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Testing Predictability and Nonlinear Dependence in the Indian Stock Market

Abstract: *This paper suggests a systematic approach to studying predictability and nonlinear dependence in the context of the Indian stock market, one of the most important emerging stock markets in the world. The proposed approach considers nonlinear dependence in returns and envisages appropriate specification of both the conditional first- and second-order moments, so that final conclusions are free from any probable statistical consequences of misspecification. To this end, a number of rigorous tests are applied on the returns, based on four major daily indices of the Indian stock market. It is found that the Indian stock market is predictable, and this observed lack of efficiency is due to serial correlation, nonlinear dependence, day-of-the week effects, parameter instability, conditional heteroskedasticity (GARCH), daily-level seasonality in volatility, the short-term interest rate (in some subperiods of some indices), and some dynamics in the higher-order moments.*

Key words: *Andrews's test, automatic variance ratio test, BDS test, market efficiency, misspecification, nonlinear dependence, predictability.*

One of the earliest and most enduring questions of financial economics is whether one can forecast financial asset prices. The concept of efficient market hypothesis (EMH), which asserts that asset price changes are unforecastable, can be traced

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back at least as far as the pioneering theoretical contribution of Bachelier (1900) and the empirical research of Cowles (1933). The modern literature on financial market efficiency begins with Samuelson (1965), who tried to prove that properly anticipated prices fluctuate randomly. In an informationally efficient market—different from an allocationally or Pareto-efficient market—price changes must be unforecastable if they are properly anticipated, that is, if they fully incorporate the expectations and information of all market participants. Fama summarizes this idea by stating that "A market in which prices always 'fully reflect' available information is called 'efficient'" (1970, p. 384). More recently, Malkiel (1992) defined informational efficiency more explicitly, implying that it is impossible to make economic profits by trading on the basis of the given information set.

Before the days of nonlinear dynamics, testing for Fama's EMH in the context of the stock market usually meant testing the null hypothesis that the autocorrelation coefficients of different lags were statistically insignificant. For this purpose, the Ljung–Box (1978) autocorrelation and regression tests used to be normally applied. But since the 1980s, it is well appreciated that a lack of linear dependence, that is, serial correlation, does not rule out nonlinear dependence, which, if present, would contradict the EMH and may aid in forecasting, especially over short time intervals. Granger and Andersen (1978) and Sakai and Tokumaru (1980) have shown that simple nonlinear models exhibit no serial correlation but contain strong nonlinear dependence. This has led several studies, such as those by Granger and Andersen (1978), Hinich and Patterson (1985), and Scheinkman and LeBaron (1989) to look for nonlinear structures in stock returns. One of the most important and useful tests available in the literature for detecting nonlinear patterns—that is, the existence of potentially forecastable structures—is from Brock et al. (1987; 1996), henceforth denoted as the BDS test. With the increasing power of computers, coupled with advances in both nonlinear dynamics and chaos, the number of studies reexamining the behavior of security returns from the standpoint of market efficiency has increased considerably. Most of these[1] have cast doubt on the conclusion of market efficiency based only on the lack of serial correlation in returns.

Apart from complicated nonlinear dependence and dynamics, there are two well-known reasons why stock prices may deviate from the random walk model. First, conditional variance of stock returns is not constant over time. This has led to the development of autoregressive conditional heteroskedasticity (ARCH) and generalized ARCH (GARCH) models (cf. Bollerslev 1986; Engle 1982). Returns based on equity prices or indices are most often found to have time-dependent conditional variance, and hence, ARCH or GARCH models are used to take care of the volatility observed in the time series of returns. Some of the tests for (linear) autocorrelation mentioned earlier perform poorly when there is conditional heteroskedasticity in the returns. Diebold (1986), Lo and MacKinlay (1988), Silvapulle and Evans (1993), and others have noted that in the presence of ARCH, the serial correlation tests, if not corrected, can result in misleading inferences.

Stock returns may also deviate from the random walk model due to what is known as calendar anomalies or effects. Many authors[2] have found that returns differ by small yet statistically significant amounts over different periods of time, such as days of the week, weeks of the month, or months of the year. These effects, if present in returns, indicate that stock prices move in predictable patterns. Additionally, there may be a predictable component in stock returns in the form of a significant time-varying risk factor.

Recent econometric advances and empirical evidence also suggest that returns are predictable to some degree. As stated in Campbell et al. (1997), modern financial economics teaches us that perfectly rational factors may account for such predictability. There are also views that changing business conditions or necessary rewards for bearing risks may lead to predictability (Campbell et al. 1997). The issue now is not one of efficiency versus inefficiency, but rather whether an apparent departure from efficiency is due to factors such as significant transaction costs, risk premiums, or human behavioral characteristics, the last one being part of what has recently been called behavioral finance.

However, debate continues over the existence of predictable patterns and the possible rejection of EMH, despite the possible roles of the above-mentioned variables and behavioral factors, along with other fundamental variables and past values of return, in explaining variations in stock returns. Some researchers are skeptical that any of these "predictable patterns" documented extensively in the literature were ever sufficiently robust to have created arbitrage opportunities to earn above-average returns without accepting above-average risks. They have also argued that pricing irregularities, and even predictable patterns that appear over time, are temporary in nature and unable to refute the hypothesis that the stock market is efficient. In this context, Malkiel's conclusion is noteworthy:

> I suspect that the end result will not be an abandonment of the belief of many in the profession that the stock market is remarkably efficient in its utilization of information. Periods such as 1999 where "bubbles" seem to have existed, at least in certain sectors of the market, are fortunately the exception rather than the rule. Moreover, whatever patterns or irrationalities in the pricing of individual stocks that have been discovered in a search of historical experience are unlikely to persist and will not provide investors with a method to obtain extraordinary returns. (Malkiel 2003, p. 80)

In all of the studies on efficiency, the underlying models are assumed to have correctly specified conditional means. It is now too well known that inferences based on models suffering from misspecification could be misleading and incorrect. For studies on efficiency in the framework of ARCH and GARCH, Lumsdaine and Ng (1999)[3] have shown that, in general, the popular Lagrange multiplier (Rao's score) test for the null of homoskedasticity leads to overrejection of the null hypothesis of conditional homoskedasticity if there is misspecification of the conditional mean. It thus becomes important to test for ARCH in the general context of

a possibly misspecified conditional mean, and then take appropriate steps to guard against misspecification in the mean function in case the test rejects the null hypothesis of no misspecification of conditional mean. As Lumsdaine and Ng have it, the misspecification problem referred to here can arise if the functional form or conditioning set is misspecified. For linear dynamic models, notable cases of such misspecifications are omitting shifts in the trend function, selecting a lag length in an autoregression that is lower than the true order, failing to account for parameter instability, and residual autocorrelation, and omitting variables. They also proposed a method of adjusting the standard ARCH test using recursive residuals, to allow for possible misspecification of unknown form. Moreover, an incorrectly specified conditional mean might well lead to misspecification of conditional variance. The GARCH model would be correctly specified only if there were no serial correlation. To solve this problem when studying serial correlation, Robinson (1991) and Wooldridge (1991a; 1991b) have suggested ways of making tests more robust for serial correlation and allowing for possible misspecification of conditional variance.

Finally, the BDS test for nonlinear dependence in GARCH-adjusted stock returns might reject the null hypothesis of independent and identically distributed (i.i.d.) returns, owing to dynamics in higher-order moments. But when the i.i.d. null is rejected in such residuals, researchers usually do not carry out further analyses to establish the existence of such higher-order dependencies in the adjusted returns. If the framework of the study is made to incorporate modeling aspects, such as proper specification of both the conditional mean and the conditional variance, then rejection of the null may be attributed to the existence of some dynamics in higher-order moments only.

The focus of this paper is to advocate a systematic approach toward studying predictability and nonlinear dependence in returns, with due emphasis on appropriate specification of the conditional first- and second-ordered moments, so that the final inferences are free from any possible consequences of misspecification. To this end, we apply a battery of tests, some of which have already been mentioned. We carry out this exercise for one of the most important emerging economies, namely, the Indian economy. But why study the Indian stock market when considering predictability and nonlinearity?

In the early 1990s, India embarked on a series of economic structural and regulatory reforms to free itself from an extremely fragile economic condition, arising primarily out of political instability, sluggish growth, and foreign exchange crisis. Consequently, fundamental changes have taken place in various sectors of the Indian economy, including, of course, the financial sector. In the Indian capital market, these include the formation of the Securities and Exchange Board of India (SEBI) as the regulatory authority of the Indian capital market; the birth of a National Stock Exchange (NSE) to compete with the Bombay Stock Exchange (BSE), the oldest stock exchange of India; the introduction of computerized screen-based

trading at both exchanges; and the dematerialization of shares. Both exchanges provide for settlement through the Clearing House/Corporation and have trade and settlement guarantees and investor protection funds. Derivative trading was introduced into the secondary segment of the Indian capital market in June 2000; SEBI approved it based on future contracts in both the BSE and NSE, in accordance with the rules, bylaws, and regulations of the stock exchanges.

Established in 1875, the BSE is India's premier stock exchange. Total market capitalization of the BSE for 2000 stood at almost Rs.7.67 trillion (US$167.83 billion). Total turnover was almost Rs.6.22 trillion (approximately US$136.11 billion), with an average daily turnover of Rs.7.23 billion (US$0.84 billion). The liberalization of the Indian economy has led to some spectacular effects. By August 2000, there were more than 530 registered foreign institutional investors (FIIs) and 35 foreign brokers. Total investment by FIIs exceeded Rs.740 billion (US$16 billion) in the primary and secondary markets. Their growth in investments—in the number of listed companies in the Indian stock exchanges, changes in trading rules, and the volume of capital raised from private investors—have helped to globalize the Indian economy and determine the international competitiveness of Indian capital markets, sparking a boom in stock prices. The real dollar price of Indian stock market equity increased by more than 300 percent from December 1984 to December 1994.

Despite a long history and voluminous turnover, however, serious, systematic, and methodologically sound studies of the Indian stock market in general, and in the context of EMH in particular, are very few. As Poshakwale (2002) has commented, not much is known about the characteristics and dynamics of Indian stock returns to begin with. Most of the studies of market efficiency for the Indian stock market have focused on traditional tests, such as those based on correlation and regression. Poshakwale (1996) presents probably the first systematic study of Indian stock market efficiency. That study and that by Gupta and Gupta (1997) found violations of weak form efficiency in the BSE. Bhaumik (1997), however, found evidence of market efficiency, although in a very limited framework of analysis. The two other notable studies of efficiency in the Indian stock market are by Basu and Morey (1998) and Kawakatsu and Morey (1999). Although they sought to find the effects of economic liberalization on the efficiency of the Indian stock market, their analyses are relevant from the standpoint of stock market predictability as well. The most recent works on this issue with Indian data are those by Bhattacharya et al. (2003), Bhole and Pattanaik (2002), Choudhry (2000), and Poshakwale (2002). These studies are very limited in scope, appropriate econometric methodology applied, data used, and inferences drawn on the efficiency of the Indian stock market. Poshakwale (2002) applied the BDS test on time series of individual stock prices to study nonlinear dependence in returns. Choudhry (2000) studied day-of-the-week effects with the daily BSE100, a broad-based index of the movement of stock prices.

Modeling Approach

In this section, we describe our approach and the tests to be used in our study. Assuming p_t to be the logarithm of stock price index P_t, return r_t is defined as $r_t = p_t - p_{t-1}$. Fama's EMH is often tested by assuming that p_t follows a random walk model under the null hypothesis. It is well known that the simplest version of the random walk model is the i.i.d. increments in which the dynamics of $\{p_t\}$ are given by the following equation:

$$p_t = \mu + p_{t-1} + \varepsilon_t, \quad \text{and} \quad \varepsilon_t \sim \text{i.i.d.}\left(0, \sigma^2\right),$$

where μ is the expected price change or drift. Independence of the increments $\{\varepsilon_t\}$ implies not only that increments are linearly uncorrelated, but that any nonlinear functions of the increments are also uncorrelated. The relevant null and alternative hypotheses are thus stated as $H_0 : r_t$ is i.i.d. and $H_1 : r_t$ is not i.i.d. Both linear and nonlinear dependencies are allowed under the alternative.

We first test the stationarity of r_t by applying the augmented Dickey–Fuller (ADF) test (Said and Dickey 1984) and Phillips–Perron (PP) test (1988). Once the stationarity of r_t is established, we carry out tests for serial correlation in r_t. To this end, we first use the automatic variance ratio test by Choi (1999). Lo and MacKinlay (1988) suggested a procedure to test EMH that was quite different from the usual test of serial correlation. The novelty of their test, known as the variance ratio test, is that it is robust to many forms of conditional heteroskedasticity. Though the variance ratio test is intuitively appealing and known to have optimal properties under certain conditions (cf. Faust 1992), it is limited regarding the choice of lag truncation point; in the absence of any objective criterion, researchers often choose it arbitrarily. In view of this shortcoming, Choi (1999) suggested that the variance ratio test be calculated by using Andrews's (1991) optimal data dependent method. This is what is known as the automatic variance ratio test.

Automatic Variance Ratio Test

To test the random walk hypothesis, the usual variance ratio estimator of Lo and MacKinlay, defined as $VR(1) = Var(p_t - p_{t-1})/1\,Var(p_t - p_{t-1})$, equals 1 at all possible lag truncation points under H_0 of no serial correlation. Hence, Lo and MacKinlay suggested comparing a consistent estimate of $VR(1)$ with one to test for EMH. It is, however, clear that the test crucially depends on the arbitrary choice of the lag truncation point. To take care of this limitation, Choi suggested using the quadratic spectral Kernel, originally from Andrews (1991). This is optimal for estimating spectral density at zero frequency, and hence, the lag truncation point is also chosen optimally. Thus, the automatic variance ratio estimator is defined as

$$V\hat{R}(l) = 1 + 2\sum_{i=1}^{n-1} K(i/l)\,\hat{\rho}(i), \tag{1}$$

where

$$\hat{\rho}(i) = \sum_{t=1}^{n-i} r_t r_{t+i} \Big/ \sum_{t=1}^{n} r_t^2$$

and

$$K(x) = \frac{25}{12\pi^2 x^2}\left[\frac{\sin(6\pi x/5)}{6\pi x/5} - \cos(6\pi x/5)\right].$$

After proper standardization of the variance ratio estimator $V\hat{R}(l)$, the standardized statistic becomes $VR = \sqrt{n/l}\ V\hat{R}[(l) - 1]/\sqrt{2}$, which is called the automatic variance ratio test statistic. Under the null hypothesis of no serial correlation, the asymptotic distribution of the statistic has been found to be standard normal (cf. Choi 1999; Priestly 1980). As this test is a two-sided test, critical values are taken from both tails of the standard normal distribution.

After we have carried out the automatic variance ratio test, we consider specifying the conditional mean of returns as well as testing for possible sources of misspecification of conditional mean; the outcome of the tests would help to ensure that the conditional mean is properly specified. As already discussed in the previous section, returns might deviate from i.i.d. because of serial correlations, seasonal effects, time-varying risk factors, conditional heteroskedasticity, and other nonlinear dependencies. Any possible misspecification of the conditional mean might include, inter alia, exclusion of contemporaneous variables. Thus, consideration of proper specification entails that we include such contemporaneous independent variables in the specification of the conditional mean of the r_t. Ang and Bekaert (2001) have found the nominal interest rate to be the most "popular" predictor of stock returns. Campbell (1987), Fama and Schwert (1977), Lee (1992), and Shiller and Beltratti (1992) have also observed that predictability in excess stock returns could be explained by the nominal interest rate.

Taking all of these into consideration, we propose the specification of the conditional mean of r_t to be as follows:

$$r_t = \sum_{k=1}^{\tilde{m}} \varsigma_k r_{t-k} + \sum_{j=1}^{d} \beta_j D_{jt} + \omega i_t + \varepsilon_t, \quad t = 1, 2, ..., n \tag{2}$$

$$\varepsilon_t \,|\, \psi_{t-1} \sim N(0, h_t),$$

where h_t represents conditional variance at time t, $D_j (j = 1, 2, ..., d)$ denotes seasonal 0–1 dummies, i_t is the nominal interest rate, $\psi_{t-1} = \{r_{t-1}, r_{t-2}, ...\}$ stands for the information set at time $t - 1$, and $\tilde{m}$ is the appropriate lag value of r_t, capturing its autocorrelations as it is determined by Hall's (1994) procedure. The specification in Equation (2) may be conveniently written, in vector notation, as

$$r_t = Z_t'\gamma + \varepsilon_t, \tag{3}$$

where $Z_t' = (r_{t-1}, ..., r_{t-m}, D_{1t}, ..., D_{dt}, i_t)$, and $\gamma' = (s_1, ..., s_m, \beta_1, ..., \omega)$.

Now, we test if this conditional mean is correctly specified. Given the specification in Equation (2), the most important source of misspecification can be parameter instability, for which we suggest applying Andrews's (1993) test.

Andrews's Test

The classic test for structural change is attributed to Chow (1960), who first proposed a test for structural breaks for stationary variables. Chow's test was developed to test the null hypothesis of parameter constancy against the alternative of a known break point a priori, under the assumption of constant variances. Because both of the assumptions—the break point being known a priori and the variance being constant—are highly restrictive, Quandt (1960) suggested testing the null hypothesis of constant coefficients against a more general alternative, where a structural change has occurred at some unknown time, and the error variance is also allowed to change. He proposed using an appropriate likelihood ratio (LR) test for all possible break dates, but as he noted on the basis of a Monte Carlo experiment, chi-square distribution is a poor approximation of this test under the null hypothesis of no structural change. Consequently, the Quandt statistic had no practical application for about three decades. In the early 1990s, the problem was primarily solved by Andrews (1993) and Andrews and Ploberger (1994). Andrews (1993) derived the asymptotic distribution of the LR test, denoted as supLR, for a onetime structural change with an unknown change point (i.e., the Quandt test) as well as analogous Wald (supW) and Lagrange multiplier/Rao's score (supLM) tests. These distributions are valid for models with no deterministic or stochastic trends, as well as for nonlinear models. Andrews (1993; 2003) also provided asymptotic critical values that are, incidentally, considerably larger than the comparable chi-square critical values (for details, see Hansen 2001; Maddala and Kim 1998).

One way to see the construction of this statistic is to obtain the supW, supLR, and supLM statistics as a function of all possible break dates. However, as pointed out by Hansen (2001), we cannot consider break dates too close to the beginning or end of the samples, as there are not enough observations to identify the subsample parameters. Conventionally, the search is confined to the range between 15 and 85 percent of the observations. This sequence of statistic values is plotted against the candidate breakpoints, then checked to see if the sequence breaks above Andrews's appropriate critical value. If it does, then we conclude that the time series has a structural break.

Treating the date of structural change (i.e., the break date) as an unknown parameter, if the null hypothesis is rejected, the issue is how to estimate the break

date. To this end, we refer to the theory of least squares estimation developed by Bai and others. Bai (1994; 1997b) also derived asymptotic distribution of the break date estimator. The method of estimation requires that the sample be split at each break date and both regression parameters and the sum of squared errors estimated separately on each subsample. Then the sum of squared errors is calculated for the entire sample. The date corresponding to the minimum full-sample sum of squared errors (equivalently, the minimum residual variance) is the break date estimate. This may be found by plotting the residual variances against the break dates.

Insofar as determining multiple break dates is concerned, Bai (1997a) and Chong (1995) suggested a sequential approach. When there are multiple structural breaks, the sum of squared errors can have a local minimum near each break date. Thus, the global minimum can be used as a break date estimator, and the other local minima may be viewed, after careful consideration, as possible break date estimators. The sample is then split at the break date estimate, and analysis continues on the subsamples.

To ensure that the conditional mean is appropriately specified, we next test, based on recursive residuals, for any remaining misspecification in the conditional mean for each of these subperiods. Many studies, including that by Lumsdaine and Ng (1999), have used such a procedure. At this point, any remaining misspecification of the conditional mean may be nonlinear. Our intuition is that any unobserved nonlinearity will be manifested in the recursive residuals, and this nonlinearity may be approximated by functions of the recursive residuals as defined in Brown et al. (1975). Kianifard and Swallow (1996) and others have also demonstrated that, among many standard tests for model misspecification, use of recursive residuals, rather than standard ordinary least squares (OLS) residuals, increases the power of such tests.

Test of Misspecification

Applying the test proposed by Lumsdaine and Ng (1999) calls for a two-step estimation procedure. Starting from $m^* + 1$ observations, where $m^* = \tilde{m} + l + 1$ ($< n$), recursive estimations of r_t on the regressors specified in the right-hand side of Equation (2) over the remaining $n - m^*$ observations are carried out in the first step. This leads to a set of recursive estimate of parameters, $\hat{\gamma}_t$, based on t observations and a set of recursive residuals, $\hat{w}_t$, defined as $\hat{w}_t = r_t - Z'_t\hat{\gamma}_{t-1}$. These recursive residuals contain information for updating $\hat{\gamma}_t$ from $\hat{\gamma}_{t-1}$ and cannot be predicted by the regression model given information at time $t - 1$. As Lumsdaine and Ng note, the recursive residuals are appealing not just because they are easy to compute, but also because $\hat{w}_{t-1}$ is in the econometrician's information set at time t. This is the reason behind using $\hat{w}_{t-1}$ in Equation (4), rather than $\hat{w}_t$, at time t. Obviously, the use of OLS residuals is invalid for the same reason. By construction, they are serially uncorrelated if the model is correctly specified. If, however, the model is

misspecified, $\hat{w}_t$ then contains information about the true conditional mean not captured by the regression function. In the second step, we estimate

$$r_t = Z_t'\gamma + f\left(\hat{w}_{t-1}\right) + \varepsilon_t, \tag{4}$$[4]

where $f(\hat{w}_{t-1})$ is a function (likely to be nonlinear) of the recursive residuals $\hat{w}_{t-1}$. In practice, we often try out

$$f\left(\hat{w}_{t-1}\right) = \tau_1 \hat{w}_{t-1}$$

$$\tau_2 \hat{w}_{t-1}^2$$

$$\tau_3 \sum_{i=1}^{t-1} \hat{w}_i$$

and

$$\tau_1 \hat{w}_{t-1} + \tau_2 \hat{w}_{t-1}^2 + \tau_3 \sum_{i=1}^{t-1} \hat{w}_i.$$

If one or more of the τ-coefficients turn out to be statistically significant, we retain the corresponding terms in conditional mean specification of r_t so that there is no inappropriate specification.

Following the approach discussed so far, we can now specify the conditional mean of r_t in Equation (2) more appropriately as

$$r_t = \sum_{k=1}^{\bar{m}} s_k r_{t-k} + \sum_{j=1}^{d} \beta_j D_{jt} + \omega i_t + \phi h_t^{\lambda} + \varepsilon_t, \tag{5}$$

where h_t is the conditional heteroskedasticity at time point t, representing risk, and λ is a transformation parameter. Although risk may have a more general representation, such as a Box–Cox transformation as suggested by Das and Sarkar (2000) for ARCH-M models, we consider, keeping in mind its limited role in this study, only three functional forms of risk: h_t, $\sqrt{h_t}$, and $\ln h_t$. Now, insofar as proper specification of h_t is concerned,

$$h_t = \alpha_0 + \sum_{j=1}^{d} \theta_j D_{jt} + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \delta_1 h_{t-1} + \ldots + \delta_p h_{t-p}, \tag{6}$$

where D_j's, $j = 1, 2, \ldots, d$, are seasonal dummies on volatility, $\alpha_0 > 0$, $\alpha_i \geq 0$ for all $i = 1, \ldots, q$, and $\delta_j \geq \forall\, j = 1, \ldots, p$. As noted by Nelson and Cao (1992), this is a sufficient condition for h_t to be positive; weaker sufficient conditions also exist.

The reason behind including seasonal dummies for the specification of h_t is that we are here concerned with proper specification of both the first- and second-order conditional moments. Hsieh (1989) has included seasonal dummies in variance. It is conceivable that if returns exhibit seasonal patterns, then observed volatility is likely to as well, though the pattern in the latter may not be the same.

The issue of appropriate specification of the conditional variance therefore reduces to a proper choice between the values of p and q of the underlying GARCH (p, q) process, as specified in Equation (6). This is done by carrying out the usual diagnostic checks of the standardized residuals as well as their squared values. Usually, tests of higher-order moments of residuals implicitly assume correct specifications for the lower moments. Because our proposed method of analysis tries to ensure that the conditional mean is properly specified, the routine diagnostic tests should yield the appropriate results. Making the tests more robust for serial correlation to allow for possible misspecification of conditional variance, as suggested by Robinson (1991) and Wooldridge (1991a; 1991b), cannot be carried out, because they are unavailable in any standard software package.

BDS Test

We now turn to detecting nonlinear dependencies in the data by using what is known in the literature as a BDS test (after Brock et al. 1996). Because it is known that financial data often possess time-varying volatilities, characterized by GARCH and its variants, the BDS would be an appropriate test for the null hypotheses of no serial correlation in r_t against the alternative of serial correlation. In fact, under the setup of the BDS test, the null hypothesis is specified as $\{r_t\}$ being i.i.d., while the alternative includes serial correlation, higher-order dependencies specified by GARCH, and other unspecified nonlinear forms. The BDS test statistic measures the statistical significance of the correlation dimension calculations. The correlation integral is a measure of the frequency with which temporal patterns are repeated in the data.

The BDS test statistic is defined as

$$\mathrm{BDS}(m,\xi) = \sqrt{n-m+1}\,\frac{T_m(\xi)}{V_m(\xi)}, \tag{7}$$

where n is the total number of observations, $T_m(\xi) = C_m(\xi) - C_1(\xi)$, $C_m(\xi)$ and $C_1(\xi)$ are the correlation integrals as defined in Brock et al., $V_m(\xi)$ is the standard error of $T_m(\xi)$ (ignoring the constant $\sqrt{n-m+1}$), and ξ and m are the distance and dimension, respectively, as defined below. This test statistic converges in distribution to $N(0,1)$ under H_0. The BDS test has the advantage that no distributional assumption needs to be made in using it as a test statistic for i.i.d. random variables. However, the user must choose two parameters: the values of ξ (the radius of the hypersphere, which determines whether two points are "close" or not) and m (the value of the

embedding dimension). As suggested by Brock et al. (1996), Hsieh (1991), and Sewell et al. (1993), in most cases, the values of ξ used are 0.5σ and σ, where σ represents the standard deviation of the linearly filtered data, and the value of m is set in line with the number of observations (e.g., using only $m \leq 5$ if $n \leq 500$). Returns are filtered for linear dependence using Equation (5). To examine whether GARCH can adequately capture the higher-order dependence structure, its standardized residuals are then tested for i.i.d. using the BDS test statistic. Since Brock et al. and Hsieh pointed out that the asymptotic standard normal distribution of the BDS statistic does not apply to GARCH standardized residuals, appropriate critical values (derived from simulation) for the BDS test, as applied to the standardized residuals of a GARCH(1,1), are taken from Brock et al. (1996) and Brooks and Heravi (1999).

Finally, if the null hypothesis of i.i.d. is not acceptable for the BDS test, we then suspect that it may be due to some dynamics in higher-order (greater than second) moments of the residuals. To this end, we advocate studying the regressions of higher-order residuals, say, $\hat{\varepsilon}_t^3$ and $\hat{\varepsilon}_t^4$, on their respective lagged values, testing whether one or more of the coefficients turn out to be significant. Obviously, in such a case, we cannot model the returns further by incorporating such dependencies in an appropriate manner, so that the residuals thus obtained would turn out to be i.i.d.

Data

Any stock market index should capture the behavior of the overall equity market, and also reflect the stock market's changing expectations about the future dividends of the country's corporate sector. Measurements of such an index should also represent the returns obtained by "typical" portfolios in the country concerned. Keeping in mind that any single index may not be very representative of all these considerations, and also that stock market indices vary in the number and composition of equities considered in the aggregation, we have considered a number of standard indices for the Indian stock market. A choice of several indices would also be useful in assessing the robustness of our findings on the efficiency of the Indian equity market.

We considered the following daily level data sets for our study: the Bombay Stock Exchange sensitive index (BSESENSEX) at a daily level, spanning January 1986 to December 2000; the Bombay Stock Exchange national index, currently known as the BSE 100, at a daily level from January 1991 to December 2000; the S&P CNX NIFTY index of the NSE from November 11, 1994, to December 31, 2000; and DOLLEX at a daily level from January 1991 to December 2000. To deal with the issue of weekends and holidays in the daily sample, we used the standard practice of dropping those days so that we can treat the resulting series as equally spaced.

To a considerable extent, the BSESENSEX (with base at 1978–79 = 100) has been effectively quantifying price movements and reflecting the sensitivity of the market. It is the oldest index in the country, consisting of thirty major chips. The daily closing price has been quoted as the value of the index at its daily level. However, the BSE national has wider coverage (100 companies) and an up-to-date adjustment mechanism in the index construction. The NSE, which came into being in 1994, is based on a sound settlement and trading system and now represents about 45 percent of total market capitalization. We have considered the S&P CNX NIFTY to be the prime index of the NSE. The fourth index, DOLLEX, is the dollar conversion of BSE-200. In the present context of foreign investors' increased willingness to trade on the Indian stock market, and also because of growth in the number of foreign financial institutions in the country, the analysis of DOLLEX should be very useful. All of these daily data sets have been downloaded from the official Web sites of the BSE and NSE (www.bseindia.com and www.nseindia.com). Since different index series started at different points in time, the spans of the data sets are different for each index.

Because the call money rate is market determined and available at the daily level, we have chosen this as the short-term interest rate. The data on the call money rate have been collected from the Reserve Bank of India, since it has been available, from January 1991 to December 2000.

Empirical Findings

In this section, we report and discuss the results of our analysis with daily level data. As already stated, the return at period t is defined by $r_t = \ln P_t - \ln P_{t-1}$, where P_t is the stock price index at period t. Hence, the analyzed data represent the continuously compounded rates of return for holding aggregate securities for one day.

The visual descriptions of the four data sets on returns are given in Figures 1 through 4. The four series appear to be stationary around zero with no deterministic trend, and they exhibit volatilities of varying degrees. Table 1 offers the usual statistical details of the data sets—the values of standard deviation, coefficients of skewness and kurtosis, and the values of the Ljung–Box test statistic for ARCH in the daily returns of BSESENSEX, BSE100, NIFTY, and DOLLEX. The means and standard deviations of the returns based on the full sample period values of the four indices show that means are not significantly different from zero. The values of the coefficient of skewness show that all of the distributions, except possibly that of NIFTY, are skewed. All of the kurtosis values, except that of NIFTY, are much larger than three. This shows that the distribution curves of BSESENSEX, BSE100, and DOLLEX have fat tails compared to normal distributions. We also find from Table 1 that in all of the series, the Ljung–Box test statistic values for the squared residuals are significant, indicating the presence of second-order dependence in returns.

Figure 1. **BSESENSEX Daily Return** (Day 1 = January 1, 1986)

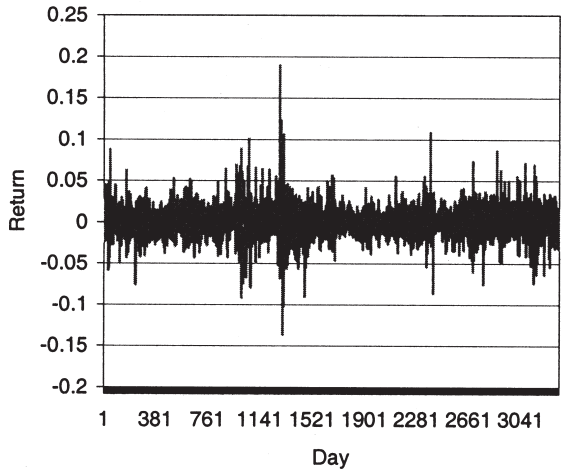
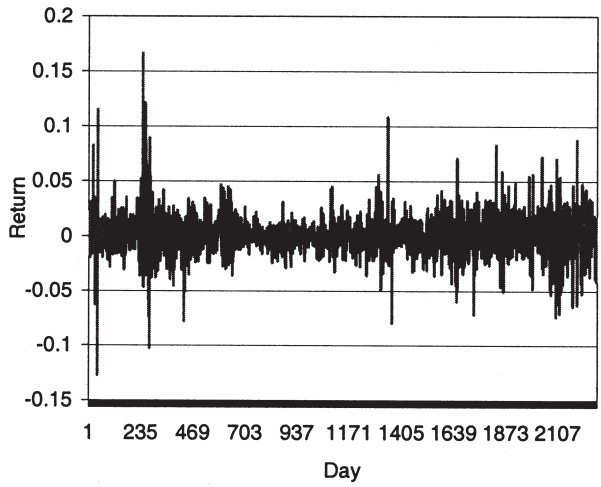


Figure 2. **BSE100 Daily Return** (Day 1 = January 1, 1991)



We then carried out ADF and PP tests of stationarity of the return series. The values of the test statistic for the four series are presented in Table 2.[5] It is evident that all of the return series are stationary at a 1 percent level of significance. Once stationarity of returns has been confirmed, we analyze the returns for the four data sets by following the procedure described in the previous section.

Except for the automatic variance ratio test and Andrews's test, all computations have been carried out with the TSP 4.3 software package. The computations

Figure 3. **NIFTY Daily Return** (Day 1 = November 7, 1994)

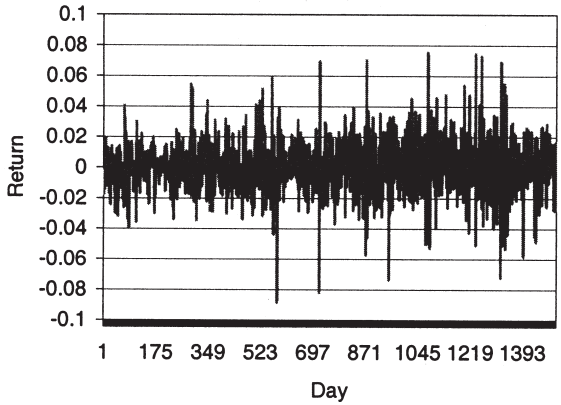
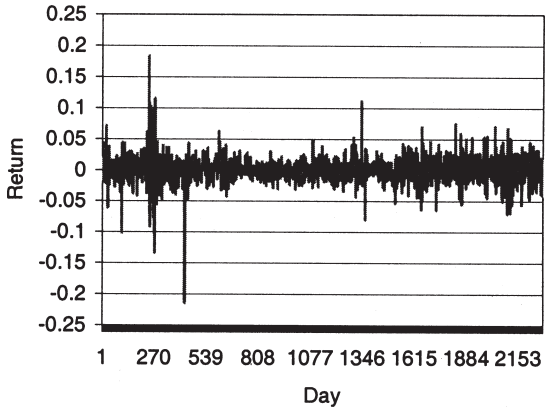


Figure 4. **DOLLEX Daily Return** (Day 1 = January 1, 1991)



for the automatic variance ratio test have been done with GAUSS, and for Andrews's, EVIEWS.

The seven stages of computations involved are as follows (in order):

1. Testing for no serial correlation by Choi's automatic variance ratio test.
2. Testing for parameter stability by Andrews's test.
3. Partitioning of the entire time period into subperiods of stable parameters by applying the method of least squares estimation for estimating break points, as proposed by Bai (1994; 1997a; 1997b) and Bai and Perron (1998).
4. Testing for misspecification of conditional mean, based on recursive residuals.

Table 1

Summary Statistics of Returns Based on BSESENSEX, BSE100, NIFTY, and DOLLEX

Index	Mean	Standard deviation	Skewness	Kurtosis	Q^2 (12)	Q^2 (22)	Q^2 (32)	Q^2 (42)
BSESENSEX	0.000595	0.0196	0.275	6.188	697.950	1,040.330	1,435.380	1,490.28
BSE100	0.000608	0.0186	0.411	7.704	366.030	600.318	699.443	735.753
NIFTY	–0.000011	0.0171	0.0642	2.508	87.270	127.645	131.902	136.965
DOLLEX	0.000113	0.0192	–0.309	14.107	273.829	369.571	508.173	516.445

Notes: $Q^2(k)$ represents the value of Ljung–Box statistics of squared returns with k degrees of freedom; further, all $Q^2(k)$ values are significant at the 1 percent level of significance.

Table 2

Unit Root Tests of Stock Returns

Index	ADF	PP	Number of observations
BSESENSEX	–10.721	–3,248.166	3,323
BSE100	–9.739	–2,260.894	2,285
NIFTY	–10.541	–1,391.202	1,506
DOLLEX	–9.221	–2,305.232	2,283

Notes: All the values of the two test statistics are significant at the 1 percent level of significance; neither a constant nor a linear trend term was included as exogenous regressor in the regressions, because Figures 1–4 do not show trend or nonzero mean in any of the four series; maximum lag length was to be 26, 20, 13, and 20 for the four regressions, respectively.

5. Testing for the adequacy of the specification of the GARCH model by standard diagnostic tests, based on standardized residuals as well as their squared residuals.
6. Testing for nonlinearity by the BDS test.
7. Testing for the presence of dynamics of higher-order moments in residuals.

Table 3 presents the results of the automatic variance ratio test. The values of the test statistic are 2.950, 5.158, 1.677, and 6.554 for BSESENSEX, BSE100, NIFTY, and DOLLEX, respectively. Comparing these with the critical values (two-sided) of $N(0,1)$ distribution, we obviously find that the null hypothesis of no serial correlation is rejected for all four returns series, although the level of significance for the NIFTY series is only 10 percent. We may thus conclude that all four stock indices are inefficient and, hence, predictable.

We present below the estimated models for returns based on BSESENSEX, BSE100, NIFTY, and DOLLEX. The model for each of the four series was estimated after considering as explanatory variables lags of r_t up to a maximum of twenty, five 0–1 dummies representing day-of-the-week effects, and the daily series of the call money rate for the short-term interest rate.[6] In all four models, the usual Ljung–Box $Q(.)$ test concludes that the residuals are white noise.

BSESENSEX

$$\hat{r}_t = \underset{(4.667)^{**}}{0.081 r_{t-1}} + \underset{(2.901)^{**}}{0.050 r_{t-17}} + \underset{(2.328)^{*}}{0.04 r_{t-20}} + \underset{(1.748)^{***}}{0.001 D5} \tag{8}$$

Table 3

Results of Automatic Variance Ratio (AVR) Test

Index	AVR test statistic
BSESENSEX	2.950**
BSE100	5.158**
NIFTY	1.677*
DOLLEX	6.554**

Notes: * indicates significant value of the test statistic at the 10 percent level of significance; ** indicates the same at the 1 percent level of significance.

BSE100

$$\hat{r}_t = \underset{(5.789)^{**}}{0.119r_{t-1}} + \underset{(3.026)^{**}}{0.062r_{t-3}} + \underset{(4.236)^{**}}{0.088r_{t-9}} + \underset{(2.441)^{*}}{0.051r_{t-10}} - \underset{(3.501)^{**}}{0.073r_{t-19}} + \underset{(2.811)^{**}}{0.002\text{D1}} \tag{9}$$

NIFTY

$$\hat{r}_t = \underset{(2.873)^{**}}{0.073r_{t-1}} - \underset{(2.599)^{**}}{0.066r_{t-6}} - \underset{(1.996)^{*}}{0.051r_{t-19}} - \underset{(3.229)^{**}}{0.003\text{D1}} - \underset{(2.543)^{*}}{0.002\text{D2}} + \underset{(6.577)^{**}}{0.006\text{D3}} \tag{10}$$

DOLLEX

$$\begin{aligned}\hat{r}_t = {} & \underset{(7.397)^{**}}{0.153r_{t-1}} + \underset{(2.699)^{**}}{0.056r_{t-3}} + \underset{(2.824)^{**}}{0.059r_{t-5}} - \underset{(2.319)^{*}}{0.049r_{t-6}} + \underset{(4.514)^{**}}{0.093r_{t-9}} \\ & + \underset{(2.267)^{*}}{0.048r_{t-17}} - \underset{(2.730)^{**}}{0.056r_{t-19}} + \underset{(2.297)^{*}}{0.002\text{D1}} - \underset{(2.012)^{*}}{0.002\text{D2}}\end{aligned} \tag{11}$$

The values in parentheses indicate the corresponding absolute values of the t-statistic; * indicates significance at the 5 percent level; ** indicates significance at the 1 percent level; and *** indicates significance at the 10 percent level.

Turning to the estimated returns equation for BSESENSEX given in Equation (8), we find that r_{t-1}, r_{t-17}, and r_{t-20} are significant, as is the D5 dummy. The latter finding suggests the Friday effect, that is, the weekend effect, is highly significant. In Equations (8) through (11), the Monday effect is significant in all of the indices except BSESENSEX. In these regressions, we have considered a moderately high

number of lags to remove any autocorrelation in the error term. Specifically, to check the lag length properly, we have followed Hall's (1994) procedure. We began with a moderate value for lag length—twenty—and then reduced it one by one until the last lag was significant.

Testing for Parameter Stability

We already mentioned that we followed Andrews's (1993) procedure for testing structural change. We now report our findings on Andrews's supW test for parameter stability in the model specified in Equation (2). In this testing procedure, the alternative is taken to be that a structural change has occurred at some unknown time, and the error variance is allowed to change. The issue of break point being assumed to be known a priori, or taken to be unknown and hence to be determined, remains debatable. Andrews's supW merely tests whether a break exists or not; it does not identify the location of the breaks. Without a known break point, we suggest estimating break points by applying the least squares method as proposed by Bai (1994; 1997a; 1997b) and others, which essentially requires searching for a break over the entire time period of observations, and then taking the minimum sum of squared errors for the full sample (as a function of the break point) as the estimate of the break date. It is conceivable that prior information exists about the dates of major shocks—real or financial—and that this suggests the approximate location of the breaks. In our case, the break points should be around the middle of 1992 and toward the end of 1996, based on the recent history of the Indian stock market. But the fact remains, as pointed out by Hansen (2001), that the results can be highly sensitive if the a priori choices are somewhat arbitrary: hence, use of this method can hardly be considered a sound scientific practice, especially because in the least squares method, the set of candidate break points obviously includes these likely locations.

Figures 5 through 8 show the results of Andrews's test for BSESENSEX, BSE100, NIFTY, and DOLLEX, respectively. In Figure 5, the maximum value of the test sequence for BSESENSEX is 22.74, which exceeds the relevant 1 percent critical value—20.47—corresponding to $p = 4$ in Andrews's (2003) table. In Andrews's test, we have chosen the trimming parameter as 15 percent. Because the maximum value of 22.74 easily exceeds the 1 percent Andrews's critical value, we conclude that the null hypothesis of no structural break is decisively rejected. Thus, our conclusion on BSESENSEX is that the series has a structural break. Through similar exercises, we have found structural breaks for each of the remaining three series. The maximum values of the corresponding test statistic sequences for BSE100, NIFTY, and DOLLEX are 19.06, 50.37, and 27.85, respectively. Comparing these with their respective Andrews's critical values, we find that while NIFTY and DOLLEX clearly indicate structural breaks at a 5 percent level of significance, the same for BSE100 holds only at a slightly higher level of significance, the critical value of a 5 percent level corresponding to $p = 6$ being 20.24.

Figure 5. **Testing for Structural Change in BSESENSEX Series** (Day 1 = June 15, 1988)

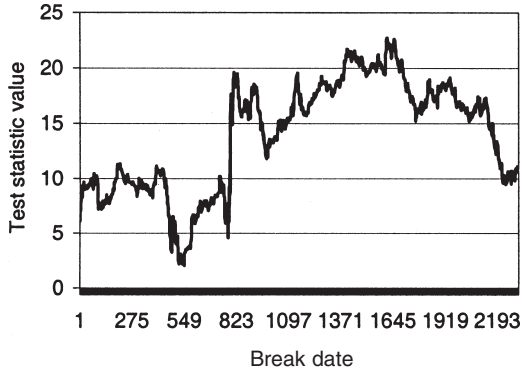
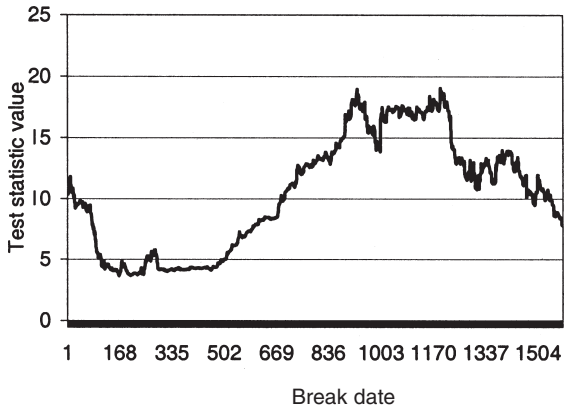


Figure 6. **Testing for Structural Change in BSE100 Series** (Day 1 = November 5, 1992)



Figures 9 through 12 show the results of our break date estimations for the series BSESENSEX, BSE100, NIFTY, and DOLLEX, respectively. For BSESENSEX (Figure 9), the minimum value for the residual variance corresponds to the break date of February 15, 1996. Likewise, the estimated break dates for BSE100, NIFTY, and DOLLEX are January 15, 1998, January 12, 1996, and December 5, 1996, respectively. Confidence intervals of the break points could be reported, but because we need to divide the whole sample period into subperiods based on this estimation exercise, we are reporting only the point estimates.

We now move on to testing for multiple break dates in the series and then estimating those break dates sequentially, as suggested by Chong (1995) and Bai (1997a). The series BSESENSEX is found to have two other breaks, on June 18,

Figure 7. **Testing for Structural Change in NIFTY Series** (Day 1 = January 1, 1996)

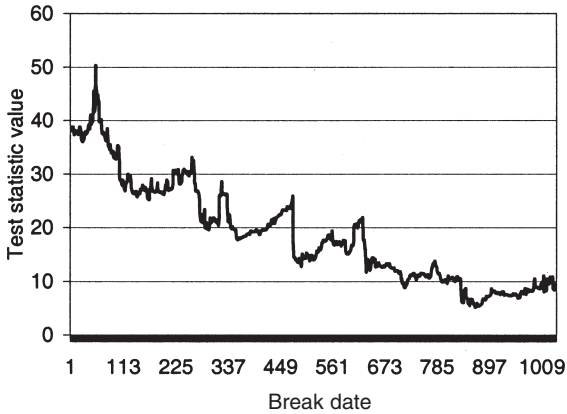
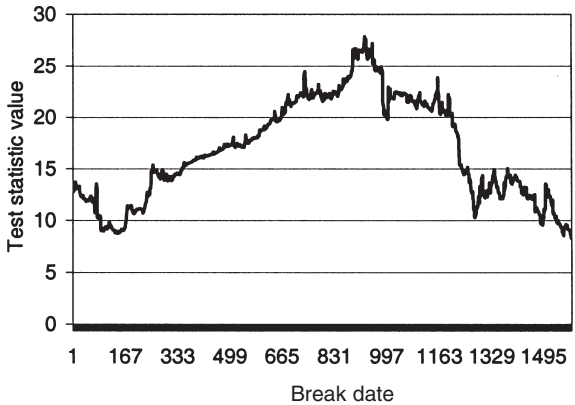


Figure 8. **Testing for Structural Change in DOLLEX Series** (Day 1 = November 4, 1992)



1990, and June 17, 1992. Thus, BSESENSEX is found to have three structural breaks. Accordingly, the series is divided into three subperiods. These subperiods, along with similar ones obtained for the other three series, are given below:

BSESENSEX: January 1986–June 1990; July 1992–February 1996; and February 1996–December 2000.

BSE100: May 1992–December 1996;[7] and December 1996–December 2000.

NIFTY: November 1994–January 1996; and January 1996–December 2000.

DOLLEX: May 1992–December 1996; and December 1996–December 2000.

Figure 9. **Least Squares Break Date Estimation of BSESENSEX Series** (Day 1 = June 15, 1988)

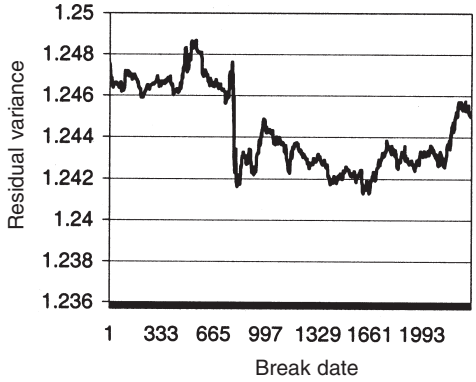
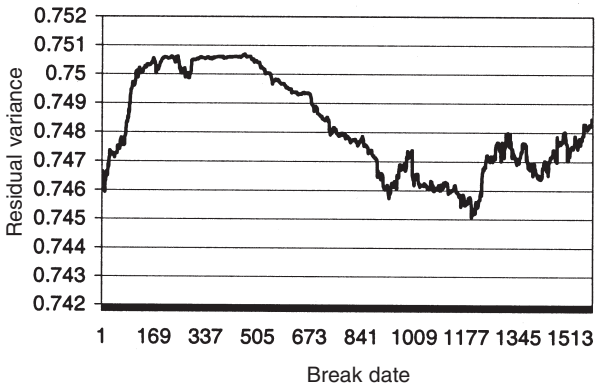


Figure 10. **Least Squares Break Date Estimation of BSE100 Series** (Day 1 = November 5, 1992)



There is a structural break in 1996 for each of the four series. This is only to be expected, after four years of reforms being pursued with vigor. While carrying out this exercise on stability, we found the subperiod covering July 1990–April 1992 to be unstable in the sense that the test suggested the presence of a number of breaks during this period, but none of the resulting subperiods were found to be stable. Hence, this subperiod was excluded from further analysis of BSESENSEX. This lack of stability may be attributable to the largest capital-market scam that the Indian economy witnessed, which ran from September 1991 to May 1992. Obviously, investor confidence was greatly shaken, and the stock market went through a period of turbulence after the scam was detected. Moreover, because India was facing a serious balance of payments problem toward the end of the 1980s and

Figure 11. **Least Squares Break Date Estimation of NSE Series** (Day 1 = January 1, 1996)

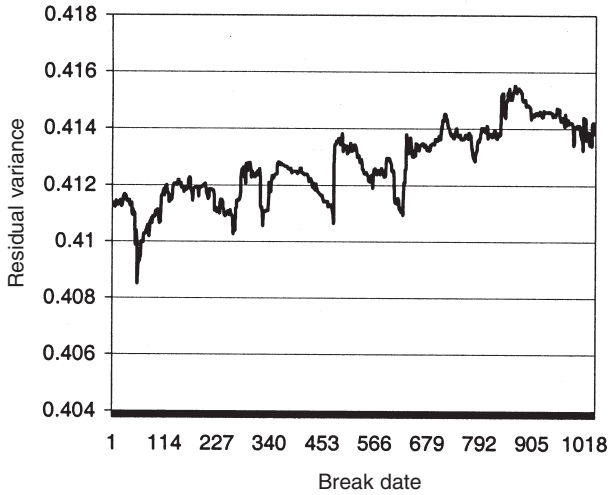
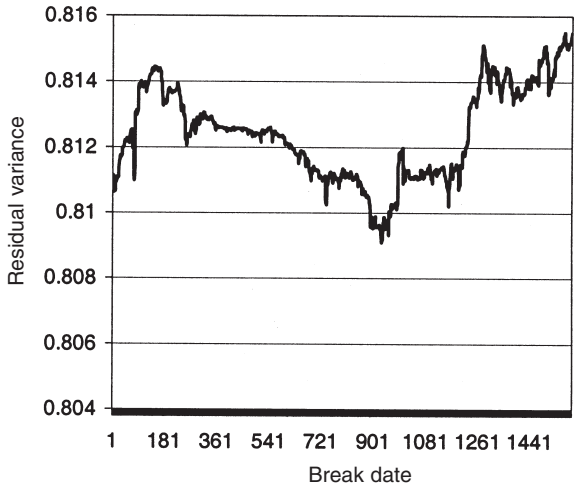


Figure 12. **Least Squares Break Date Estimation of DOLLEX Series** (Day 1 = November 2, 1992)



early 1990s, leading to the decision to open and liberalize the Indian economy, the period July 1990–June 1992 was already somewhat unstable.

Our findings on the partitioning of time periods are thus consistent with major developments in the Indian capital market and other sectors of the economy during the 1990s. Kulkarni (1997) has pointed out that the Indian market was in the

midst of a bear phase since the early 1990s due to political instability and the foreign exchange crisis. The aforementioned scam in the Indian capital market was unearthed in April 1992, and as a consequence, the government bestowed more power on the Securities and Exchange Board of India (SEBI), which, in turn, immediately swung into action. To curb speculation in the BSE, SEBI scrapped the forward-trading *(badla)* mechanism in December 1993, though it was reintroduced in January 1996.

The specifications used to carry out the structural break tests for the four series—that is, Equations (8) to (11)—are based on a full sample model selection procedure that assumes no breaks. An alternative to this approach, as suggested by one of the referees, could be to choose a "fixed" specification, such as an AR(1) model with five dummies representing day-of-the-week effects. We carried out the computations required for this approach and obtained the same conclusions regarding the existence of breaks. For the break-point estimates, the results were found to be almost the same as those for the full sample case. The subperiods obtained by this approach are as follows

BSESENSEX: January 1986–April 1990; May 1992–February 1996; and February 1996–December 2000.

BSE100: May 1992–December 1996 and December 1996–December 2000.

NIFTY: November 1994–January 1996 and January 1996–December 2000.

DOLLEX: May 1992–December 1996 and December 1996–December 2000.

As before, the subperiod covering almost the same span, April 1990–April 1992, for BSESENSEX was found to be unstable. We thus find that the two approaches produce the same empirical conclusions on both the existence and the location of structural breaks in the four returns series.

Testing for Misspecification

We now report the results of the recursive residual-based test of misspecification of conditional mean. The test examines whether or not the conditional mean is still misspecified. After obtaining recursive residual $\hat{w}_t's$, as discussed above, and then including terms such as $\hat{w}_{t-1}$, $\hat{w}^2_{t-1}$, $\hat{w}^3_{t-1}$, $\Sigma_{i=1}^{t-1}\hat{w}_i$, we obtain the estimated models for each of the subperiods in all four data sets. For the sake of brevity, we report only results concerning BSESENSEX as follows.

Subperiod 1 (January 1986–June 1990)

$$\hat{r}_t = \underset{(0.383)}{-0.059r_{t-1}} \underset{(1.878)^{***}}{-0.066r_{t-2}} \underset{(2.679)^{**}}{+0.087r_{t-7}} \underset{(2.339)^{*}}{+0.090r_{t-8}} \underset{(1.119)}{+0.002D5}$$
$$\underset{(1.649)^{***}}{+0.183\hat{w}_{t-1}} \underset{(1.227)}{1.206\hat{w}^2_{t-1}} \underset{(1.157)}{-31.125\hat{w}^3_{t-1}} \tag{12}$$

Subperiod 2 (July 1992–February 1996)

$$\hat{r}_t = \underset{(0.763)}{0.117 r_{t-1}} - \underset{(1.792)^{***}}{0.081 r_{t-2}} - \underset{(3.091)^{**}}{0.004 D5} - \underset{(1.109)}{0.00006 i_t} - \underset{(0.037)}{2.280 r_{t-1}^3}$$
$$+ \underset{(1.377)}{0.212 \hat{w}_{t-1}} - \underset{(0.017)}{0.019 \hat{w}_{t-1}^2} - \underset{(0.814)}{46.640 \hat{w}_{t-1}^3} \tag{13}$$

Subperiod 3 (February 1996–December 2000)

$$r_t = -\underset{(0.651)}{0.112 r_{t-1}} - \underset{(2.585)^{**}}{0.074 r_{t-6}} + \underset{(2.148)^{*}}{0.062 r_{t-9}} - \underset{(1.930)^{***}}{0.056 r_{t-11}} - \underset{(2.511)^{*}}{0.072 r_{t-18}}$$
$$- \underset{(0.762)}{0.086 r_{t-19}} + \underset{(1.871)^{***}}{0.002 D1} + \underset{(1.207)}{0.212 \hat{w}_{t-1}} - \underset{(1.536)}{1.139 \hat{w}_{t-1}^2} - \underset{(1.888)^{***}}{25.012 \hat{w}_{t-1}^3} \tag{14}$$

The values in parentheses represent corresponding absolute values of *t*-statistics; *indicates significance at the 5 percent level, ** indicates significance at 1 percent, and *** at 10 percent.

It is evident from the above estimated equations that none of the coefficients associated with $\hat{w}_{t-1}$, $\hat{w}_{t-1}^2$, $\hat{w}_{t-1}^3$, $\Sigma_{i=1}^{t-1}\hat{w}_i$ is significant, even at the 5 percent level, in any of the three subperiods. Thus, we can conclude that there is no further misspecification in the conditional mean in the three subperiods.

Testing for Adequacy of GARCH Specifications

Now that the conditional mean of returns has been properly specified, we estimate this model along with the GARCH assumption for conditional heteroskedasticity, h_t, as specified in Equation (6). For reasons mentioned above, the specification of h_t involves dummies representing day-of-the-week effects. The estimated models for r_t and h_t for the four data sets are given in Table 4.

For each of these estimated models, the adequacy of the estimated GARCH model was examined so that no second-order conditional moment was misspecified. This was done by studying the behavior of standardized residuals and squared standardized residuals. The Ljung–Box Q(.) statistic values pertaining to these residuals are given in Table 5. Barring a few cases, especially those in subperiod 1 of DOLLEX, none of these values is significant for all four data sets and their subperiods, indicating the adequacy of the estimated GARCH specifications. In most cases, GARCH (1,1) is the most appropriate specification, along with some day-of-the-week effects. If we look at estimated values from Table 4, we can make the following observations

1. The call money rate is not significant in most of the cases except BSESENSEX, and again, for BSESENSEX, it is significant for subperiod 2

Table 4

Estimates of Parameters in Conditional Mean and Variance

	BSESENSEX			BSE100		NIFTY		DOLLEX	
	Subperiod			Subperiod		Subperiod		Subperiod	
Variable	I	II	III	I	II	I	II	I	II
r_{t-1}	0.099	0.285	0.092	0.346	0.118	0.418	0.190	0.334	0.119
	(2.810)	(7.205)	(2.826)	(10.189)	(3.131)	(6.155)	(5.057)	(10.429)	(3.163)
r_{t-2}	–0.078	–0.118	—	–0.139	—	–0.148			
	(2.278)	(3.095)		(3.596)		(2.356)			
r_{t-3}				0.087					
				(2.547)					
r_{t-6}	—	—	–0.10	—	–0.094		–0.083		
			(3.591)		(3.253)		(2.799)		
r_{t-7}	0.074	—	—	—	—				
	(2.153)								
r_{t-8}	0.061	—	—	—	—				
	(1.752)#								
r_{t-9}				—	—				
r_{t-11}	—	—	–0.072	—	—				
			(2.811)						
r_{t-15}	—	—	—	—	—			–0.084	
								(3.999)	
r_{t-18}	—	—	–0.072	—	—				
			(2753)						

r_{t-19}	—	—	–0.055	—	–0.090		–0.082		
			(2.035)		(3.553)		(3.121)		
D1	—	—	–0.004	—	0.007	–0.005			–0.008
			(2.734)		(7.776)	(3.566)			(8.823)
D3	—	—	—	—	0.002		0.008		
					(1.909)#		(7.399)		
D5	—	0.003	—	0.00195	—			0.004	
		(3.727)		(2.629)				(4.508)	
r^3_{t-1}				—	—		–93.01		
							(5.470)		
i_t	—	–0.00008	—	—	—				
		(2.170)							
Constant	0.000002	—	0.00002	0.000003	0.00008	0.00001	0.00001	0.00001	0.00005
	(0.408)^		(1.305)#	(3.342)	(5.918)	(1.672)	(1.319)#	(4.713)	(4.197)
ε^2_{t-1}	0.048	0.106	0.148	0.077	0.241	0.199	0.065	0.218	0.166
	(3.342)	(4.407)	(4.831)	(5.564)	(5.323)	(3.263)	(5.051)	(14.68)	(4.488)
h_{t-1}	0.888	0.869	0.60	0.904	0.539	0.740	0.875	0.731	0.698
	(23.847)	(38.212)	(8.978)	(68.232)	(8.556)	(9.303)	(37.32)	(29.912)	(11.531)
D1	0.00008	—	0.0002	—	—		0.00004		
	(3.024)		(9.139)				(2.338)		
D3	—	—	0.00006	—	—				
			(2.230)						
D4	—	0.230	—	—					
		(3.346)							

Notes: Values in parentheses indicate corresponding absolute values of *t*-statistics; all values in the table are significant at either the 1 percent or 5 percent level of significance except those (1) indicated by #, which are significant at the 10 percent level only, and (2) marked by ^, which are not significant at any of these standard levels.

Table 5

Diagnostic Checking of Residuals from the Estimated GARCH Models

Index	$Q(12)$	$Q(22)$	$Q(32)$	$Q(42)$	LM-statistic[a]
			Standardized residual $\hat{\varepsilon}_t / \sqrt{\hat{h}_t}$		
BSESENSEX					
Subperiod I	3.89	9.16	19.12	26.02	0.153
Subperiod II	7.62	18.13	30.09	41.28	0.244
Subperiod III	14.02	22.72	36.04	47.71	0.008
BSE100					
Subperiod I	10.00	17.30	22.16	32.68	0.009
Subperiod II	17.73	24.61	33.34	42.45	0.251
NIFTY					
Subperiod I	8.57	15.76	18.12	30.56	0.475
Subperiod II	7.73	14.60	22.88	26.87	1.252
DOLLEX					
Subperiod I	19.99	30.15	41.82	61.00*	35.505
Subperiod II	19.78	30.91	40.83	48.68	0.426
			Squared standardized residual $\hat{\varepsilon}_t^2 / \hat{h}_t$		
BSESENSEX					
Subperiod I	3.10	9.70	20.32	20.32	0.00003
Subperiod II	9.473	14.36	21.17	24.01	0.008
Subperiod III	7.573	32.21	43.79	45.47	0.083
BSE100					
Subperiod I	10.88	13.16	16.65	26.45	0.005
Subperiod II	3.87	37.96*	42.71	45.79	0.047
NIFTY					
Subperiod I	21.71*	27.91	36.61	43.72	0.008
Subperiod II	7.71	27.17	31.55	37.88	0.018
DOLLEX					
Subperiod I	41.76**	49.28**	52.32**	56.74	194.89**
Subperiod II	3.459	46.33**	49.35*	52.52	0.044

Notes: [a] LM-statistic stands for the usual LM test for GARCH model; * indicates significance at the 5 percent level; ** indicates significance at the 1 percent level; $Q(k)$ represents the Ljung–Box statistic value with k degrees of freedom.

only. Since in the Indian capital market BSESENSEX is the most representative index of the economy, these findings on the significance of the call money rate that pertain to the second half of the last decade in particular suggest that the Indian government's present policy of reducing the interest rate to encourage investment in the stock market is likely to be effective in due course.

2. Day-of-the week effects are present in most of the cases, in both mean and volatility specifications. These findings indicate that values of r_t are often predictable from consideration of the daily pattern. However, there is no uniform day-of-the week effect across all subperiods for any index. For instance, in BSESENSEX, Friday is significant for subperiod 2, and Monday for subperiod 3. Again, for BSE100, while no day-of-the-week effect is present for subperiod 1, Monday is significant for subperiod 2. For NIFTY, Monday is significant for subperiod 1 and Wednesday for subperiod 2. For DOLLEX, Friday is significant for subperiod 1 and Monday for subperiod 2. While the presence of Monday and Friday effects are quite understandable, the same for D3 (Wednesday) in subperiod 2 of NIFTY is explained by the fact that the settlement period for NIFTY is from Wednesday to the following Tuesday.
3. Some lagged values of r_t are significant in each of these estimated models. We allowed for a moderately high lag length to free the error in the model from autocorrelation. In most of the cases, lag 1 was found to be significant, so that the role of the previous day's return in prediction is empirically established. However, in some cases, lags 18 and 19 were found to be significant, indicating a monthly effect in the returns, because there are, on average, twenty observations in a month.
4. Daily-level seasonality was found to be present in volatility equations in some of the subperiods of some data sets, indicating day-of-week effects in volatility as well. In most cases, the day effects in h_t were not the same as they were in r_t, the exception being subperiod 3 of BSESENSEX. Thus, predictability in expected returns is accompanied by a change in the conditional variance of the Indian stock market. But because the nature of dependence in mean and volatility are different, investors ought to consider jointly predicting stock market returns and volatility. Exploitation of both sources of predictability is expected to result in investment strategies that outperform strategies that exploit only one source.
5. In one case, subperiod 1 of BSE100, some polynomial of recursive residuals—$\hat{r}^3_{t-1}$—was found to be significant in the mean part of the model. This means that there are some nonlinearities yet to be captured in the actual model.
6. In none of the subperiods was risk factor significant, indicating that time-varying risk premia have no role in explaining inefficiencies in the Indian capital market.

Detecting Nonlinear Dependencies

By following the procedure proposed above, we have now reached the step of detecting nonlinear dependencies in the residuals. This is indeed important, because there is growing evidence that stock prices often show complex regularities. We have, therefore, applied the BDS test for detecting i.i.d. systems from nonlinear dependencies. Table 6 presents the results of this exercise.

The first column in Table 6 gives the values of the distance, ξ, measured in terms of one-half and one times the standard deviation of linearly filtered data used in the study; the values of the number of embedding dimensions m are given in column 2. The values of BDS test statistics for all subperiods appear in the rest of the columns. The series are examined up to ten dimensions, when the number of observations exceeds five hundred. For the observations less than or equal to five hundred, we use embedding dimensions up to five. It is known that acceptance of the null hypothesis of i.i.d. observations indicates that the observations are purely random, meaning that there are no nonlinear dependencies of any kind. In that event, we could conclude that series behavior has no exploitative value. As for computations, we have used the standardized residuals $\hat{\varepsilon}_t/\hat{h}_t$, obtained in Equation (6). Obviously, these are filtered of all linear dependencies of r_t. Also, the appropriate critical values for the BDS test have been obtained from Brock et al. (1991). We find that the BDS test statistic values for all four stock indices are significant compared to the nonstandard critical values at standard levels of significance for many of the values of ξ/σ and m considered for this study. These computations indicate, as displayed in Table 6, that in most cases, particularly for higher values of m ($m > 5$), the null of i.i.d. observations is rejected. Thus, we can conclude that GARCH has been found to be somewhat inadequate in capturing all of the nonlinear dependencies in the series.

Testing for the Presence of Dynamics of Higher-Order Moments

Finally, we carry out the last step of our analysis. What we attempt here is to find out whether there are dynamics in the higher-order moments (say, the third or fourth) so that the remaining dependencies could be explained. To this end, we considered dynamic relations involving $\hat{\varepsilon}_t^3$ and $\hat{\varepsilon}_t^4$ and found the following estimated relations for the different indices.

BSESENSEX:

$$\text{Subperiod I } \hat{\varepsilon}_t^3 = \underset{(2.230)^{*}}{-0.073}\hat{\varepsilon}_{t-1}^3$$

$$\text{Subperiod II } \hat{\varepsilon}_t^3 = \underset{(3.239)^{**}}{0.113}\hat{\varepsilon}_{t-5}^3 \text{ and } \hat{\varepsilon}_t^4 = \underset{(2.609)^{**}}{0.091}\hat{\varepsilon}_{t-5}^4$$

Table 6

GARCH Adjusted BDS Test Statistic Values

		BSESENSEX		
ξ/σ	m	Subperiod I	Subperiod II	Subperiod III
0.5	2	–0.260[a]	0.145[a]	0.370[a]
0.5	3	5.554	2.962	2.634
0.5	4	27.700	19.169	33.184
0.5	5	90.757	–12.384	39.113
0.5	6	–7.969	–8.719	–11.842
0.5	7	–5.900	–6.457	–8.872
0.5	8	–4.526	–4.956	–6.889
0.5	9	–3.564[a]	–3.906	–5.494[a]
0.5	10	–2.864[a]	–3.142	–4.471[a]
1	2	1.642*	–2.080	0.241[a]
1	3	0.872[a]	1.634*	0.085[a]
1	4	1.933	1.998	1.303*
1	5	5.070	12.872	0.649[a]
1	6	–9.162	–10.200	12.055
1	7	–6.871	–7.666	–78.310
1	8	–5.339	–5.972	–7.535
1	9	–4.260	–4.777	–6.059
1	10	–3.469	–3.900	–4.539

		BSE100		NIFTY	
ξ/σ	m	Subperiod I	Subperiod II	Subperiod I	Subperiod II
0.5	2	1.220[a]	–2.474	–0.538[a]	2.760
0.5	3	4.067	–5.234	–8.473	3.155
0.5	4	2.540	–5.162	–4.235	–8.277
0.5	5	–1.488	–1.436[a]	–2.414[a]	–14.380
0.5	6	–1.026[a]	–1.023[a]		–10.213
0.5	7	–7.647	–7.660		–7.629
0.5	8	–5.907	–5.946		–5.905
0.5	9	–4.685[a]	–4.739[a]		–4.692[a]
0.5	10	–4.547[a]	–8.363		–3.805[a]
1	2	1.786	–0.898[a]	–4.082[a]	2.087
1	3	1.618	–0.027[a]	–8.181	2.935
1	4	4.121	–1.994	–6.284	3.006
1	5	1.032	–4.626	–3.859	–4.253
1	6	–1.174	–7.221		–1.794
1	7	–8.850	–8.363		–8.479
1	8	–6.916	–6.544		–6.621
1	9	–5.550	–5.258		–5.308
1	10	–4.547	–4.313		–4.343

(continues)

Table 6 (*continued*)

		DOLLEX	
ξ/o	m	Subperiod I	Subperiod II
0.5	2	–3.420	–3.584
0.5	3	–3.054	–2.360
0.5	4	–17.177	–9.036
0.5	5	–11.191	–13.837
0.5	6	–7.873	–9.850
0.5	7	–5.823	–7.345
0.5	8	–4.463	–5.722
0.5	9	–3.511[a]	–4.558[a]
0.5	10	–2.818[a]	–3.706[a]
1	2	–1.248[a]	–0.804[a]
1	3	–0.843[a]	–0.059[a]
1	4	–1.045[a]	–1.955
1	5	9.192	–5.867
1	6	18.809	–2.591[a]
1	7	–6.516	–8.083
1	8	–5.053	–6.322
1	9	–4.022	–5.078
1	10	–3.2667	–4.162

Notes: Values of BDS test statistic from standardized residuals are compared with the simulated values given in Brock et al. (1991); values with superscript a indicate nonsignificance at the 5 percent level; values with * indicate significance at the 5 percent level; all others are significant at the 1 percent level; ξ, m, and σ stand for distance, embedding dimension, and the standard deviation of the linearly filtered data, respectively.

BSE100:

$$\text{Subperiod I } \hat{\varepsilon}_t^3 = \underset{(3.912)^{**}}{-0.051}\hat{\varepsilon}_{t-4}^3 \text{ and } \hat{\varepsilon}_t^4 = \underset{(3.220)^{*}}{0.031}\hat{\varepsilon}_{t-4}^4$$

$$\text{Subperiod II } \hat{\varepsilon}_t^3 = \underset{(2.738)^{*}}{-0.092}\hat{\varepsilon}_{t-1}^3 \text{ and } \hat{\varepsilon}_t^4 = \underset{(2.596)}{0.081}\hat{\varepsilon}_{t-1}^4$$

NIFTY:

$$\text{Subperiod I } \hat{\varepsilon}_t^3 = \underset{(2.440)}{0.158\hat{\varepsilon}_{t-2}^3} + \underset{(2.541)^*}{0.165\hat{\varepsilon}_{t-3}^3} + \underset{(5.370)^{**}}{0.347\hat{\varepsilon}_{t-4}^3} \text{ and } \varepsilon_t^4 = \underset{(6.241)^{**}}{-0.417\hat{\varepsilon}_{t-4}^4}$$

$$\text{Subperiod II } \hat{\varepsilon}_t^3 = \underset{(2.639)}{-0.068\hat{\varepsilon}_{t-2}^3} \text{ and } \hat{\varepsilon}_t^4 = \underset{(2.261)^*}{0.065\hat{\varepsilon}_{t-3}^4}$$

DOLLEX:

Subperiod I: No significant relation exists.

$$\text{Subperiod II } \hat{\varepsilon}_t^3 = \underset{(2.311)^*}{-0.073\hat{\varepsilon}_{t-2}^3} \text{ and } \hat{\varepsilon}_t^4 = \underset{(1.954)^*}{0.61\hat{\varepsilon}_{t-2}^4}$$

The absolute values of *t*-statistics are indicated within parentheses. * indicates significance at the 5 percent level; ** indicates significance at 1 percent.

From these estimated equations, we find that the residuals have third- or fourth-order dependencies on their own lagged values, implying that dynamics in higher-order moments are significant in explaining inefficiencies in the Indian stock market. No modeling framework is available where dependencies across third- or fourth-order moments can be explicitly incorporated, leading possibly to residuals finally becoming i.i.d., but as far as Indian stock returns are concerned, we find that, in addition to second-order dependence in the returns, higher-order (third or fourth) dependencies are also significant.

Concluding Remarks

In this paper, we proposed a systematic approach to studying stock market efficiency with the aim of identifying the factors that make stock returns predictable, after ensuring appropriate specification of first- and second-order conditional moments. In this approach, inefficiency has been defined to include nonlinear dependence in the returns as well. Consideration for appropriate specification is due to standard tests for conditional heteroskedasticity presuming proper specification of the conditional mean, and hence, any misspecification of the conditional mean or variance could lead to misleading inferences about the model on returns—and consequently, on the predictability of the stock market.

This modeling approach has been applied for the Indian stock market. Incorporating short-term interest rates through the call money rate, risk by conditional heteroskedasticity, 0–1 dummies for day-of-the-week effects, and lagged values of return in the conditional mean—and assuming GARCH specification and 0–1

dummies to represent daily-level seasonality in conditional heteroskedasticity—we have applied the automatic variance ratio test, Andrews's test, tests based on recursive residuals, and the BDS test. We find that there is statistical evidence in favor of two structural breaks in the Indian stock market, one in the middle of 1992 and the other in late 1996, which is consistent with the recent history of the Indian stock market. We also find some predictability in the Indian stock market, represented by four standard daily indices—BSESENSEX, BSE100, NIFTY, and DOLLEX—that can be attributed to serial correlation, nonlinear dependence, day-of-the-week effects, parameter instability, conditional heteroskedasticity (GARCH), daily-level seasonality in volatility, and the call money rate (in some subperiods of some indices only). Further, we find that the null of i.i.d. residuals was rejected by the BDS test, even in the case of standardized residuals of the properly specified models, leading us to conclude that incorporating second-order dependence through GARCH is inadequate to capture all potential nonlinearities in the returns for all indices. We have also observed that the remaining nonlinearities could be attributed to the existence of dynamics in the higher-order moments.

Can investors in the Indian stock market really exploit the sources of observed dependencies in daily returns, which are primarily either their own past or simply calendar dummies, to make a profit? Based on our findings on predictability, we may conclude that investors can, in fact, benefit. Statistical tests based on large data sets can have severe limitations. Standard tests may find statistically significant effects even when there are small deviations from the null hypothesis, and it is likely that most empirical studies evaluating within-sample predictability overstate out-of-sample predictability because of overfitting, finite sample biases, and data snooping. Despite this, the fact remains that the majority of the literature focuses on the statistical evidence of predictable time variation in expected returns. Further, econometric evidence for structural change—or stated differently, the nonexistence of a stable relationship for prediction of returns—is quite a common finding in economic time-series modeling, especially if the span of the series is long enough, because "structural change is pervasive in economic time series relationships" (Hansen 2001, p. 127). In such cases, it is prudent to keep in mind that only short-term predictions should be made, and that the relations should be updated with the passage of time when more observations become available.

Notes

1. See Hsieh (1991), Opong et al. (1999), Sewell et al. (1993), and Willey (1992), among others.

2. See, for example, Engle et al. (1987), Fama and French (1988), French (1980), Keim and Stambaugh (1984), and Rogalski (1984).

3. See also Giles et al. (1993), Tong (1990), and Weiss (1986).

4. We use the same notation ε_t for the disturbance term in Equation (4), with the understanding that ε_t represents the error associated with the correctly specified mean function.

5. In carrying out ADF and PP tests, maximum lag lengths were chosen to be 26, 20,

13, and 20 for BSESENSEX, BSE100, NIFTY, and DOLLEX, respectively. Because all four return series do not show any deterministic trend or nonzero mean, stationarity tests were performed using the pure random walk model.

6. In the computations for daily returns on BSESENSEX, the call money rate variable could not be included in the model, because this data set is available from January 1991 only.

7. Bai's estimation procedure produced 0.7451 as the residual variance for the full sample, and this was for January 15, 1998. However, the value closest to this one was 0.7457, which corresponds to December 10, 1996. Because the difference in values is practically negligible, and the later date conforms to the well-established fact that the Indian stock market experienced a structural break in 1996, we have taken December 1996 as the break point for the BSE100 series.

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