Wood (1998), 'Conditional Variance and Nonlinearity in the Polish Emerging Market', in J. Choi and J. Doukas (eds.), *Emerging Capital Markets: Financial and Investment Issues* (Quorum Books, Westport), pp. 205–24.

Said, S. and D. Dickey (1984), 'Testing For Unit Roots in ARMA Models of Unknown Order, *Biometrika*, Vol. 71, pp. 599–607.

Scheinkman, J.A. and B. Le Baron (1989), 'Nonlinear Dynamics and Stock Returns', *Journal of Business*, Vol. 62, pp. 311–37.

Sewell, S., R. Stansell, I. Lee and M.-S. Pan (1993), 'Nonlinearities in Emerging Foreign Capital Markets, *Journal of Business Finance & Accounting*, Vol. 20, pp. 237–48.

Theodossiou, P. and U. Lee (1995), 'Relationship between Volatility and Expected Returns across International Stock Markets', *Journal of Business Finance & Accounting*, Vol. 22, pp. 289–301.

Willey, T. (1992), 'Testing For Nonlinear Dependence in Daily Stock Indices', *Journal of Economics and Business*, Vol. 44, No. 1, pp. 63–76.

Wood, D. and S. Poshakwale (1997), 'Market Anomalies in Selected Emerging and Developed Stock Markets', *Asia-Pacific Journal of Accounting*, Vol. 4, No. 1, pp. 73–92.

Yadav, P., K. Paudyal and P. Pope (1996), 'Non-linear Dependence in Daily Stock Index Returns: Evidence from Pacific Basin Markets, *Advances from Pacific Basin Markets*, Vol. II, pp. 349–78.

________ ________ ________ (1999), 'Non-linear Dependence in Stock Returns: Does Trading Frequency Matter?', *Journal of Business Finance & Accounting*, Vol. 26, Nos 5 & 6, pp. 651–79.

© Blackwell Publishers Ltd 2002