LONG MEMORY AND LINKAGE DYNAMICS BETWEEN EQUITY AND FOREIGN EXCHANGE MARKETS IN INDIA – AN EMPIRICAL EVIDENCE

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DECLARATION

I, **GOLAKA C NATH**, hereby declare that the thesis titled **"LONG MEMORY AND LINKAGE DYNAMICS BETWEEN EQUITY AND FOREIGN EXCHANGE MARKETS IN INDIA – AN EMPIRICAL EVIDENCE"** is the outcome study of my own undertaken under the able guidance of Dr. Y V Reddy, Reader and Head, Department of Commerce, Goa University. It has not been previously formed the basis for the award of any degree, diploma or certificate of this or any other University. I have duly acknowledged all the sources used by me in the preparation of this thesis.

Date: 10-02-2004

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CERTIFICATE

This is to certify that the thesis titled "**LONG MEMORY AND LINKAGE DYNAMICS BETWEEN EQUITY AND FOREIGN EXCHANGE MARKETS IN INDIA - AN EMPIRICAL EVIDENCE**" is the record of the original work done by Shri Golaka C Nath, under my guidance. The results of research presented in this thesis have not previously formed the basis for the award of any degree, diploma or certificate of this or any other University.

Date: 10-02-2004

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DEDICATED TO

MY BELOVED

FATHER-IN-LAW

LATE SALIL KUMAR GHOSH

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Date: 10-02-2004 **GOLAKA C NATH**

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ABBREVIATIONS

ACF	: Auto Correlation Function
ARCH	: Auto Regressive Conditional Heteroskedasticity
ADR	: American Depository Receipts
ALM	: Asset Liability Management
ARFIMA	: Auto Regressive Fractionally Integrated Moving Average
ARMA	: Auto Regressive Moving Average
BIS	: Bank for International Settlement
BSE	: Bombay Stock Exchange
CAC	: Capital account Convertibility
DJIA	: Dow Jones Industrial Average
ECB	: External Commercial Borrowing
EMH	: Efficient market Hypothesis
FII	: Foreign Institutional Investors
GARCH	: Generalised Auto Regressive Conditional Heteroskedasticity
GDR	: Global depository Receipts
IGARCH	: Integrated Generalised Auto Regressive Conditional Heteroskedasticity
IISL	: Indian Index Products and Services Ltd.
INR	: Indian Rupee
LERMS	: Liberalised Exchange Rate Management System
MRS	: Modified Rescaled Range
NASDAQ	: National Association of Stock Dealers Automated Quote
NSEIL	: National Stock Exchange of India

NYSE	: New York Stock Exchange
OLS	: Ordinary Least Square
PACF	: Partial Auto-correlation Function
RBI	: Reserve Bank of India
REER	:Real effective Exchange Rate
RS	: Rescaled Range
S&P	: Standard & Poor
SEBI	: Securities and Exchange Board of India
USD	: US Dollars ($)
VaR	: Value at Risk
VAR	: Vector Auto Regression
VR	: Variance Ratio

CHAPTER I

I.0 OBJECTIVE and MOTIVATION

A random process is called a long memory process if it has an autocorrelation function that is not integrable. This implies that values from the distant past can have significant effect on the present and implies anomalous diffusion. Long memory process has been observed in different natural and human phenomena ranging from the level of rivers to the temperature of the Earth. In financial stream, there has been a long-standing debate as to whether or not prices have long memory properties. The economic time series can exhibit long-range dependence has been a hypothesis of many early theories of the trade and business cycle. Such theories were often motivated by the distinct but non-periodic cyclical patterns that typified plots of economic aggregates over time, cycles of many periods, some that seem nearly as long as the entire span of the example. The presence of long memory component in asset returns has important implications for many of the paradigms used in the modern financial economics. More recent events have a greater impact than distant events, but there is still residual influence from distant past. On a broader scale, a system that exhibits long memory process and satisfies the required statistics is the possible result of a long stream of interconnected events. It has been well accepted in literature that volatility of prices is a long memory process. This has resulted in development of ARCH/GARCH models to capture volatility.

Mandelbrot (1971)[1] was first among many researchers that considered the possibility and implications of persistent statistical dependence in asset returns though Hurst (1951, 1965)[2] first recorded long memory process empirically while studying the water level in Nile River. Hydrology is the oldest discipline in which a non-cyclic long-run dependence has been reported. In particular, the rescaled range or commonly known as *R/S* analysis has been invented by Hurst (1951,1965) when he was studying the Nile in order to describe the long-term dependence of the water level in rivers and reservoirs. Later his method attracted much attention in the context of fractional Brownian motion.

There have been studies that supported the long memory process in financial markets data of developed markets like US, Japan, Europe, etc. Greene and Fielitz (1977)[3] claimed to have found long- range dependence in the daily returns of many securities listed on the NYSE. Very little work on long memory process has been done in Indian context. Indian financial markets, specifically stock and foreign exchange markets have been going through liberalization process since early 1990s. Many regulatory and institutional changes have been introduced during last one decade or so that has strengthened the financial market structure in India. Today Indian capital market is considered at par with the developed markets. Foreign exchange market in India has been developing well. The country introduced current account convertibility in 1994 and steadily has been working on capital account convertibility.

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[1] Mandelbrot, B.B.(1971). "When Can Price be Arbitraged Efficiently? A Limit to the Validity of the Random Walk and Martingale Models," *Review of Economics and Statistics*, 53, 3, 225-236.

[2] Hurst, H.E.(1951). "Long-Term Storage Capacity of Reservoirs," *Transactions of the American Society of Civil Engineers*, 116, 770-799 and H. E. Hurst, R. Black, and Y. M. Sinaika,(1965) *Long-Term Storage in Reservoirs: An Experimental Study* ~Constable, London..

[3] Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. Journal of Financial Economics, 4, 339–349.

The regulatory changes in financial markets in India has changed the microstructure and moved the market towards higher level of transparency. The availability of market price data has enthused researchers to look at Indian market to study the market efficiency. The financial markets are also getting interlinked more and more as foreign investment is coming to the Indian market. About USD23billion as in December 2003[1] has been invested in Indian capital market by Foreign Institutional Investors and many Indian firms are raising resources from international markets through ADR/GDR issues. The FII investment has special importance as these entities take foreign exchange risk and price risk by investing in Indian market. Heavy inflows of foreign exchange due to FII investment also affect the equilibrium exchange rate of the domestic currency. The listing of the Indian stocks in foreign markets has also helped triggering interlinkages between stock and foreign exchange market.

Long memory process has been appealing and has important implications for financial markets, equity and foreign exchange market in particular. The objective of the present study is to understand the long memory process in Indian capital and foreign exchange markets as well as to understand the linkage dynamics of these markets that will help understanding the market from a closer quarter and frame policy guidelines.

I.1 ARRANGEMENT OF CHAPTERS

The study has been arranged in the following manner: Chapter II introduces the subject of long memory and market intelinkages, Chapter III explains in detail the relationship

[1] SEBI website: http://sebi.gov.in

between market efficiency and long memory process, Chapter IV reviews the existing literature on the subject, Chapter V details the methodology used for the study, Chapter VI explains the data and data characteristics, Chapter VII gives the results of study and Chapter VIII reports the finding and conclusions.

CHAPTER II

II.0. INTRODUCTION

Financial markets play a prominent role in any economy, developed or emerging. It helps in reallocation of scare resources among market participants. It redistributes resources from savers community to entrepreneurs. Financial market efficiency has been a well-acclaimed subject studied by academicians, market participants and researchers. The subject is well written through voluminous literature and tested for developed as well as emerging markets with varying results. Financial markets have been a subject of study since ages and there has been an increasing trend to apply the theories developed and experimented in other streams of science and social science in studying financial markets. Researchers study financial markets from efficiency point of view looking at the data generated out of the actions and reactions of the market participants. Behaviour of the market participants is captured by their respective transactions they carry out in the market. An investor takes a decision to buy or sell an asset on the basis of information available to him. An investor would take a decision to cash his private information that may not be available to others. All market participants use publicly available information but they behave differently depending upon their risk perception. Using the same information, an investor makes a buy decision while another makes a sale decision.

Are financial asset returns predictable? This is a question that has engendered a huge volume of serious academic research and popular debate. Yet, as several studies would

suggest, the question is far from settled; and even the interpretation of the notion of "predictability" is subject to debate. (Fama (1991), Forbes (1996), Lo and MacKinlay (1999)). The most basic hypothesis about asset prices predictability, specifically stock prices, is the random walk hypothesis. If stock prices follow a random walk, then stock returns, which are just the log price increments, are serially uncorrelated and therefore cannot be predictable. Hence considering the above logic, the financial asset prices like stocks or foreign exchange cannot have long-term memory. The random walk hypothesis has been extensively tested, but researchers keep returning to it from time to time because it is the most basic hypothesis about financial asset return predictability and because tests of the random walk hypothesis appear to vary considerably in power depending on: the exact version of the hypothesis tested; the alternative hypothesis against which it is tested; and, not least, on the frequency, span, and country of the dataset on which it is tested. Literature suggests that developed markets like US are informationally efficient and the financial market asset prices follow a random walk. Efficient markets are priced so that all public information, both fundamental and price history, is already discounted.

The question being asked: is it possible for stock market prices to be predictable to some degree in an efficient market using the available tools. The link between the Random Walk Hypothesis and the Efficient Markets Hypothesis is a source of debate in financial literature. Under very special circumstances, e.g., risk neutrality, the two are equivalent. However, LeRoy (1973)[1], Lucas (1978)[1], and many others have shown in

[1] Leroy, S. F., (1973) "Risk Aversion and the Martingale Property of Stock Returns," *International Economic Review,* 14,436-446.

many ways and in many contexts that the random walk hypothesis is neither a necessary nor a sufficient condition for rationally determined security prices. In other words, unforecastable prices need not imply a well-functioning financial market with rational investors, and forecastable prices need not imply the opposite.

Nevertheless, one of the central insights of modern financial economics is the necessity of some trade-off between risk and expected return. In particular, if a financial asset's expected price change is positive, it may be just the reward/return needed to attract investors to hold the asset and bear the associated risks. Indeed, if an investor is sufficiently risk averse, he might gladly pay to avoid holding a financial asset that has unforecastable returns. In such a world, the random walk hypothesis - a purely statistical model of returns--need not be satisfied even if prices do fully reflect all available information. This was demonstrated conclusively by LeRoy (1973) and Lucas (1978), who constructed explicit examples of informationally efficient markets in which the efficient markets hypothesis holds but where prices do not follow random walks.

Grossman (1976)[2] and Grossman and Stiglitz (1980)[3] have gone even further. They have argued that perfectly informationally efficient markets are impossibility, for if markets are perfectly efficient, the return to gathering information is nil, in which case there would be little reason to trade and markets would eventually collapse.

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[1] Lucas, R. E., (1978): 'Asset Prices in an Exchange Economy," *Econometrica,* 46, 429-1446.
[2] Grossman, S., (1989): The Informational Role of Prices, MIT Press, (Cambridge, MA, 1989).
[3] S. Grossman and J. E. Stiglitz, (1980): *On the impossibility of informationally efficient markets*, Amer. Econ. Rev. 70, 393-408.

Alternatively, the degree of market inefficiency would determine the effort investors are willing put to gather and trade on private information; hence a non-degenerate market equilibrium will arise only when there are sufficient profit opportunities, i.e., market inefficiencies, to compensate investors for the costs of trading and information-gathering. The profits earned by these investors may be viewed as economic rents that accrue to those willing to engage in such activities and this would be distinctly different from the normal return that a not so enthusiastic investor would earn using all public information.

The question arises: who are the providers of these rents? Black (1986)[1] gives us a provocative answer: noise traders, individuals who trade on what they think is information but is in fact merely noise. More generally, at any time there are always investors who trade for reasons other than information--for example, those with unexpected liquidity needs--and these investors are willing to "pay up" for the privilege of executing their trades immediately.

These investors may well be losing money on average when they trade with information-motivated investors, but there is nothing irrational or inefficient about either group's behavior. In fact, an investor may be trading for liquidity reasons one day and for information reasons the next, and losing or earning money depending on the circumstances surrounding the trade. Even after decades of research and literally

[1] Black, Fischer., 1986, "Noise", *Journal of Finance.* VOL XLI, No. 3, July 1986

thousands of journal articles, economists have not yet reached a consensus about whether markets--particularly financial markets--are efficient or not.

Tests of the efficient markets hypothesis may not be the most informative means of gauging the efficiency of a given market. What is often of more consequence is the relative efficiency of a particular market, relative to other markets, e.g., futures vs. spot markets. Financial markets are no different in principle, only in degrees. Consequently, the profits that accrue to an investment professional need not be a market inefficiency, but may simply be the fair reward to breakthroughs in financial technology.

A market may be defined as efficient in the informational sense if the prices of the assets traded on that market instantaneously reflect all available information. Efficiency is achieved through arbitrage between traders.

II.1 Market Efficiency

Informational efficiency plays an important role in financial markets, be it equities, derivatives, bonds, foreign exchange, etc. Fama (1970)[1] in his seminal paper categorised three types of market efficiency: weak, semi-strong and strong. Since then, efficient markets hypothesis has been widely applied to a variety of financial markets. The efficient market hypothesis is one of the cornerstones of modern financial economics. The efficient market hypothesis is the idea that information is quickly and efficiently incorporated into asset prices, so that old information cannot be used to

[1] Fama, E. F.: (1970) "Efficient Capital Markets: A Review of Theory and Empirical Work," Journal of Finance, 25 (No. 2, 1970), 383-417.

foretell future price movements. The random walk model of asset prices is an extension of the efficient market hypothesis, as are the notions that the market cannot be consistently beaten, arbitrage is impossible, and "free lunches" are generally unavailable. The weak-form efficient market hypothesis stipulates that current asset prices already reflect past price and volume information -- chart data. Consequently, trend analysis is useless for predicting future price changes. The semistrong-form efficient market hypothesis states that all publicly available information is similarly already incorporated into asset prices, and so a firm's financial statements are of no help in forecasting future price movements and securing high investment returns. The strong-form efficient market hypothesis stipulates that private information too, is quickly incorporated by market prices and therefore cannot be used to reap abnormal trading profits.

According to the efficient market hypothesis an efficient capital market is one in which security prices adjust rapidly to the arrival of new information, and therefore, the current prices of securities reflect all information about the security. Three sets of assumptions imply an efficient capital market: (a) an efficient market requires that a large number of competing profit-maximizing participants analyze and value securities, each independently of the others, (b) new information regarding securities come to the market in a random fashion, and the timing of one announcement is generally independent of others, and (c) the competing investors attempt to adjust security prices rapidly to reflect the effect of new information. Although the price adjustment may be imperfect, it is unbiased. This means that sometimes the market will over-adjust or

under-adjust, but an investor cannot predict which will occur at any given time. If we believe that efficient market hypothesis is a valid proposition, then the current asset prices should reflect all generally available information. The efficient market hypothesis implies that since market prices reflect all available information, including the information about the future, the only difference between the prices at P_t and P_{t+1} are events that we cannot possibly predict, i.e. a random event. Hence, in an efficient market, stock prices can be statistically tested for random walk hypothesis.

The efficient markets hypothesis and the notions connected with it have provided the basis for a great deal of research in financial economics. A voluminous literature has developed supporting this hypothesis. Briefly stated, the hypothesis claims that asset prices are rationally related to economic realities and always incorporate all the information available to the market. This implies the absence of exploitable excess profit opportunities. The early survey of Fama (1965)[1] concluded that the stock market was efficient. He analyzed the distribution of a large data set and showed that empirical evidence seems to confirm the random walk hypothesis: a series of prices changes have no memory. The main theoretical explanation that lies behind this observation is the efficient market hypothesis. The efficient market hypothesis has received a lot of empirical support in the academic literature during seventies and eighties. This line of thought has always been received with a lot of skepticism in the professional community, which led to the use of charts and technical analysis rules for trading strategies in markets. Professionals have always claimed that classical statistical tests

[1] Fama, E. F.(1965) "The Behavior of Stock Market Prices," *Journal of Business* 38, 1965.

are mainly linear and therefore, unable to capture the complex pattern of price changes exhibit. However despite the widespread allegiance to the notion of market efficiency, a number of studies have suggested that certain asset prices are not rationally related to economic realities.

II.2 Long Memory

Efficient market hypothesis states that market price of assets are more of random walk under special conditions of risk neutrality, as new information cannot be predicted ahead of time using the historical price data of the financial assets. Hence there cannot be any existence of memory component in asset prices. However, there have been many studies on developed as well as emerging financial markets that have refuted the case of random walk in asset prices while some have found the markets are informationally efficient.

The existing work on long memory in asset returns derives largely from the pioneering work of Hurst (1951)[1]. Hurst was a hydrologist who began working on he Nile River Dam project in about 1907. Greene and Fielitz (1977)[2] and Aydogan and Booth (1988)[3] both test for long memory using the rescaled range statistic of Hurst (1951). Lo (1991)[4], using a modified rescaled range (R/S) statistic, ands no evidence of long memory in a

[1] Hurst, H.E.(1951). "Long-Term Storage Capacity of Reservoirs," *Transactions of the American Society of Civil Engineers*, 116, 770-799.
[2] Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. Journal of Financial Economics, 4, 339–349.
[3] Aydogan, K. and G.G. Booth(1988). "Are There Long Cycles in Common Stock Returns," *Southern Economic Journal*, 55(July), 141-149.
[4] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

sample of U.S. stock returns. Mills (1993)[1], using the modified R/S statistic and the semi-parametric approach of Geweke and Porter-Hudak (1983), finds weak evidence of long memory in a sample of monthly U.K. stock returns. Lobato and Savin (1998)[2] find no evidence of long memory in daily S&P 500 returns over the period July 1962 - December 1994. Interestingly, Lobato and Savin (1998) found some evidence of long memory in the squared return data, which supports the conclusions of Ding, Granger and Engle (1993).

Recent evidence on the presence of long memory in stock returns is mixed. Whereas many studies and evidence for long horizon predictability in stock returns (see Fama and French (1988)[3], Porterba and Summers (1988)[4], Mills (1993)), other authors (Goeztman and Jorion (1993)[5], Nelson and Kim (1993), and Malliaropolous (1996)) argue that converse is true. Where evidence of long horizon predictability is found, it is usually attributed to time variation in expected returns, or speculative bubbles, periods of marked divergence between the price of an asset and its fundamental, or true value. Campbell (1991)[6] and Campbell and Ammer (1993)[7] argue that persistence in equity

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[1] Mills, T. (1993),"*Is there long-term memory in UK stock returns*?," Applied Financial Economics 3, 293-302.

[2] Lobato I.N. and Savin N.E (1998): "Real and Spurious Long Memory Properties of stock Market Data", Department of Economics, University of Iowa, Iowa City.

[3] Fama, E. and K. French (1988),"*Permanent and Temporary Components of Stock Prices*," Journal of Political Economy 96, 246-273.

[4] Poterba, J.M. and Summers, L.H., 1988, Mean reversion in stock prices: evidence and implications, Journal of Financial Economics 22, 27-59.

[5] Goetzmann, William N., and Phillipe Jorion. "Testing the Predictive Power of Dividend Yields." *Journal of Finance*, 48 (1993), pp. 663-679.

[6] Campbell, John Y. (1991), A Variance Decomposition for Stock Returns, *Economic Journal*, 101 (405), March, 157-179

[7] Campbell, John Y. (1991), A Variance Decomposition for Stock Returns, *Economic Journal*, 101 (405), March, 157-179

returns underlies this long horizon forecast power. That is, this observed forcastabilty may be attributed to long range dependence, or long memory, in the returns time series.

The long memory concept is useful in understanding the behaviour of the financial assets returns and their volatility as well. Asset price volatility has been well studied with help of advanced concepts like GARCH (Generalized Autoregressive Conditional Hetertoskedasticity). Previous analysis of the volatility in financial series, as measured by the log-squared, squared or absolute return of a financial instrument, have proved fruitful in identifying economic series which exhibit long memory. (Breidt et. al(1998)[1], Anderson and Bollerslev (1997a)[2], Bollerslev and Mikkelsen (1996)[3], Baillie, et.al(1996)[4], Ding, et.al (1993)[5] and Dacorogna et.al (1993)). In the past the volatility of returns has been modeled as short memory ARCH or stochastic volatility models, whole correlation decays exponentially to zeros as time interval increases, and as a near integrated IGARCH model (Engel and Bollerslev (1986)).

Long-term dependence in financial market data has been well studied and well documented. However, most of the studies on long-term dependence have been confined to non-Indian markets. Indian stock and foreign exchange markets have been

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[1] Breidt, F.J., N. Crato, and P. de Lima (1998), "On the Detection and Estimation of Long-Memory in Stochastic Volatility," *Journal of Econometrics*, 83, 325-348.

[2] Andersen, T.G. and T. Bollerslev (1997a), "Intraday Periodicity and Volatility Persistence in Financial Markets," *Journal of Empirical Finance*, 4, 115-158.

[3] Bollerslev, Tim, and Mikkelsen, H O A, (1996): "Modeling and pricing long memory in stock market volatility" Journal of Econometrics, 73, 151-184

[4] Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 74, 3–30.

[5] Ding, Z., Granger, C.W. J., and Engle, R.F. (1993), A long memory property of stock market returns and a new model, Journal of Empirical Finance, 1, 83—106.

going through many structural changes since early 1990s when India decided to introduce financial sector liberalization and opened up its economy. Many regulatory and administrative changes have helped the market to improve efficiency and better price discovery. These developments helped in reducing the irregularities in the financial markets and today price discovery mechanism is more efficient compared to mid and late nineties. In the light of the changing environment, it would be necessary to study the long-term dependence characteristics of the stock and foreign exchange market through long memory process. Once long memory process is studied it would be interesting to see the cointegration of these markets and their long run interlinkages. The objective of this thesis is to study the long memory process in stock as well as foreign exchange market and to study their long-term as well as short-term intelinkages.

The motivation of this study is drawn from the fascinating concept of long memory application to financial market assets in term of its returns as well as volatility. Indian financial markets have been going through liberalization process since 1990. There are many regulatory changes in equity as well as foreign exchange markets to defuse the bottlenecks in the market structure and improve the level of information dissemination. In the process, the study also tries to understand the interlinkages of various macroeconomic factors to stock market in India and interlinkages between Indian stock market with that of advanced and emerging markets in the world. The study uses the Variance Ratio, Rescaled Range Analysis, Johansen's cointegration techniques, Granger's causality concepts to study the long memory, short memory and interlinkages.

II.3 Market Linkage Dynamics

The Asian crisis of 1997-98 has made a strong pitch for dynamic linkage among global markets as well as between stock prices and exchange rates. During the crisis period, the world has noticed that the emerging markets collapsed due to substantial depreciation of exchange rates (in terms of US$) as well as dramatic fall in the stock prices. This has become important again from the view point of large cross border movement of funds due to portfolio investment and not due to actual trade flows, though trade flows have some impact on stock prices of the companies whose main sources of revenue comes from foreign exchange. In retrospect of the literature, a number of hypotheses also support the existence of a causal relation between stock prices and exchange rates. For instance, 'goods market approaches' (Dornbusch and Fischer, 1980) suggest that changes in exchange rates affect the competitiveness of a firm as fluctuations in exchange rate affects the value of the earnings and cost of its funds as many companies borrow in foreign currencies to fund their operations and hence its stock price. A depreciation of the local currency makes exporting goods attractive and leads to an increase in foreign demand and hence revenue for the firm and its value would appreciate and hence the stock prices. On the other hand, an appreciation of the local currency decreases profits for an exporting firm because it leads to a decrease in foreign demand of its products. However, the sensitivity of the value of an importing firm to exchange rate changes is just the opposite to that of an exporting firm. In addition, variations in exchange rates affect a firm's transaction exposure. That is, exchange rate movements also affect the value of a firm's future

payables (or receivables) denominated in foreign currency. Therefore, on a macro basis, the impact of exchange rate fluctuations on stock market seems to depend on both the importance of a country's international trades in its economy and the degree of the trade imbalance.

An alternative explanation for the relation between exchange rates and stock prices can be provided through 'portfolio balance approaches' that stress the role of capital account transaction. Like all commodities, exchange rates are determined by market mechanism, i.e., the demand and supply condition. A blooming stock market would attract capital flows from foreign investors, which may cause an increase in the demand for a country's currency. The reverse would happen in case of falling stock prices where the investors would try to sell their stocks to avoid further losses and would convert their money into foreign currency to move out of the country. There would be demand for foreign currency in exchange of local currency and it would lead depreciation of local currency. As a result, rising (declining) stock prices would lead to an appreciation (depreciation) in exchange rates. Moreover, foreign investment in domestic equities could increase over time due to benefits of international diversification that foreign investors would gain. Furthermore, movements in stock prices may influence exchange rates and money demand because investors' wealth and liquidity demand could depend on the performance of the stock market.

Although theories suggest causal relations between stock prices and exchange rates, existing evidence on a micro level provides mixed results. Jorion (1990, 1991)[1], Bodnar and Gentry (1993)[2], and Bartov and Bodnar (1994)[3] all fail to find a significant relation between simultaneous dollar movements and stock returns for U.S. firms. He and Ng (1998)[4] find that only about 25 percent of their sample of 171 Japanese multinationals has significant exchange rate exposure on stock returns. Griffin and Stulz's (2001)[5] empirical results show that weekly exchange rate shocks have a negligible impact on the value of industry indexes across the world. However, Chamberlain, Howe, and Popper (1997)[6] find that the U.S. banking stock returns are very sensitive to exchange rate movements, but not for Japanese banking firms. While such findings are different from those reported in prior research, Chamberlain *et al.*(1997) attributed the contrast to the use of daily data in their study instead of monthly data as used in most prior studies.

On a macro level, the empirical research documents relatively stronger relationship between stock price and exchange rate. Ma and Kao (1990)[7] find that a currency appreciation negatively affects the domestic stock market for an export-dominant country and positively affects the domestic stock market for an import-dominant

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[1] Jorion, P. (1990), "The Exchange Rate Exposure of U.S. Multinationals," *Journal of Business* 63, 331-345. and Jorion, P. (1991), "The Pricing of Exchange Rate Risk in the Stock Market," *Journal of Financial and Quantitative Analysis* 26, 363-376.

[2] Bodnar, G., and W. Gentry, 1993, Exchange rate exposure and industry characteristics: Evidence from Canada, Japan, and the USA, *Journal of International Money and Finance* 12, 29-45.

[3] Bartov, E., and G. Bodnar, 1994, Firm valuation, earnings expectations, and the exchange-rate exposure effect, *Journal of Finance* 49, 11755-1785.

[4] He, J. and L. K. Ng, (1998), "The Foreign Exchange Exposure of Japanese Multinational Corporations," *Journal of Finance* 53, 733-753.

[5] Griffin, J. M. and R. M. Stulz (2001), "International Competition and Exchange Rate Shocks: A Cross-Country Industry analysis of Stock Returns," *Review of Financial Studies* 14, 215-241.

[6] Chamberlain, S.; J. S. Howe, and H. Popper (1997), "The Exchange Rate Exposure of U. S. and Japanese Banking Institutions," *Journal of Banking and Finance* 21, 871-892.

[7] Ma, C. K. and G. W. Kao (1990), "On Exchange Rate Changes and Stock Price Reactions," *Journal of Business Finance & Accounting* 17, 441-449.

country, which seems to be consistent with the goods market theory. Ajayi and Mougoue (1996)[1], using daily data for eight countries, show significant interactions between foreign exchange and stock markets, while Abdalla and Murinde (1997)[2] document that a country's monthly exchange rates tends to lead its stock prices but not the other way around. Pan, Fok & Lui (1999)[3] used daily market data to study the causal relationship between stock prices and exchange rates and found that the exchange rates Granger-cause stock prices with less significant causal relations from stock prices to exchange rate. They also find that the causal relationship have been stronger after the Asian crisis.

In the context of Indian economy, however, study in the similar direction is not available, though the issue is gaining importance in recent years. Like other Asian emerging economies, Indian equity market has continued to grow and has seen the relaxation of foreign investment restrictions primarily through currency deregulation. During the 1990s, India has initiated the financial sector reforms by way of adopting international practices in its financial market. Parallel to this, the issuance of ADR's and GDR's has facilitated the trade of foreign securities on the NYSE, NASDAQ or on non-American exchanges. Over the years, Indian Rupee is slowly moving towards full convertibility, which has also had an impact in the Indian capital market as international investors have invested about US $23 billion in Indian capital market as of Dcember

[1] Ajayi, R. A. and M. Mougoue (1996), "On the Dynamic Relation between Stock Prices and Exchange Rates," *Journal of Financial Research* 19, 193-207.
[2] Abdalla, I. S. A. and V. Murinde (1997), "Exchange Rate and Stock Price Interactions in Emerging Financial Markets: Evidence on India, Korea, Pakistan, and Philippines," *Applied Financial Economics* 7, 25-35.
[3] Pan, Fok & Lui (1999), *Dynamic Linkages Between Exchange Rates and Stock Prices: Evidence from Pacific Rim Countries*, Shippensburg University Working Papers.

2003. The two-way fungibility of ADRs/GDRs allowed by RBI has also possibly enhanced the linkages between the stock and foreign exchange markets in India. In this background, this study aims at examining the dynamic linkages between foreign exchange of Indian Rupee and stock market price index in India.

CHAPTER III

III.0 MARKET EFFICIENCY AND LONG MEMORY

Fama et al. (1969)[1]: "an "efficient" market, i.e., a market that adjusts rapidly to new information."

Fama (1970)[2]: A market in which prices always "fully reflect" available information is called "efficient.""

Jensen (1978)[3]: "A market is efficient with respect to information set $[theta]_t$ if it is impossible to make economic profits by trading on the basis of information set $[theta]_t$."

Fama (1991)[4]:"I take the market efficiency hypothesis to be the simple statement that security prices fully reflect all available information. A precondition for this strong version of the hypothesis is that information and trading costs, the costs of getting prices to reflect information, are always 0 (Grossman and Stiglitz (1980)). A weaker and economically more sensible version of the efficiency hypothesis says that prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed marginal costs (Jensen (1978))."

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[1] Fama, E. F., L. Fisher, M. C. Jensen and R. Roll, 1969, "The Adjustment of Stock Prices to New Information," *International Economic Review* 10, 1-21.

[2] Fama, E. F., : (1970) "Efficient Capital Markets: A Review of Theory and Empirical Work," Journal of Finance, 25 (No. 2, 1970), 383-417.

[3] Jensen, M C (1978): *Some anomalous evidence regarding market efficiency.* Journal of Financial Economics, 6:95--101.

[4] Fama, E. F.(1991): "Efficient Capital Markets: II," Journal of Finance, 46 (No. 5, 1991), 1575-1618.

Malkiel (1992)[1]: "A capital market is said to be efficient if it fully and correctly reflects all relevant information in determining security prices. Formally, the market is said to be efficient with respect to some information set...if security prices would be unaffected by revealing that information to all participants. Moreover, efficiency with respect to an information set implies that it is impossible to make economic profits by trading on the basis of [that information set]."

Fama (1998):"...market efficiency (the hypothesis that prices fully reflect available information)..."
"...the simple market efficiency story; that is, the expected value of abnormal returns is zero, but chance generates deviations from zero (anomalies) in both directions."

The study of market efficiency can be traced back at least as far as the pioneering theoretical contribution of L Bachelier (1900)[2] and empirical research of Cowles(1933). Maurice Kendall (1953) in The Analysis of Economic Time Series, Part I: Prices, *Journal of the Royal Statistical Society 96* examined recurrent patterns of peaks and troughs in economic performance of firms through price behaviour assuming that stock prices reflect the prospects of the firms. He found to his great surprise that he could identify no predictable patterns in stock prices. Prices seemed to evolve randomly.

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[1] Malkiel, B., (1992), "Efficient market hypothesis," in Newman, P., Milgate, M. and Eatwell, J.(eds.), *New Palgrave Dictionary of Money and Finance*, Macmillan, London, pp739.
[2] Bachelier, L.:- *"Theorie de la speculation"*, Gauthier-Villars, Paris (1900). Reprinted in English (A.J.Boness, trans.) in P.H. Cootner (ed.),*"The Random Character of Stock-market prices"*, M.I.T. Press, Cambridge, Mass., (1964), pp. 17-78.

These prices were as likely to go up, as they were to do down on any particular day, regardless of past performance. The data provided no way to predict the price movements. At first blush, Kendall's results were disturbing to financial economists and they seemed to imply that the stock market is dominated by erratic market psychology and it follows no logical rules. However, it soon became apparent that random price movements indicated a well functioning market, not an irrational one.

More generally, one might say that any information that could be used to predict the asset prices should have already been reflected in asset prices. As soon as there is any indication that an asset is under-priced and therefore offers an opportunity for profit, investors would flock to buy the asset and hence they would bid up to the fair price. This would ensure that the prices would return to their ordinary level communicated with the risk of the asset. However, this information may not be available to all at the same time and that may lead to some price anomalies. But if prices are bid immediately to fair levels, given all available information, it must be that they increase or decrease only in response to new information. And no new information can be predictable beforehand, asset prices are also not predictable. This is the essence of the arguments that financial market prices like stocks and foreign exchange follow random walk that is price changes should be random and unpredictable. Randomly evolving stock prices are necessary consequence of intelligent investors competing to discover relevant information on which to buy and to sell stocks before the rest of the market becomes aware of that information.

It is common to distinguish among three versions of Efficient Market Hypothesis: the weak, semi-strong and strong forms. These versions differ by their notions of what is meant by the term "all available information". The weak-form hypothesis asserts that stock prices already reflect all information that can be derived by examining market trading data such as the history of prices, trading volume and short interest. This version tells us that the trend analysis is fruitless. Past trade price data are publicly available and virtually costless to obtain. If such data provides some information about future prices, then all investors would have already used the same and past prices must have taken into considerations of such information. The semi-strong form hypothesis states that all publicly available information regarding the prospects of a firm must be reflected already in the stock price. Such information includes, in addition to the past date, fundamental data on the firms operations. If an investor has access to such information which is generally available publicly, one would expect it o have been reflected in prices. Finally the strong form hypothesis states that stock prices reflect all information relevant to the firm, even including the information available to company insiders. Hence this might have been already reflected in stock prices as well because informed traders would have already set the prices depending upon the quality of the information.

An *efficient capital market* is an arena in which many participants, with similar investment objectives and access to the same information, actively compete. The stock market—with numerous profit-motivated professional and private investors continually searching for misvalued securities—certainly provides such a setting. Profit-motivated investors do have strikingly similar objectives. Each prefers a high rate of return to a

low one, certainty to uncertainty, low risk to high risk, and so forth. Furthermore, securities law provides that both parties to a transaction must have access to the same material facts. The efficient market hypothesis asserts that it would be impossible consistently to outperform the market—which reflects the composite judgment of millions of participants—in an environment characterized by many competing investors, each with similar objectives and equal access to the same information. In the context of this hypothesis, "efficient" means that the market is capable of quickly digesting new information on the economy, an industry, or the value of an enterprise and accurately impounding it into securities prices. In such markets participants can expect to earn no more, nor less, than a fair return for the risks undertaken.

In an efficient market, for example, news of an earnings increase would be quickly and accurately assessed by the combined actions of literally millions of investors and immediately reflected in the price of the stock. The purported result of this efficiency is that whether you buy the stock before, during, or after the earnings news, or whether another stock is purchased, only a fair market rate of return can be expected-commensurate with the risk of owning whatever security is bought.

III.1 Forms of the Efficient Market Hypothesis

The efficient market hypothesis does not by any means deny the profitability of investing. It merely states that the rewards obtainable from investing in highly competitive markets will be fair, on the average, for the risks involved. Importantly, however, the three forms of the efficient market hypothesis hold that acting on publicly

available information cannot improve one's performance beyond the market's assessment of a fair rate of return. The weak form of the efficient market hypothesis describes a market in which historical price data are efficiently digested and, therefore, are useless for predicting subsequent stock price changes. This is distinguished from a semistrong form under which all publicly available information is assumed to be fully discounted in current securities prices. Finally, the strong form describes a market in which not even those with privileged information can obtain superior investment results.

If the stock market efficiently digests all available information, as the progressively stronger forms of the hypothesis imply, there is little justification for seeking extraordinary gains from investing. However, this does not lessen the importance of investing. It merely changes the underlying investment philosophy of a prudent and knowledgeable investor from that of trying to beat the other person to one of seeking a rate of return that is consistent with the level of risk accepted. Thus, rather than being the all-encompassing specter of gloom which some people assume it to be, the efficient market hypothesis in its various forms provides a useful benchmark. From its perspective, researchers can determine how "efficiently" or "inefficiently" information is processed. It is thus possible to scrutinize the market's ability to impound various kinds of information into securities prices.

It should prove useful to discuss the association between two forms of the efficient market hypothesis and two popular approaches to investment analysis-fundamental and

technical. *Fundamental* investment analysts base their predictions of stock price behavior on factors which are "fundamental" or internal to a company, its industry, or the economy (for example earnings' products, management, competition, consumer spending and so on). A market fundamentalist might issue a purchase recommendation for a company which has consistently shown year-to-year earnings increases and is in an industry that he or she believes will grow faster than the economy. *Technical* analysts, by contrast, hold that all such fundamental factors are reflected in the market behavior of the stock. Thus, to a pure technician, all data of importance are internal to the stock market, and future stock-price movements can be predicted from the diligent study of historical stock market information (for example, changes in stock prices and trading volume). A market technician might, therefore, base a buy recommendation on a certain pattern of recent price and volume changes.

The weak form of the efficient market hypothesis holds that information on the past movements of stock prices and volumes cannot be used to predict future stock prices. Under the weak form of the efficient market hypothesis, information on historical price trends is of no value for the prediction of either the magnitude or direction of subsequent price changes. As such, the weak form is directly opposed to the basic premise of technical analysis. Similarly, the semistrong form of the efficient market hypothesis holds that all publicly available information (as well as forecasts developed from such data) is of no value in the prediction of future prices. Thus, the semistrong form of the hypothesis is diametrically opposed to the concept of fundamental analysis.

Thus, two conclusions can be drawn with regard to the weak form of the efficient market hypothesis:

1. The weak form of the efficient market hypothesis is a valid description of the market for anyone who is interested in developing profitable investment strategies from historical price or volume information.

2. There is neither a theoretical foundation nor empirical support for technical analysis based on historical price and volume data.

The semi-strong form of the efficient market hypothesis however, raises serious questions about an analysts' ability to develop useful earnings forecasts. Specifically, this form of the hypothesis holds that the analysis of any publicly available information is pointless because all such information is already reflected in stock prices. The evidence here is again clear. First, it has been shown that period-to-period earnings changes behave in accordance with a random-walk model. This means that the common practice of basing future earnings projections on historical patterns of earnings changes is of no value. Second, studies which have examined the behavior of stock prices prior to unexpected earnings changes dramatize that the market is remarkably efficient at accurately anticipating such fluctuations. This evidence indicates that the marketplace is filled with competent analysts who, as a whole, accurately forecast earnings. In this extremely competitive arena it is doubtful that a few superior earnings forecasters consistently "beat the market to the punch." Dividend information raises a significant challenge to the efficient market hypothesis. There is evidence to support the contention that dividend changes mirror management's largely correct assessment of a firm's

future. A systematic examination of other levels of the information hierarchy reveals only isolated exceptions to a purely efficient market setting. There is evidence, for example, that professional opinions on stocks can cause price movements and that secondary distributions by sellers, whom the market views as "knowledgeable," precede price declines.

In its strong form, the efficient market hypothesis holds that even investors with privileged information cannot use that information to develop profitable investing strategies. Not surprisingly, there is little support for this hypothesis. Management insiders do have extra insight into their company's future. Also, there is evidence that stock exchange specialists cause abnormal patterns of fractional price movements. Given the evidence, the stock market can accurately be described as a "nearly efficient" marketplace. Unquestionably, if an opportunity for inordinate profit presents itself in the market, it will not go unnoticed. In such a marketplace one would not expect prices to deviate by much, or for long, from what is perceived to be a "fair" price by the myriad market participants.

III.2 Long Memory and Market Efficiency

An important class of time series models are the so-called long memory processes which were introduced by Mandelbrot and Van Ness (1968)[1], Granger and Joyeux (1980)[2], and Hosking (1981)[3]. A simple property of long memory processes is that

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[1] Mandelbrot, B. and Van Ness, J. (1968) *Fractional Brownian motions*, fractional noises and applications. SIAM Review 10, pp. 422-437.

[2] C.W.J. Granger and R. Joyeux. "*An introduction to long memory time series and fractional di#erencing*," J. of Time Series Analysis, vol. 1, pp. 15-30, 1980.

[3] Hosking, J.R.M. (1981). '*Fractional differencing*', Biometrika, Vol. 68,pp. 165 -- 176.

whilst the autocorrelations decrease, they decrease very slowly. Therefore, the past influences the future in a manner reminiscent of chaotic processes. It is interesting to notice that many of the empirical studies use temporally aggregated data, such as monthly time series, for the test of long memory process. We now have available financial data that are sampled on many different frequencies. This availability naturally raises questions of temporal aggregation in long memory processes. Ding, Granger and Engle (1992)[1] conjectured that temporal aggregation does not change the long memory property of the return series. It is shown that at low frequencies, the decay rate of the spectral density functions of long memory processes is not affected by sampling intervals. Therefore, the true long memory parameter can be estimated by considering low frequencies regardless of the sampling interval.

There have been several papers analyzing the long term properties of stock returns. Greene and Fielitz (1977)[2] used the R/S statistic (Hurst (1951)) to test for long term dependence in the daily returns of 200 individual stocks on the NYSE from December 23, 1963 to November 29, 1968 and claim to have found significant evidence. Lo (1991)[3] criticized these results on the grounds that this evidence was due to short term correlation. He proposed a modified version of the R/S statistic to test robustly for long term dependence, and found no evidence in favor of long run dependence of the

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[1] Ding, Z., Granger, C.W. J., and Engle, R.F. (1993), A long memory property of stock market returns and a new model, Journal of Empirical Finance, 1, 83—106.
[2] Greene, M. T. and B. D. Fielitz (1977): *Long-Term Dependence in Common Stock Returns*, Journal of Financial Economics, 4, 339-349. 24
[3] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

monthly and daily returns on CRSP stock indices. Ding et al. (1993)[1] examined the long memory properties of several transformations of the absolute value of daily returns on the S&P 500, including squared returns, and found considerable evidence of long memory in the squared returns, but conducted no formal test.

An important issue in the empirical analysis of financial time series is whether holding period returns on a risky asset are serially independent, which is required by the efficient market hypothesis. The evidence is mixed. For instance, using a variance-ratio test Lo and MacKinley (1988)[2] and Poterba and Summers (1988)[3], concluded that stock returns exhibit mean reversion. Fama and French (1988)[4], who examined the autocorrelations of one-period returns, also found mean reversion. By contrast, using a generalised form of rescaled range (R/S) statistic, Lo (1991)[5] found no evidence against the random walk hypothesis. Using annual data and allowing for fractional alternatives, Caporale and Gil-Alana (2001)[6] reported that US stock returns are close to being an I(0) series, and pointed out that their degree of predictability depends on the process followed by the error term.

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[1] Ding, Z., Granger, C.W. J., and Engle, R.F. (1993), A long memory property of stock market returns and a new model, Journal of Empirical Finance, 1, 83—106.

[2] Lo, A. and C. MacKinlay,(1988), "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies* 1, 41-66.

[3] Poterba, J., and L Summers (1987): "Mean Reversion in Stock Returns: Evidence and Implications," forthcoming in *Journal of Financial Economics*

[4] Fama, E. and K. French (1988),"*Permanent and Temporary Components of Stock Prices*," Journal of Political Economy 96, 246-273.

[5] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

[6] G.M. Caporale & L.A. Gil-Alana (2001) Unemployment and input prices. A fractional cointegration approach Discussion Paper 56, SFB373, Humboldt-Universität zu Berlin.

The study of long range dependence clearly requires sufficiently long series to justify the application of large sample inference rules based on semiparametric models, whilst no finite sample theory yet exists for rules of parametric inference on long memory. In particular, Granger and Ding (1995)[1] modelled absolute returns as a long-memory process, and established some stylised facts (temporal and distributional properties) which hold for them. However, Granger and Ding (1995) found that the parameters of the long-memory model vary considerably from one subseries to the next. Ryden et al (1998)[2] claimed that the temporal higher-order dependence observed in return series are better described by a hidden Markov model, and again reported that the parameter estimates of the model differ depending on the subseries being considered. Their model, though does not account for an important distributional property of absolute returns (i.e. their very slowly decaying autocorrelation function). This is reproduced by Granger and Terasvirta (1999)[3] in the context of a nonlinear model.

The fact that the "long memory" property might reflect the presence of breaks had already been pointed out by Lobato and Savin (1998)[4], though they did not find any evidence to this effect when splitting their sample in two. In a subsequent paper, Aggarwal et al (1999)[5] used a pre-determined break procedure to investigate this issue.

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[1] Granger, C. W. J., & Ding, Z. (1995). Some properties of absolute return: An alternative measure of risk. Annales d'Economie et de Statistique, 40, 67–91.

[2] Robert, C. P., Ryden, T., and Titterington, D. M. (2000). *Bayesian inference in hidden Markov models through the reversible jump Markov chain Monte Carlo method.* Journal of the Royal Statistical Society, Series B, 62(1):57--75.

[3] Granger C and T Terasvirta (1999): Simple Non-linear Time series Modelwith Misleading Linear Properties, Economic Letter, 62, 161-165

[4] Lobato I.N. and Savin N.E (1998): "Real and Spurious Long Memory Properties of stock Market Data", Department of Economics, University of Iowa, Iowa City.

[5] Aggarwal, R., Inclan, C., Leal, R., 1999, Volatility in Emerging Stock Markets, *Journal of Financial and Quantitative Analysis*, Forthcoming.

Granger and Hyung (1999)[1] applied instead the method of Bai and Perron (1998)[2] for estimating multiple breaks at unknown dates, and that of Inclan and Tiao (1994)[3] for changes in variance. They concluded that a series with breaks can mimic the properties of an *I(d)* process (such as the autocorrelations), where *d* is a fraction whose value depends on the number of breaks for a given sample size. Their simulation results indicate that "long memory" is more likely to be exhibited by absolute returns because of the presence of breaks than their being an *I(d)* process. They estimated the parameter *d* for the various subperiods as suggested by Geweke and Porter-Hudak (1983)[4], and found strong evidence of long memory in absolute stock returns for all subperiods. However, they also found that the value of *d* changes considerably from one period to another, and suggested that a time-varying *d* is evidence that a linear model with occasional breaks is appropriate for stock returns.

III.3 Rationality of Market Interlinkages

There have been several reasons that the need for well-developed, efficient and integrated financial markets is being increasingly stressed in modern literature on economics and finance. In finance theory, this refers to a market condition that reduces arbitrage opportunities and also helps investors to diversify their portfolio across different markets (and hence reduce risk exposures). An economist considers one such

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[1] Granger, C.W.J. & N. Hyung (2000) *Occasional Structural Breaks and Long Memory*, revised version of UCSD Working Paper 99-14.

[2] Bai, J. and P. Perron, (2001), "*Computation and Analysis of Multiple Structural Change Models*," manuscript, Boston University.

[3] Inclan, C., Tiao, G.C., 1994, Use of Cumulative Sum of Squares for Retrospective Detection of Change of Variance, *Journal of the American Statistical Association,* 89, 913-923.

[4] Geweke, J., & Porter-Hudak, S. (1983). The estimation and application of long memory time series models. Journal of Time Series Analysis, 4, 221–238. 14

development as a facilitator of savings, investment and consequent economic growth. Moreover, under such development, as impulses in one market get reflected quickly in other markets, transmission mechanism of monetary policy becomes smooth and speedy and thus policy intervention becomes more effective in bringing fruits in desired direction within specified time horizon. The development of deep and integrated financial markets, therefore, has been emphasised by monetary policy makers in modern days. In fact, this has been a precondition for 'inflation targeting approach', a new paradigm of monetary policy, to function credibly and effectively.

Prior to 1990s, Indian financial system was full of substantial structural rigidities and was under sever administrative control. Administered interest rate structure, thin foreign exchange market and prevailing fixed exchange rate mechanism, under-developed secondary markets for government securities, lack of adequate depth of money and capital markets, and also inadequate institutional arrangements/framework are a few characteristics of the financial sector, which had resulted into substantial amount of segmentation of financial markets during those years. One of the major objectives of the economic reforms that have been initiated in India since 1991, therefore, has been development of financial markets into an integrated one. Accordingly, several policy measures have been taken, in phases, towards innovations of new financial instruments, improving market depth/conditions, strengthening institutional and regulatory framework and so on. Now, it is believed that Indian financial system has achieved the international standard in its market practices.

Some of the specific developments that have taken place during the reforms process and might have impacted on the extent of financial markets integration are[1] (i) dismantling of various price and non-price controls in financial markets; (ii) like other Asian emerging economies, Indian equity market has continued to grow and has seen the relaxation of foreign investment restrictions primarily through country deregulation; (ii) the issuance of ADR/GDRs has facilitated the trade of foreign securities on the NYSE, NASDAQ or on non-American exchanges; (iii) allowing Indian Rupee to be determined by market forces (though at times market intervention by Reserve Bank of India, the concerned authority, took place). Gradual move towards full convertibility of Indian Rupee has had an impact in the Indian capital market as international investors have invested substantial amount (about US $23 billion) in Indian capital market; (iv) the two-way fungibility of ADRs/GDRs allowed by RBI has also possibly strengthened the linkages between the stock and foreign exchange markets in India.

In view of above, the extent of financial markets integration in the liberalisation era needs to be scrutinized empirically. Though some recent studies have investigated related issues, further research on the subject is needed primarily because the Indian economy is still passing through a transition phase and impact of reform measures initiated in different phases during the liberalisation era might have not yet reflected fully in the economy. Thus, the extent of markets integration is perhaps changing over time – indicating the possibility of getting different conclusion on market integration for the period, which was not covered in previous studies. Moreover, a fresh investigation

[1] One may refer to Bhoi and Dhal (1998); Nag and Mitra (1999-2000), Nath and Samanta (2003), among others for discussion on related issues.

is needed for examining the robustness of empirical results on methodological choice. In this context, this study aims at assessing the changing level of integration between foreign exchange and capital markets in India during recent years.

III.4 Financial Markets in India

III.4.1 Reforms in Indian Capital Market

Over the last few years, SEBI has announced several far-reaching reforms to promote the capital market and protect investor interests. Reforms in the secondary market have focused on three main areas: structure and functioning of stock exchanges, automation of trading and post trade systems, and the introduction of surveillance and monitoring systems. Computerized online trading of securities, and setting up of clearing houses or settlement guarantee funds were made compulsory for stock exchanges. Stock exchanges were permitted to expand their trading to locations outside their jurisdiction through computer terminals. Thus, major stock exchanges in India have started locating computer terminals in far-flung areas, while smaller regional exchanges are planning to consolidate by using centralized trading under a federated structure. Online trading systems have been introduced in almost all stock exchanges. Trading is much more transparent and quicker than in the past. Until the early 1990s, the trading and settlement infrastructure of the Indian capital market was poor. Trading on all stock exchanges was through open outcry, settlement systems were paper-based, and market intermediaries were largely unregulated. The regulatory structure was fragmented and there was neither comprehensive registration nor an apex body of regulation of the securities market. Stock exchanges were run as "brokers clubs" as their management

was largely composed of brokers. There was no prohibition on insider trading, or fraudulent and unfair trade practices. Since 1992, there has been intensified market reform, resulting in a big improvement in securities trading, especially in the secondary market for equity. Most stock exchanges have introduced online trading and set up clearing houses/corporations. A depository has become operational for scripless trading and the regulatory structure has been overhauled with most of the powers for regulating the capital market vested with SEBI. The Indian capital market has experienced a process of structural transformation with operations conducted to standards equivalent to those in the developed markets. It was opened up for investment by foreign institutional investors (FIIs) in 1992 and Indian companies were allowed to raise resources abroad through Global Depository Receipts (GDRs) and Foreign Currency Convertible Bonds (FCCBs). The primary and secondary segments of the capital market expanded rapidly, with greater institutionalization and wider participation of individual investors accompanying this growth. However, many problems, including lack of confidence in stock investments, institutional overlaps, and other governance issues, remain as obstacles to the improvement of Indian capital market efficiency.

With the objectives of improving market efficiency, enhancing transparency, preventing unfair trade practices and bringing the Indian market up to international standards, a package of reforms consisting of measures to liberalize, regulate and develop the securities market was introduced. The practice of allocation of resources among different competing entities as well as its terms by a central authority was discontinued. The issuers complying with the eligibility criteria were allowed freedom to issue the

securities at market determined rates. The secondary market overcame the geographical barriers by moving to screen based trading. Trades enjoyed counter-party guarantee. The trading cycle shortened to a day and trades are settled within 3 working days, while all deferral products were banned. Physical security certificates almost disappeared. A variety of derivatives were permitted. The principal reform measures undertaken in the last decade are[1]:

- **SEBI Act, 1992** gave way to create a regulator (SEBI), empowered it adequately and assigned it with the responsibility for (a) protecting the interests of investors in securities, (b) promoting the development of the securities market, and (c) regulating the securities market. Its regulatory jurisdiction extends over corporates in the issuance of capital and transfer of securities, in addition to all intermediaries and persons associated with securities market. All market intermediaries are registered and regulated by SEBI. SEBI was given full authority and jurisdiction over the securities market under the Act, and was given concurrent/delegated powers for various provisions under the Companies Act and the SC(R)A.

- **DIP Guidelines** are the driving force for market regulation. In the interest of investors, SEBI issued Disclosure and Investor Protection (DIP) guidelines. The guidelines aim to secure fuller disclosure of relevant information about the issuer and the nature of the securities to be issued so that investors can take informed decisions. The companies can access the market only if they fulfill minimum eligibility norms such as track record of distributable profits and net

[1] The section has been written on the basis of Indian Securities Market – A Review, NSE, 2003

worth. In case they do not do so, they can access the market only through book building with minimum offer of 50% to qualified institutional buyers.

- **Screen Based Trading** was introduced where a member can punch into the computer quantities of securities and the prices at which he likes to transact and the transaction is executed as soon as it finds a matching sale or buy order from a counter party. It allows faster incorporation of price sensitive information into prevailing prices, thus increasing the informational efficiency of markets. It enables market participants to see the full market on real-time, making the market transparent. It allows a large number of participants, irrespective of their geographical locations, to trade with one another simultaneously, improving the depth and liquidity of the market. It provides full anonymity by accepting orders, big or small, from members without revealing their identity, thus providing equal access to everybody.

- **Trading Cycle** changes were made to introduce rolling cycles from an account period cycle. Rolling settlement on T+5 basis was introduced in respect of specified scrips reducing the trading cycle to one day. It was made mandatory for all exchanges to follow a uniform weekly trading cycle in respect of scrips not under rolling settlement. All scrips moved to rolling settlement from December 2001. T+5 gave way to T+3 from April 2002 and T+2 in April 2003. The market also had a variety of deferral products like modified carry forward system, which encouraged leveraged trading by enabling postponement of settlement. The deferral products have been banned.

- **Derivatives Trading** was introduced in June 2000 to provide for hedging to

market participants. Derivative trading took off in June 2000 on two exchanges. The market presently offers index futures and index options on two indices and stock options and stock futures on individual stocks (53 in NSE as of September 2003) and futures in interest rate products like notional 91-day T-Bills and notional 10-year bonds.

- **Demutualisation** was aimed to corporatise the stock exchanges by which ownership, management and trading membership would be segregated from one another. A few exchanges have already initiated demutualisation process. Government has offered a variety of tax incentives to facilitate corporatisation and demutualization of stock exchanges.

- **Depositories Act** helped in faster settlement system. To obviate the problems associated with physical and paper-based settlement, the Depositories Act, 1996 was passed to provide for the establishment of depositories in securities with the objective of ensuring free transferability of securities with speed, accuracy and security by (a) making securities of public limited companies freely transferable subject to certain exceptions; (b) dematerialising the securities in the depository mode; and (c) providing for maintenance of ownership records in a book entry form. In order to streamline both the stages of settlement process, the Act envisages transfer of ownership of securities electronically by book entry without making the securities move from person to person. In order to promote dematerialisation, the regulator mandated trading and settlement in demat form in an ever-increasing number of securities in a phased manner. The stamp duty on transfer of demat securities was waived. Two depositories, *viz.* NSDL and

CDSL, have come up to provide instantaneous electronic transfer of securities. At the end of March 2003, 4,761 and 4,628 companies were connected to NSDL and CDSL respectively. The number of dematerialised securities increased to 76.9 billion at the end of March 2003. As on the same date, the value of dematerialsied securities was Rs.5,875 billion and the number of investor accounts was 4,042,973. Electronic settlement accounts for over 99% of turnover settled by delivery.

- **Risk Management** system were augmented to encompass capital adequacy of members, adequate margin requirements, limits on exposure and turnover, indemnity insurance, on-line position monitoring and automatic disablement, etc.

- **Globalisation:** Indian securities market is getting increasingly integrated with the rest of the world. Indian companies have been permitted to raise resources from abroad through issue of ADRs, GDRs, FCCBs and ECBs. ADRs/GDRs have two-way fungibility. Indian companies are permitted to list their securities on foreign stock exchanges by sponsoring ADR/GDR issues against block shareholding. NRIs and OCBS are allowed to invest in Indian companies. FIIs have been permitted to invest in all types of securities, including government securities. The investments by FIIs enjoy full capital account convertibility. They can invest in a company under portfolio investment route upto 24% of the paid up capital of the company. This can be increased up to the sectoral cap/statutory ceiling, as applicable, provided this has the approval of the Indian company's board of directors and also its general body. The two-way fungibility for ADRs/GDRs has

been permitted by RBI, which meant that the investors (foreign institutional or domestic) in any company that has issued ADRs/GDRs can freely convert the ADRs/GDRs into underlying domestic shares. The table III-1 gives the FII investment in Indian market since 1994-95 that clearly shows that market reforms is bearing fruit and attracting investment from abroad.

Table III-1: Trends in FII Investment in Indian Capital market

Period	Purchases (Rs. mn.)	Sales (Rs. mn.)	Net Investment (Rs. mn.)	Cumulative Net Investment (Rs. mn.)	Net Investment (US$ mn.)	Cumulative Net Investment (US$ mn.)
1994-95	76,311	28,348	47,963	47,963	1,528	3,167
1995-96	96,935	27,516	69,420	117,384	2,036	5,202
1996-97	155,539	69,794	85,745	203,129	2,432	7,634
1997-98	186,947	127,372	59,574	262,703	1,650	9,284
1998-99	161,150	176,994	-15,845	246,857	-386	8,898
1999-00	568,555	467,335	101,219	348,077	2,339	11,237
2000-01	740,506	641,164	99,342	447,419	2,159	13,396
2001-02	499,199	411,650	87,552	534,972	1,846	15,242
2002-03	470,601	443,710	26,889	561,861	562	15,804

Source: SEBI

The domestic secondary market activity has been increasing steadily both in equity as well as in derivatives segments: The Table III-2 and Table III-4a, b, c give the trends in domestic secondary market activity.

Table III-2: Trends in Indian Capital (Secondary) Market								
Month/Year	No. of trades (lakh)	Traded Quantity (lakh)	Turnover (Rs.cr)	Average Daily Turnover (Rs.cr)	Average Trade Size	Demat Securities Traded (lakh)	Demat Turnover	Market Capitalisation (Rs.cr)*
1994-1995	3	1,391	1,805	17	60,167	--	--	363,350
1995-1996	66	39,912	67,287	276	101,950	--	--	401,459
1996-1997	264	135,561	295,403	1,176	111,895	--	--	419,367
1997-1998	381	135,685	370,193	1,520	97,164	--	--	481,503
1998-1999	546	165,327	414,474	1,651	75,911	8,542	23,818	491,175
1999-2000	984	242,704	839,052	3,303	85,270	153,772	711,706	1,020,426
2000-2001	1,676	329,536	1,339,510	5,337	79,923	307,222	1,264,337	657,847
2001-2002	1,753	278,408	513,167	2,078	29,274	277,717	512,866	636,861
2002-2003	2,398	364,065	617,989	2,462	25,771	364,049	617,984	537,133
Apr-03	207	31,448	48,971	2,449	23,657	31,448	48,971	530,630
May-03	250	44,001	54,690	2,604	21,876	44,001	54,690	612,030
Jun-03	267	51,896	61,586	2,933	23,066	51,896	61,586	678,550
Jul-03	320	64,906	78,878	3,429	24,649	64,906	78,878	719,145
Aug-03	322	84,554	85,347	4,267	26,505	84,554	85,347	836,651
Sep-03	346	71,848	103,345	4,698	29,852	71,848	103,345	863,481
Oct-03	358	71,768	115,595	5,026	32,315	71,768	115,595	926,748
Nov-03	307	56,716	92,886	4,644	30,304	56,716	92,886	979,541

Source: NSEIL

Table III-3a: Trends in Indian Derivatives Market				
	Index Futures		Stock Futures	
Month/ Year	No. of contracts	Turnover (Rs. cr.)	No. of contracts	Turnover (Rs. cr.)
2000-01	90,580	2,365	-	-
2001-02	1,025,588	21,482	1,957,856	51,516
2002-03	2,126,763	43,952	10,676,843	286,533
Apr.2003	362,157	6,993	1,291,493	29,749
May.2003	325,784	6,283	1,354,581	32,752
June.2003	439,151	9,348	1,694,505	46,505
July.2003	641,002	14,743	2,282,426	70,515
Aug.2003	990,731	24,989	2,620,897	91,288
Sep.2003	1,676,358	45,861	3,122,432	113,874
Oct.2003	1,866,407	56,433	3,469,563	146,378
Nov.2003	1,557,909	49,486	2,761,725	122,463

Source: NSEIL

Table III-3b: Trends in Indian Derivatives Market								
	Index Options				Stock Options			
	Call		Put		Call		Put	
Month/ Year	No. of contracts	Notional Turnover (Rs. cr.)	No. of contracts	Notional Turnover (Rs. cr.)	No. of contracts	Notional Turnover (Rs. cr.)	No. of contracts	Notional Turnover (Rs. cr.)
2001-02	**113,974**	**2,466**	**61,926**	**1,300**	**768,159**	**18,780**	**269,370**	**6,383**
2002-03	269,674	5,669	172,567	3577	2,456,501	69,643	1,066,561	30,488
Apr.2003	54,890	1,091	31,107	616	297,270	7,471	168,553	4,098
May.2003	53,198	1,039	30,109	578	332,529	8,861	155,849	3,911
June.2003	55,874	1,206	34,895	735	383,603	11,303	132,498	3,738
July.2003	87,149	2,040	50,669	1,164	495,853	16,180	162,501	5,190
Aug.2003	96,875	2,477	54,649	1,362	434,526	16,028	116,370	4,219
Sep.2003	110,014	3,088	69,920	1,924	401,660	16,377	101,555	4,025
Oct.2003	89,794	2,758	60,330	1,812	401,218	18,352	101,893	4,625
Nov.2003	71,696	2,313	48,281	1,534	269,032	13,314	61,295	3,061

Source: NSEIL

Table III-3c: Trends in Indian Derivatives			
Month/ Year	No. of contracts	Turnover (Rs. cr.)	Average Daily Turnover (Rs. cr.)
2000-01	**90,580**	**2,365**	**12**
2001-02	**4,196,873**	**101,925**	**413**
2002-03	16,768,909	439,863	21,158
Apr.2003	2,205,470	50,019	2,501
May.2003	2,252,050	53,423	2,544
June.2003	2,750,294	73,017	3,477
July.2003	3,720,563	109,850	4,776
Aug.2003	4,314,098	140,363	7,018
Sep.2003	5,481,939	185,150	8,416
Oct.2003	5,989,205	230,362	10,016
Nov.2003	4,769,938	192,171	9,609

Source: NSEIL

III.4.2 Reforms in Indian Foreign Exchange Market

The movement towards market determined exchange rates in India began with the official devaluation of the rupee in July 1991. In March 1992 a dual exchange rate system was introduced in the form of the Liberalized Exchange Rate Management

System (LERMS). Under this system all foreign exchange receipts on current account transactions were required to be submitted to the Authorized dealers of foreign exchange in full, who in turn would surrender to RBI 40% of their purchases of foreign currencies at the official exchange rate announced by RBI. The balance 60% could be retained for sale in the free market. As the exchange rate aligned itself with market forces, the Re/$ rate depreciated steadily from 25.83 in March 1992 to 32.65 in February 1993. The LERMS as a system in transition performed well in terms of creating the conditions for transferring an augmented volume of foreign exchange transactions onto the market. Consequently, in March 1993, India moved from the earlier dual exchange rate regime to a single, market determined exchange rate system. The deepening of the foreign exchange market has been aided by the implementation of some of the recommendations of the Sodhani Committee on Foreign Exchange Markets (1995) and the Tarapore Committee on Capital Account Convertibility (1997). The Sodhani Committee (1995) made recommendations to develop, deepen and widen the forex market. A number of its recommendations regarding introduction of various products and removal of restrictions in foreign exchange markets to improve efficiency and increase integration of domestic foreign exchange markets with foreign markets have been implemented. Liberalisation measures undertaken on the capital account relate to foreign direct investment, portfolio investment, investment in joint ventures/wholly owned subsidiaries abroad, project exports, opening of Indian corporate offices abroad, and raising of Exchange Earners Foreign Currency entitlement. While trade flows and foreign investment have had a role to play in the determination of the exchange rate, another important development that has led to the

capital movements has been the reform that has taken place in other segments of financial markets in India. This has led to increasing integration of broad segments of the market such as the money market, government securities, capital market and the foreign exchange market. Market participants and move from one market to the other leading to inter-linking of these markets. The link between the forex and domestic market has increased due to the freedom given to banks to maintain foreign currency assets and liabilities that can be swapped into rupees and vice versa. On the liabilities side there are foreign currency borrowings from overseas offices, borrowings for lending to exporters, foreign currency non-resident deposits (FCNR-B) deposits and Exchange Earners Foreign Currency deposits of corporates. Banks are permitted to use these funds either for raising rupee resources through swaps or for lending in foreign currency. Banks have been allowed to lend in foreign currency to companies in India for any productive purpose without linking to exports or import financing. Corporates can substitute rupee credit for foreign credit as they now have the choice to borrow either in foreign currency or rupees depending on the cost, taking both interest cost and exchange risk into account. Evidence suggests that the nineties have seen growing inter-linkages between money, foreign exchange and government securities markets. Not only is a large component of our trade and capital flows dollar denominated, the dollar is the intervention currency of the RBI. This has clearly been demonstrated not only in the 1993-95 episode when the value of the rupee was kept constant against the dollar for 16 months, but also later whenever there was a pressure on the rupee dollar rate, the RBI intervened to prevent appreciation of the rupee. The other rates in the market are determined broadly by the movement of the dollar against various currencies. Since it is

the dollar and not the rupee that is a major currency in international markets, arbitrage ensures that the value of the rupee expressed in yen cannot be significantly different from what the dollar-rupee-yen rate would set it at (apart from some transaction costs). Consequently it was decided that a dollar-centric model would be more appropriate than a model that separately tries to forecast the rupee- yen, rupee-pound, rupee-mark, rupee-franc, rupee-lira etc. rates, since these rates cannot diverge from the rate set by international markets for dollar versus other currencies.

India's approach to reserve management, until the balance of payments crisis of 1991 was essentially based on the traditional approach, i.e., to maintain an appropriate level of import cover defined in terms of number of months of imports equivalent to reserves. For example, the RBI's Annual Report 1990-91 stated that the import cover of reserves shrank to 3 weeks of imports by the end of December 1990, and the emphasis on import cover constituted the primary concern say, till 1993-94. The approach to reserve management, as part of exchange rate management, and indeed external sector policy underwent a paradigm shift with the adoption of the recommendations of the High Level Committee on Balance of Payments (Chairman: Dr. C. Rangarajan). The Committee recommended that while determining the target level of reserve, due attention should be paid to the payment obligations in addition to the level of imports. The committee recommended that the foreign exchange reserves targets be fixed in such a way that they are generally in a position to accommodate imports of three months. In the view of the Committee, the factors that are to be taken into consideration in determining the desirable level of reserves are: the need to ensure a reasonable level of confidence in the international financial and trading communities about the capacity of

the country to honour its obligations and maintain trade and financial flows; the need to take care of the seasonal factors in any balance of payments transaction with reference to the possible uncertainties in the monsoon conditions of India; the amount of foreign currency reserves required to counter speculative tendencies or anticipatory actions amongst players in the foreign exchange market; and the capacity to maintain the reserves so that the cost of carrying liquidity is minimal. With the introduction of market determined exchange rate as mentioned in the RBI's Annual Report, 1995-96 a change in the approach to reserve management was warranted and the emphasis on import cover had to be supplemented with the objective of smoothening out the volatility in the exchange rate, which has been reflective of the underlying market condition. Against the backdrop of currency crises in East-Asian countries, and in the light of country experiences of volatile cross-border capital flows, the Reserve Bank's Annual Report 1997-98 reiterated the need to take into consideration a host of factors, but is noteworthy for bringing to the fore the shift in the pattern of leads and lags in payments/receipts during exchange market uncertainties and emphasized that besides the size of reserves, the quality of reserves also assume importancc. Highlighting this, the Report stated that unencumbered reserve assets (defined as reserve assets net of encumbrances such as forward commitments, lines of credit to domestic entities, guarantees and other contingent liabilities) must be available at any point of time to the authorities for fulfilling various objectives assigned to reserves. As a part of prudent management of external liabilities, the RBI policy is to keep forward liabilities at a relatively low level as a proportion of gross reserves and the emphasis on prudent reserve management i.e., keeping forward liabilities within manageable limits, was

highlighted in the RBI's Annual Report, 1998-99. The RBI Annual Report, 1999-2000 stated that the overall approach to management of India's foreign exchange reserves reflects the changing composition of balance of payments and liquidity risks associated with different types of flows and other requirements and the introduction of the concept of liquidity risks is noteworthy. The policy for reserve management is built upon a host of identifiable factors and other contingencies, including, *inter alia*, the size of the current account deficit and short term liabilities (including current repayment obligations on long term loans), the possible variability in portfolio investment, and other types of capital flows, the unanticipated pressures on the balance of payments arising out of external shocks and movements in repatriable foreign currency deposits of non-resident Indians. While focusing on prudent management of foreign exchange reserves in recent years, RBI's Annual Report 2000-01 elaborated on 'liquidity risk' associated with different types of flows. The Report stated that with the changing profile of capital flows, the traditional approach of assessing reserve adequacy in terms of import cover has been broadened to include a number of parameters which take into account the size, composition, and risk profiles of various types of capital flows as well as the types of external shocks to which the economy is vulnerable. Ex-Governor Jalan's latest statement on Monetary and Credit Policy (April 29, 2002) provides, an up-to-date and comprehensive view on the approach to reserve management and of special significance is the statement : "a sufficiently high level of reserves is necessary to ensure that even if there is prolonged uncertainty, reserves can cover the "liquidity at risk" on all accounts over a fairly long period. Taking these considerations into account, India's foreign exchange reserves are now very comfortable." ...."the

prevalent national security environment further underscores the need for strong reserves. We must continue to ensure that, leaving aside short-term variations in reserves level, the quantum of reserves in the long-run is in line with the growth of the economy, the size of risk-adjusted capital flows and national security requirements. This will provide us with greater security against unfavourable or unanticipated developments, which can occur quite suddenly." The above discussion points to evolving considerations and indeed a paradigm shift in India's approach to reserve management. The shift has occurred from a single indicator to a menu or multiple indicators approach. Furthermore, the policy of reserve management is built upon a host of factors, some of them are not quantifiable, and in any case, weights attached to each of them do change from time to time.

The foreign exchange market is growing steadily. The average monthly turnover in the merchant segment of the forex market increased from USD 20 billion in 1999-2000 to USD 23 billion during 2000-01. The average monthly turn over in the inter bank foreign exchange market has also increased to USD 90 billion in 2000-01. A survey of the foreign exchange market turn over during April 2001 by the BIS in which 43 countries including India participated reveals the interesting fact that while forex turn over world over has declined considerably as compared to 1998, India bucks this trend by showing an increased turn over. The market is skewed with a handful of public-sector banks accounting for the major share of the merchant transactions and the private and foreign banks having a greater share of inter-bank business. It is conducive for healthy market development to have much larger number of players active in the market

with enhanced volumes of business. The presence of increased number of players and larger volumes alone lend certainly greater depth to the forex market leading to a more efficient functioning. Forex derivatives have not picked up sufficiently. The development of a vibrant derivatives market in India would critically depend on the growth in the rupee based derivative products, which in turn depends on a well developed and liquid forward dollar-rupee market.

In the context of integration of Indian financial market with international markets, the move towards capital account convertibility, which has an important bearing on our forex market, assumes paramount significance. Some of the preconditions/signposts for capital account convertibility, as mentioned in the CAC committee report, such as, fiscal consolidation, mandated inflation rate, consolidation of the financial sector, adequacy of foreign exchange reserves, sound BoP situation, etc., need to be adhered to properly before rupee is made fully convertible on capital account. As CAC integrates both the real as well as the financial sectors with the international economy, the impact of external impulses would be felt more strongly, which makes it imperative to have the preconditions in place before full capital account convertibility is allowed.

In the present context, the major thrust of RBI Policies would continue to focus on the development of deep, liquid and integrated financial markets. The importance attached to the forex market would be evident from preamble to the newly enacted Foreign Exchange Management Act. One of the main objectives of the FEMA is to promote the orderly development of the foreign exchange market in India.

The first issue that would need to be addressed relates to depth and liquidity in the market particularly in the forward segment. It is well known that barring well-developed markets, forward markets are rather shallow in many of the emerging countries. In most of the developing markets, liquidity is not there for maturities are not available beyond one year period. In other words, in markets dominated by trade related flows and which are not financially driven, where capital controls exist, liquidity across the spectrum as seen in the developed markets, may prove to be difficult at least in the early stages of development of the market.

In recent years, India has experienced a significant spurt in forex inflows. Net capital flows increased from an average of US $ 5.8 billion per annum in the second half of the 1980s to US $ 9.1 billion per annum in the second half of 1990s and peaked at US $ 12.6 billion or 2.7 per cent of GDP in 2002-03. In addition, the current account of the balance of payments also registered a surplus during 2001-02 and 2002-03. With a view to neutralising the impact of excess forex flows, resulting from current and capital account surpluses, the Reserve Bank has intervened in the foreign exchange market in regular intervals. As a result, the Foreign Currency Assets (FCA) of the Reserve Bank rose by US $ 21.3 billion (Rs.92,358 crore) during 2002-003 and US $ 19.6 billion (Rs.77,730 crore) during 2003-04 (up to November 21, 2003) (**Table III-4**). On a year-on-year basis, the accretion to FCA was US $ 28.1 billion (Rs.1,14,087 crore). The foreign exchange reserves increased from US $ 54 billion as at the end of March 2002 to US $ 95 billion as on November 21, 2003 and about US$100 billion as of December 2003.

The liquidity impact of large inflows was managed mainly through the repo and reverse repo auctions under the day-to-day Liquidity Adjustment Facility (LAF). Liquidity absorption through LAF repos on a daily average basis, amounted to Rs.11,212 crore during 2002-03 and Rs.29,310 crore during 2003-04 (up to October). The LAF operations were supplemented by outright open market operations, i.e. outright sales of the government securities, to absorb liquidity on an enduring basis. OMO sales amounted to Rs.52,716 crore during 2002-03 and Rs.35,733 crore during 2003-04 (up to November 21). Including the amounts sold to the State Governments for investment of their durable surplus/reinvestment of maturity proceeds, and investments in the Consolidated Sinking Fund (CSF) and the Guarantee Redemption Fund (GRF), the open market sales of the Reserve Bank amounted to Rs.53,780 crore during 2002-03 and Rs36,360 crore during 2003-04 so far (up to November 21) (**TableIII-4).** Unlike in the previous years, there was no open market purchases during these two years. The Reserve Bank, however, took devolvements during 2002-03, while securities were privately placed with the Reserve Bank in both 2002-03 and 2003-04. After netting out the securities either privately placed with or devolved on the Reserve Bank, the net OMO sales amounted to Rs.17,605 crore during 2002-03 and Rs.31,360 crore during 2003-04 (up to November 21). As a result, there has been a progressive reduction in the quantum of securities with the Reserve Bank. This apart, as per the current operations, the usage of the entire stock of securities for outright open market sales is constrained by the allocation of a part of the securities for day-to-day LAF operations as well as for investments of surplus balances of the Central Government, besides investments by the State Governments in respect of earmarked funds (CSF/GRF) while some of the

government securities are also in non-marketable lots. Hence, although the outstanding stock of government securities amounted to Rs.93,281 crore as at end-October, 2003, only about two-thirds of the amount were readily available for the conduct of OMO. The position in respect of accretion to the foreign currency assets and the OMO operations is presented in **Table III-4**.

Table III-4:Accretion to Foreign Currency Assets and Open Market Operations (1996-97 to 2003-04) (Rs. Crore)

Year	Accretion to Foreign Currency Assets	Open Market Purchases	Open Market Sales*	Net OMO Sales	Net OMO Sales (net of Private Placements and Devolvements)
1	**2**	**3**	**4**	**5 = 4-3**	**6**
1996-97	21,922	623	11,206	10,583	6,885
1997-98	22,139	467	8,081	7,614	-5,414
1998-99	22,905	0	26,348	26,348	-11,857
1999-2000	27,512	1,244	36,614	35,370	8,370
2000-01	31,558	4,471	23,795	19,324	-11,827
2001-02	64,636	5,084	35,419	30,335	1,443
2002-03	92,358	0	53,780	53,780	17,605
2003-04 (April-November 21)	77,730	0	36,360	36,360	31,360

Source: RBI

India has come a long way since the onset of economic reforms in 1991, which was largely triggered by serious difficulties on the external front. In over a decade of economic reforms, the level of foreign exchange reserves has steadily increased from US$ 5.8 billion as at end-March 1991 to US$ 75.4 billion by end-March 2003 and further to US $ 91.1 billion by end-September 2003 and now hovers around US $ 102 billion.

III.5.1 Motivation and Research Gap

Though substantial amount of research work has been done on market efficiency and long memory on developed markets for testing the presence of long memory of financial asset prices, relatively very little has been done concerning Indian stock market. Few studies have been done using Indian market data of pre-reforms period or using a small part of reforms period. Most of the studies have been done using the macro data like market indices but not using data of individual stocks. Another important area need to be researched is interlinkage between the stock prices and the exchange rate in terms of returns and volatilities. The study first makes an endeavor to understand the applicability of long memory concept to Indian financial markets and see if the data can be used to develop trading strategies for traders to exploit any profit opportunity. If such memory exists, what are the policy implications for the regulators to manage the risk in these markets? Second, the study also makes an attempt to understand the dynamic linkages between Indian stock and foreign exchange market in terms of the return and volatilities. Very little work has been done on the subject concerning Indian markets. Both these markets have undergone substantial transformation due to regulatory changes taking place in the aftermath of introduction of financial sector reforms. The present study is important as existing studies rely primarily on evidence from analyzing industrialized countries, with less attention paid to non-industrial economies. And unlike developed countries, most developing countries tend not to adopt a freely floating exchange rate system and have more capital control. India is such an economy where we have substantial amount of control with regard to capital account. It would seem reasonable to expect that for a country that does not employ a freely floating exchange rate system, exchange rates might not fully

response to stock price movements. And similarly capital control might reduce dynamic linkages between foreign exchange and equity market. Hence, examining Indian economy would enable us to check the impact of the degree of financial market liberalization and exchange rate management on the linkages between foreign exchange and equity markets. Further, during Asian crisis of 1997, we have both exchange rate as well as the equity market in major emerging Asian economies faced severe depreciation. The tumbling down stock price and the plunging currency value during the crisis reinforce the conventional impression that stock prices and exchange rates tend to move in a tandem, though it is not clear whether a casual relation exists from exchange rates to stock prices or the other way round.

The main objective of this study is to study the long memory process of both equity and foreign exchange market in India and to find out their long term as well as short term interlinkages using robust methodologies concentrating on the post reforms period. On the background of this, it has become important to test the long memory existence in Indian market taking the stock market data for last one decade or so to coincide the reforms process in the financial market during which substantial regulatory changes have taken place and the market practices have changed dramatically and various hedge products have been introduced to improve the risk management. This study is desirable as the methods used for the study are robust and the period of study is also covers a long period of time that no previous study on Indian market considered so far. Another factor is the choice of a market representative index has a bearing on the study. A comparative study has been made between two important indices in India (S&P CNX NIFTY and

BSE SENSEX) and it has been found that S&P CNX NIFTY has been less risky but has provided higher returns for which liquidity in S&P CNX NIFTY contracts have been extremely high whereas the contracts on BSE SENSEX have very low liquidity (Nath, 2002). We have used S&P CNX NIFTY for our study. Hence this study will provide a positive value to the existing literature.

During last one decade, the Indian financial system has been subjected to substantial reforms with far reaching consequences. These reforms process has helped in dramatic improvement in transparency level in financial markets including stock market. The regulatory changes that have taken place during last one decade of financial sector reforms has led us to believe that financial market have become more efficient with respect to the price discovery mechanism and helped the market to grow exponentially. The country has also experienced the mild contagion effect of financial crisis in International markets and successfully sailed through the period of Asian crisis not significantly jeopardizing the interest of the domestic economy. There have been significant changes in the regulations for smooth and efficient functioning of capital market in the country. The market has undergone substantial change due to introduction of hedging products like futures and options. Risk management system has been changing in keeping pace with change in scenario. Other reforms in the form of deregulation of interest rate, tax reforms, banking sector reforms, reforms in the external sector, etc. has also helped market participants to value assets according to their intrinsic values. Liquidity has greatly increased as the market spread has reached the far away villages bringing investors together. The concept of developing a large

order book in the stock market made the pricing of stocks more accurate and efficient and also resulted in bringing down the bid/ask spread benefiting the investors community as a whole. International investors' access to the domestic market has also helped in increasing liquidity. All these helped in better dissemination of information and hence possibly increased the level of efficiency in asset prices. The level of such efficiency in prices need to be tested with various models that exist in the literature. The earlier work done on Indian market (Basu and Morey (1998)[1] and Barman and Madhusoodan (1993)[2], Thomas (1995)[3] concentrated mostly in the pre-reforms period. Reforms process has led to a regime shift and hence it is necessary to test the market for long memory with the market data after the introduction of financial sector reforms.

Further, like other Asian emerging economies, Indian equity market has continued to grow and has seen the relaxation of foreign investment restrictions primarily through country deregulation. During the 1990s, India has initiated the financial sector reforms by way of adopting international practices in its financial market. Parallel to this, the issuance of ADR/GDRs has facilitated the trade of foreign securities on the NYSE, NASDAQ or on non-American exchanges. Over the years, Indian Rupee is slowly moving towards full convertibility, which has also had an impact in the Indian capital market as international investors have invested about US $23 billion in Indian capital market. The two-way fungibility of ADRs/GDRs allowed by RBI has also possibly enhanced the linkages between the stock and foreign exchange markets in India. In this

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[1] Basu & Morey (1998): Stock Market Prices in India after Economic Liberalization, EPW, February 14, 1998

[2] RBI Occassional Papers, 1993

[3] Thomas, Susan (1995), Heteroskedasticity Models on the BSE, Working Paper, (homepage of author)

background, this study aims at examining the dynamic linkages between foreign exchange of Indian Rupee and stock market price index in India.

In summary, the main objectives of this dissertation to understand the baehaviour of capital and foreign exchange markets in post-liberalization period (1990-2003) in terms of:

- **the existence of long memory process in capital and foreign exchange markets in India.**
- **the linkage dynamics of important macroeconomic variables like exchange rate, short-term and long term interest rate, foreign exchange reserves, wholesale price index, oil price index, index of industrial production, real effective exchange rate, money supply, etc. in Indian economy and the short – term and long term interlinkage of capital market indicator variable with other important macroeconomic variables.**
- **the linkage dynamics of Indian capital market with the global developed as well as emerging markets like the USA, the UK, France, Singapore, Hong Kong, Taiwan etc. to understand the interlinkages.**
- **the long term as well as short term linkage dynamics between capital and foreign exchange markets in India.**

CHAPTER IV

IV.0 LITERATURE REVIEW

IV.1 Long Memory

IV.1.1 Long memory evidence in stock market

The potential presence of stochastic long memory in financial asset returns has been an important subject of both theoretical and empirical research. If assets display long memory, or long-term dependence, they exhibit significant autocorrelation between observations widely separated in time. Since the series realizations are not independent over time, realizations from the remote past can help predict future returns. Persistence in share returns has a special claim on the attention of investors because any predictable trend in returns should be readily exploitable by an appropriate strategy by the market participants.

If asset prices display long memory, or long-term dependence, they exhibit significant autocorrelation between observations widely separated in t ime. This implies that what has happened not only in recent past but long time back has a bearing on the today's market prices and hence existence of an autocorrelation between these observations. Today's risk containment policies followed in Indian securities market is built on the basis of historical price behaviour. Since the series realizations are not independent over time, realizations from the remote past can help us predict future movements in asset prices. Persistence in share returns has a special claim on the attention of investors

because any predictable trend in returns should be readily exploitable by an appropriate strategy.

A number of studies have tested the long memory hypothesis for stock market returns. Peters (1989)[1] used Hurst Rescaled Range (R/S) analysis to measure non-periodic cycles in financial data. He concluded that capital market prices do not reflect information immediately, as the efficient market hypothesis assumes, but rather follow a biased random walk that reflects persistence. Using the rescaled range (R/S) method, Greene and Fielitz (1977)[2] also reported evidence of persistence in daily U.S. stock returns series. Barkoulas and Baum[3] used Spectral Regression Test to test the long memory of US stocks and found only few stock do have long memory.

However, according to some authors, the classical R/S test is biased toward finding long-term memory too frequently. Stock market returns may follow biased time paths that standard statistical tests cannot distinguish from random behavior. Rescaled range analysis can be used to detect long-term, non-periodic cycles in stock market returns. If this technique is not applied correctly, however, then it can be influenced by short-term biases, leading to the erroneous conclusion that the stock market has long-term memory.

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[1] Peters, Edgar E. (1989) "Fractal Structure In The Capital Markets" *Financial Analysts Journal*; Jul/Aug 1989;

[2] Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. Journal of Financial Economics, 4, 339–349.

[3] Barkoulas and Baum, Long Term Dependence In Stock Returns, Working Paper, http://fmwww.bc.edu/EC-P/WP314.pdf

The results are mixed, but all the authors agreed that identification of long memory is very significant in at least two senses: (a) the time span and strength of long memory will be an important input for investment decisions regarding investment horizons and composition of portfolios; and (b) prediction of price movements will be improved. On the background of this, it has become important to test the long memory existence in Indian market taking the stock market data for last one decade during which substantial regulatory changes have taken place and the market practices have changed dramatically and various hedge products have been introduced to improve the risk management.

Lo (1991)[1] developed a modified R/S method, which addresses some of the drawbacks of the classical R/S method. Using the variant of R/S analysis, Lo finds no evidence to support the presence of long memory in U.S. stock returns. Applying Lo test, which does not rely on standard regression techniques and is robust to short-term dependence, provides statistical support for the hypothesis that stock market returns follow a random walk (Ambrose, 1993). Using both the modified R/S method and the spectral regression method, Cheung and Lai (1995)[2] find no evidence of persistence in several international stock returns series. Crato (1994)[3] reports similar evidence for the stock returns series of the G-7 countries using exact maximum likelihood estimation. Wright (1999)[4] used

[1] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

[2] Cheung, Y.-W., & Lai, K. S. (1995). A search for long memory in international stock market returns. Journal of International Money and Finance, 14, 597–615.

[3] Crato, N. (1994). Some international evidence regarding the stochastic behavior of stock returns. Applied Financial Economics, 4, 33–39.

[4] Wright J H (1999): Long Memory in Emerging stock Market Returns, International Finance Discussion paper, No. 650, Federal Reserve System,

ARFIMA model to test long memory in emerging market including India and came up with the conclusion that emerging markets appear to have considerable serial correlation which stands contrast to the results for the developed markets like US, where there is little evidence for any serial correlation in stock returns.

The primary focus of these studies has been the stochastic long memory behaviour of stock returns in major capital markets. In contrast, the long memory behaviour in smaller markets has received little attention. Contrary to findings for major capital markets, Barkoulas, Baum, and Travlos(1999)[1] in a Working Paper found significant and robust evidence of positive long-term persistence in the Greek stock market.

Experts on financial markets and economists on both Random Walk and Efficient Market Hypothesis have undertaken good amount of research work. However, long memory models are relatively new to applied economics. Though its origin dates back to Mandelbrot's (1969) work, it was not until 1980's that researchers began to apply the rescaled range analysis, one of the tools in the long memory theory, to financial markets and macroeconomic prices. In 1991 Lo modified the classical R/S method. Based on Beran (1994)[2], a stationary process with long memory has the following qualitative features:

- Certain persistence exists. In some periods the observations tend to stay at high levels, in some other periods, the observations tend to stay at low levels.

[1] Barkoulas J T, Baum C F, Travlos M (1999): Long memory in Greek stock Market, Applied Financial Economics.

[2] Beran, J. (1994): *Statistics for Long Memory Processes*, Chapman and Hall, New York.

- During short time periods, there seem to be periodic cycles, However looking through the whole process, no apparent periodic cycles could be identified.
- Overall, the process looks stationary.

It is not hard to find evidence to argue that price series with random appearance might be non-linear dynamic. But it is difficult to say what kind of non-linear dynamics. Another commonly used stochastic model ARCH and its variants share similar symptoms with long memory models, such as non-normality and heteroscedasticity, but they have totally different generating mechanisms and implications. A time series with ARCH property typically has two components, a conditional mean and a conditional variance function. The non-linearity of the series comes from the non-linearity of the conditional variance. An ARCH model that fits the data well could improve the prediction of the variances of prices but not the price itself (Bera and Higgins (1995)[1]). A long memory model is a single mean equation (system) and has a flexible structure. It represents short as well as long memory simultaneously.

Dependence over nonperiodic cycles is defined as the presence of extended periods of similar behavior which are of unequal duration [Booth, Kaen and Koveos(1982)[2]]. Mandelbrot(1972)[3] argues that rescaled range (R/S) analysis can detect nonperiodic cycles even when the cycles have lengths greater than or equal to the sample period.

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[1] Bera, A., and M. Higgins (1993): "*ARCH models: properties, estimation and testing*," Journal of Economic Surveys.

[2] Booth, G.G., Kaen, F.R. and P.E. Koveos (1982) "Persistent Dependence in Gold Prices," *Journal of Financial Research,* 5, 1, 85-93.

[3] Mandelbrot, B. (1972) "Statistical Methodology for Non-period Cycles: From the Covariance to R/S analysis," *Annals of Economic and Social Measurement* 1, 1972.

The importance of Mandelbrot's(1972)[1] argument is that it raises the question of whether R/S analysis can be used to detect long term dependence in stock prices. Long term dependence to Mandelbrot(1972) means the "Joseph effect", named after the Old Testament prophet who foretold of seven years of prosperity followed by seven years of famine [Mandelbrot and Wallis(1968)[2]]. The "Joseph effect" implies that a time series has infinite memory, that is, an event occurring today will still have an effect on events occurring into perpetuity. In studies of geophysical records, Mandelbrot and Wallis (1969) found a number of series with infinite memory. However, the type of time series found in this field very possibly has finite memory cycles that are longer than their time samples, and hence, the infinite memory result. Mandelbrot(1971)[3] was the first to suggest that R/S analysis could be useful in studies of economic data and provided an economic rationale. In Mandelbrot(1972), it was further argued that R/S analysis was superior to autocorrelation and variance analysis since it could consider distributions with infinite variance and was superior to spectral analysis because it could detect nonperiodic cycles.

The problem with Mandelbrot's analysis was the adherence to processes with infinite memory. In the mathematics of fractal geometry developed in Mandelbrot (1982)[4], fractals will continue to scale to infinity. Peters (1991, p.82)[5], on the other hand, argues

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[1] Mandelbrot, B. (1972) "Statistical Methodology for Non-period Cycles: From the Covariance to R/S analysis," *Annals of Economic and Social Measurement* 1, 1972.
[2] Mandelbrot, B.B. and J.R. Wallis (1969). "Some Long-Run Properties of Geophysical Records," *Water Resources Research*, 5, 2, 321-340.
[3] Mandelbrot, B.B.(1971). "When Can Price be Arbitraged Efficiently? A Limit to the Validity of the Random Walk and Martingale Models," *Review of Economics and Statistics*, 53, 3, 225-236.
[4] Mandelbrot, B.B.(1982). *The Fractal Geometry of Nature*, New York, W.H. Freeman, 1982.
[5] Peters, Edgar(1991): *Chaos and Order in the Capital Markets*. John Wiley & Sons, Inc

that in nature fractals will stop scaling at a finite point. Consistent with Peters (1991)[1], it can be reasonably argued that economic time series have finite memory and R/S analysis must be used over subperiods in order to discover the length of the finite memory or the average nonperiodic cycle. Most academic studies to this point have assumed Mandelbrot's infinite memory process and perform the R/S analysis only on the complete sample. Mandelbrot, however, does acknowledge the existence of finite memory. In Mandelbrot and Wallis(1969)[2], it is noted that observations far removed in time can be considered independent and that the R/S analysis will asymptotically approach a random process. With shorter lags, the dependence will be evident, but a "break" will occur at longer lags and independence will be obtained. Since Mandelbrot and Wallis(1969) do not observe such a "break" in geophysical records, they consider, for practical purposes, that these time series exhibit infinite memory. Mandelbrot(1972)[3] discusses that there can be short term R/S dependence where a time series has a finite but long memory. It may well be that the time series has a finite memory and R/S analysis will indicate dependence, but, at longer lags, a "break" toward random behavior occurs. From a very long run viewpoint, Mandelbrot(1972) considers this dependence to be a special transient, but goes on to say that this does not lessen the importance of the finite memory component. In fact, Mandelbrot and Wallis(1969), as well as Peters(1991), use R/S analysis to detect the well known 11year cycle in sunspot activity. They add a warning that processes with a strong periodic

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[1] Peters, Edgar(1991): *Chaos and Order in the Capital Markets*. John Wiley & Sons, Inc

[2] Mandelbrot, B.B. and J.R. Wallis (1969). "Some Long-Run Properties of Geophysical Records," *Water Resources Research*, 5, 2, 321-340.

[3] Mandelbrot, B. (1972) "Statistical Methodology for Non-period Cycles: From the Covariance to R/S analysis," *Annals of Economic and Social Measurement* 1, 1972.

element will affect the Hurst phenomenon, but again they are examining the data for infinite memory and feel that these "subharmonics" complicate the issue. In economics, following Peters'(1991)[1] argument we would expect to find finite memory processes, and the "break" in the R/S analysis detects these finite memory non-periodic cycles. Peters(1991) uses R/S analysis and a Hurst(1951)[2] regression to examine stock market indices for persistent finite memory and finds evidence of a four year cycle. However, his analysis may be biased by short term Markovian dependence. Davies and Harte (1987)[3] show that conventional R/S analysis using a Hurst regression can be biased toward accepting a long term dependence hypothesis even when the true process is first order autoregressive. As a result, Lo(1991)[4] developed a modified R/S test that allows for short-term dependence, non-normal distributions, and conditional heteroscedasticity under the null hypothesis. In addition, Cheung (1993)[5] uses Monte Carlo simulation to show that the modified R/S test is robust to nonstationary variance and ARCH (autoregressive conditional heteroscedasticity) effects. The only problem is that the Lo(1991) modification does assume an infinite memory process. Fortunately, like R/S analysis, it too can be used on different sub-periods [Cheung and Lai (1993)[6]].

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[1] Peters, Edgar(1991): *Chaos and Order in the Capital Markets*. John Wiley & Sons, Inc.

[2] Hurst, H.E.(1951). "Long-Term Storage Capacity of Reservoirs," *Transactions of the American Society of Civil Engineers*, 116, 770-799.

[3] Davies, R.B. and D.S. Harte (1987), "Tests for Hurst Effect," *Biometrika*, 74, 1, 95-101.

[4] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

[5] Cheung, Yin-Wong. "*Test for Fractional Integration: A Monte Carlo Investigation*," Journal of Time Series Analysis, 1993,

[6] Cheung, Y. and K.S. Lai (1993), "Do Gold Market Returns Have Long Memory?" -*Financial Review*, 28, 2, 181-202.

Helms (et al 1984)[1] applied rescaled range analysis to detect the existence of long memory in the futures prices of the soyabean complex. With the Hurst exponent in the range of 0.5 to 1 indicating long memory, the authors found that the Hurst exponents ranges from 0.558 to 0.71 for daily prices of two futures contracts in 1976 and from 0.581 to 0.67 for intra-day prices of 5 contracts in 1977-78. Fung and Lo's (1993) long memory study analyzed the prices of two interest rate futures markets, Eurodollars and Treasury Bills. The results from the classical R/S analysis and Lo's (1991)[2] modified R/S analysis provide no evidence of the existence of the long memory and support for the weak form EMH. Peters (1994)[3] noteed that most financial markets are not Gaussian in nature and tend to have sharper peaks and fat tails, a phenomenon well known in practice. One of the key observations made by Peters (1994) is the fact that most financial markets have a long memory, what happens today affects the future forever. Our motivation comes clearly from Peters, (1994) Fractal Market Hypothesis.

Long memory analysis have been conducted for stock prices (Greene and Fielitz (1997), Aydogan and Booth (1988), Lo (1991), Cheung, Lai and Lai (1993), Cheung and Lai (1995), Barkoulas and Baum (1997)), spot and futures currency rates (Booth, Kaen and Koveos (1982a) Cheung (1993a), Cheung and Lai (1993), Bhar (1994), Fang, Lai and Lai (1994), Barkoulas, Labys and Onochie (1997a)), gold prices (Booth, Kaen and Kovoes (1982b)), Cheung and Lai (1993)), international spot commodity prices

[1] Helms, B. P., Kaen, F. R. and Rosenman, R. E. (1984): "*Memory in commodity futures contracts*", Journal of Futures Markets 4, 4, 559--567.
[2] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.
[3] E. Peters, *Fractal Market Hypothesis: Applying Chaos Theory to Investment and Economics,* John Wiley, 1994.

(Barkoulas, Labys, and Onochie (1976)), and commodity and stock index futures (Helms, Kaen and Koveos (1984), Barkoulas, Labys, and Onochie (1997)), inflation rate (Scacciavillani (1994), Hassler and Wolters (1995), spot and forward metal prices (Fraser and MacDonald (1992)). Fung et al (1994) considered intraday stock index futures and tested for long memory by using variance ratio, R/S and AFIMA models.

Recent evidence on the presence of long memory in stock returns is mixed. The results are mixed, but the identification of long memory is very significant in at least two senses: (a) the time span and strength of long memory will be an important input for investment decisions regarding investment horizons and composition of portfolios; and (b) prediction of price movements will be improved. Whereas many studies found evidence for long horizon predictability in stock returns (see Fama and French (1988), Porterba and Summers (1988), Mills (1993), other authors (Goeztman and Jorion (1993), Nelson and Kim (1993), and Malliaropolous (1996)) argue that converse is true. Where evidence of long horizon predictability is found, it is usually attributed to time variation in expected returns, or speculative bubbles, periods of marked divergence between the price of an asset and its fundamental, or true value. Campbell (1991)[1] and Campbell and Ammer (1993)[2] argue that persistence in equity returns underlies this long horizon forecast power. That is, this observed forcastabilty may be attributed to long range dependence, or long memory, in the returns time series. Lo (1991)[3], using a

[1] Campbell, John Y. (1991), A Variance Decomposition for Stock Returns, *Economic Journal*, 101 (405), March, 157-179

[2] Campbell, John Y. and John Ammer (1993), What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns, *Journal of Finance*, 48 (1), March, 3-37

[3] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

modified rescaled range (R/S) statistic, finds no evidence of long memory in a sample of U.S. stock returns. Mills (1993)[1], using the modified R/S statistic and the semi-parametric approach of Geweke and Porter-Hudak (1983)[2], finds weak evidence of long memory in a sample of monthly U.K. stock returns. Lobato and Savin (1998)[3] found no evidence of long memory in daily Standard and Poor 500 returns over the period July 1962 - December 1994. Interestingly, Lobato and Savin (1998) found some evidence of long memory in the squared return data, which supports the conclusions of Ding, Granger and Engle (1993)[4].

Using rescaled range analysis, Green et al. (1977)[5] found significant long range dependence in many series of securities listed on the New York Stock Exchange. Peters (1991, 1994)[6] confirms long term positive dependence for the Dow Jones and the S&P500; the same result is achieved by Cheung (1993)[7] for some time series of exchange rates; for their part, Booth et al. (1982)[8] found positive long-term dependence in foreign exchange rates during the flexible regime and negative dependence in the fixed period. Long range dependence in the daily stock returns is also uncovered by Lo

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[1] Mills, T. (1993),"*Is there long-term memory in UK stock returns*?," Applied Financial Economics 3, 293-302.

[2] Geweke, J., & Porter-Hudak, S. (1983). The estimation and application of long memory time series models. Journal of Time Series Analysis, 4, 221–238. 14

[3] Lobato I.N. and Savin N.E (1998): "Real and Spurious Long Memory Properties of stock Market Data", Department of Economics, University of Iowa, Iowa City.

[4] Ding, Z., Granger, C.W. J., and Engle, R.F. (1993), A long memory property of stock market returns and a new model, Journal of Empirical Finance, 1, 83—106.

[5] Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. Journal of Financial Economics, 4, 339–349.

[6] Peters, Edgar(1991): Chaos and Order in the Capital Markets. John Wiley & Sons, Inc.and E. Peters, Fractal Market Hypothesis: Applying Chaos Theory to Investment and Economics, John Wiley, 1994.

[7] Cheung, Y (1993). "Test for Fractional Integration: A Monte Carlo Investigation," *Journal of Time Series Analysis*, forthcoming.

[8] Booth, G.G., Kaen, F.R. and P.E. Koveos (1982) "Persistent Dependence in Gold Prices," *Journal of Financial Research,* 5, 1, 85-93.

et al. (1988) but, reexamining the estimation procedure, Lo (1991)[1] himself rejects the long term dependence for the same data set. Using the modified R/S analysis introduced by Lo (1991), Jacobsen (1996)[2] does not find evidence of long-term dependence in some European and Japanese stock indices return series. Little evidence against the random walk is also offered by Pan et al. (1997) for some currency futures prices. The same result had been reached by Cha (1993) for some financial indicators referred to Korea and Sweden. Also Hiemstra et al. (1997)[3], analyzing 1,952 common stocks, conclude that long memory is not a widespread characteristic, whereas Willinger et al. (1999)[4] found long-range memory, but claim that the evidence is not conclusive since the values of H are very close to the threshold of independence (H = 0.5). Finally, using the spectral regression method, Barkoulas et al. (1999)[5] found robust evidence of positive long-term persistence in the Greek stock market. Via the estimators introduced by Péltier et al. (1994)[6], empirical evidence is here offered that, under the assumption of log-normal distribution of the one-dimensional returns, H is time-changing. If so, R/S analysis (and more generally any asymptotic method) only estimates a sort of coarse mean value of the sequence (Ht). This would give a rationale for the apparently contradictory results above recalled; the presence or the absence of long-term memory could in fact depend on the local behaviour of Ht in the examined time span. As

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[1] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

[2] Jacobsen, B. (1996) "*Long Term Dependence in Stock Returns*," Journal of Empirical Finance, 3, 393 -- 420.

[3] Hiemstra, C., & Jones, J. D. (1997). Another look at long memory in common stock returns. Journal of Empirical Finance, 4, 373–401.

[4] Willinger, W., Taqqu, M. S., & Teverovsky, V. (1999). Stock market prices and long-range dependence. Finance and Stochastics, 3, 1-13.

[5] Barkoulas J T, Baum C F, Travlos M (1999): Long memory in Greek stock Market, Applied Financial Economics.

[6] Péltier R.F., Lévy Véhel J. (1995), Multifractional brownian motion: definition and preliminary results, Rapport de Recherche n. 2645, INRIA

previously recalled, many methods are available for estimating the Hurst exponent: R/S analysis, absolute value, variance-based and spectrum based techniques, Whittle-like estimators and so on (a detailed survey can be found in Taqqu et al. (1998))[1]. The advantage of almost all these estimators is to be robust with respect to infinite variance processes but, on the other hand, their main weakness is to be asymptotic; large samples are needed to obtain reliable estimates for H. If this is not a problem with simulated sample paths (Mandelbrot et al. (1979)[2], Taqqu et al. (1998)), the matter is not so much simple for actual time series, particularly for financial ones. In this case the use of asymptotic methods gives sensible sample estimates only if the process is truly short (long)-term dependent and this implicit assumption is the same as putting the cart before the horse. In fact, applying an asymptotic estimator to actual data means to assume that a unique Hurst exponent does characterize the whole time series, and there is no way to know a priori how correct this assumption is. At this regard, some drawbacks of R/S analysis applied to mean nonstationary processes were examined by Klemeš (1974)[3] and Battacharya et al. (1983)[4], but when H is allowed to change over time a different type of variance nonstationarity must be considered.

Mandelbrot's work on the use of the Rescaled Adjusted Range Statistic (R/S) stimulated the use of this statistic for analyzing the fractal behavior and stochastic memory of

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[1] Taqqu, M. S., & Teverovsky, V. (1996). Semi-parametric graphical estimation of long-memory data. in P. M. Robinson & M. Rosenblatt (Eds.), Athens conference on applied probability and time series. Volume II: Time series analysis in memory of E. J. Hannan. New York: Springer.

[2] Mandelbrot, B and Taqqu M S (1979): Robust R/S Analysis of long run serial correlation in 42nd Session in the International Statistical Institute Mariala, Book 2, pp 69-99

[3] Klemeš, V. (1974), "The Hurst Phenomenon: A Puzzle?," *Water Resources Research*, 10, 675-688.

[4] Bhattacharya, R.N., Gupta, V.K. and Waymire, E. (1983), "The Hurst Effect Under Trends," *Journal of Applied Probability*, 20, 649-662.

financial time series. Using R/S analysis, Greene and Fielitz (1977), Booth, Kaen, and Koveos (1982a, 1982b) and other researchers arrived at the surprising conclusion that some financial time series have long-memory behavior. In particular, Helms et al. (1984)[1] analyzed price changes in futures' contracts and claimed that the returns of the series display long-memory characteristics. The claim of long memory on commodity futures' price changes goes further than the simple claim of some statistical dependence that could improve the predictability of the prices: it states that correlations between price changes die out very slowly, in a sense made precise below, so that the actual movements in the market are stochastically influenced by the recent to the most remote past.

The primary focus of these studies has been the stochastic long memory behaviour of stock returns in major capital markets. In contrast, the long memory behaviour in smaller markets has received little attention. Contrary to findings for major capital markets, Barkoulas, Baum, and Travlos (2000)[2] in a Working Paper found significant and robust evidence of positive long-term persistence in the Greek stock market. Wright (1999)[3] used AFRIMA model to test long memory in emerging market including India and came up with the conclusion that emerging markets appear to have considerable serial correlation which stands contrast to the results for the developed markets like US, where there is little evidence for any serial correlation in stock returns.

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[1] Helms, B. P., Kaen, F. R. and Rosenman, R. E. (1984): "*Memory in commodity futures contracts*", Journal of Futures Markets 4, 4, 559--567.

[2] Barkoulas, J. T., Baum, C. F., & Travlos, N. (2000). Long memory in the Greek stock market, Applied Financial Economics, 10, 177–184.

[3] Wright J H (1999) Long memory in Emerging Market Stock Returns, Federal Reserve Discussion Paper, IFDP # 650

As already we have explained above, variety of procedures have been developed to test for predictability over different time horizons. Two of the most popular are Lo and MacKinley's (1988)[1] variance ratio (VR) test and Lo's (1991)[2] modified rescaled range (MRS) test. The former is primarily a test for short-range dependence and the latter a test for long-range dependence. Informally, short-range dependence occurs in a time series when there is some relationship between realizations at different dates, but the maximum dependence between realizations at any two dates becomes negligible as the time-span between the two dates increases. Long-range dependence exists when the dependence between realizations remains non-negligible as the time-span increases. Examples of short-range dependence include most classes of ARMA model which are integer-differenced to achieve stationarity.

The potential presence of stochastic long memory in economic and financial time series has been an important subject of both theoretical and empirical research. The long-memory, or long-term dependence, property describes the high-order correlation structure of a series. If a series exhibits long memory, there is persistent temporal dependence between observations widely separated in time. Such series exhibit hyperbolically decaying autocorrelations and low-frequency spectral distributions. Fractionally integrated processes can give rise to long memory (refer to Mandelbrot (1977), Granger and Joyeux (1980), Hosking (1981)). On the other hand, the short-

[1] Lo, A. and C. MacKinlay,(1988), "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies* 1, 41-66.
[2] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

memory, or short-term dependence, property describes the low-order correlation structure of a series. Short-memory series are typified by quickly declining autocorrelations and high-frequency spectral distributions. Standard autoregressive moving average processes cannot exhibit long-term (low-frequency) dependence as they can only describe the short-run (high-frequency) behavior of a time series. The presence of fractional structure in asset returns raises a number of theoretical and empirical issues. First, as long memory represents a special form of nonlinear dynamics, it calls into question linear modeling and invites the development of nonlinear pricing models at the theoretical level to account for long memory behavior. Mandelbrot (1971)[1] observes that in the presence of long memory, the arrival of new market information cannot be fully arbitraged away and martingale models of asset prices cannot be obtained from arbitrage. Second, pricing derivative securities with martingale methods may not be appropriate if the underlying continuous stochastic processes exhibit long memory. Third, statistical inferences concerning asset pricing models based on standard testing procedures may not be appropriate in the presence of long-memory series (Yajima (1985)[2]). Finally, as long memory creates nonlinear dependence in the first moment of the distribution and generates a potentially predictable component in the series dynamics, its presence casts doubt on the weak form of the market efficiency hypothesis. The price of an asset determined in an efficient market should follow a martingale process in which each price change is unaffected by its predecessor and has no memory. The presence of long memory in asset returns implies significant

[1] Mandelbrot, B.B.(1971). "When Can Price be Arbitraged Efficiently? A Limit to the Validity of the Random Walk and Martingale Models," *Review of Economics and Statistics*, 53, 3, 225-236.
[2] Yajima, Y., 1985, Estimation of long memory time series models, Australian Journal of Statistics 27, 303-320.

autocorrelations between distant observations. Consequently, past returns can help predict future returns, and the possibility of consistent speculative profits arises.

Given the implications of long memory for the theory and practice of financial economics, a number of studies have investigated the issue of persistence in financial asset returns. Using the rescaled-range (R/S) method, Greene and Fielitz (1977) report long memory in daily stock returns series. This result is overturned by Lo (1991) via the development and implementation of the more appropriate modified R/S method.

Literature available depicts studies concerning developed and emerging markets, though major work has been undertaken for developed market like US. The unavailability of reliable data may one of the important reasons why very few studies have been undertaken in emerging markets. For Indian financial market very few studies have tested long memory component. Some important work has been done by Barman and Madhusoodan (1993)[1], Thomas (1995)[2] and Basu & Morey (1998)[3] covering Indian market. Basu & Morey used Variance Ratio Test methodology devised by Lo and MacKinlay to test the long memory of the Indian stock market. Nath (2001)[4], Nath and Reddy(2002)[5] studied long memory of Indian equity market using Variance Ratio test and classical R S Analysis and observed that R S analysis showed signs of trend-

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[1] Barman R and Madhusoodan T P (1993): RBI Occasional papers

[2] Thomas S(1995): Heteroskedasticity in BSE Returns, Working Paper (author's homepage)

[3] Basu & Morey: Stock Market Prices in India after Economic Liberalization, EPW February 14, 1998

[4] Nath, G C (2001): "Long Memory of Indian Stock Market – An Empirical evidence" - 5th Annual Capital Market Conference (December 2001) of UTIICM, India

[5] Nath G C, Reddy Y V (2002): "Long Memory of Rupee Dollar Exchange Rate – An Empirical Evidence" - 6th Annual Capital Market Conference (December 2002) at UTI Institute of Capital Markets, Mumbai,

reinforcing tendency structure in the daily returns data. But they found that Variance Ratio test gives a clear mean reversion tendency.

IV.1.2 Long memory evidence in Foreign exchange Market

A number of empirical studies (see Booth, Kaen and Koveos, 1982; Cheung, 1993; Batten and Ellis 1996) employ the rescaled range statistical procedure, originally developed by Hurst (1951), to identify long-term return anomalies in currency markets. However, Fama (1998)[1] argues that this type of anomaly may be sensitive to the method employed and will tend to disappear when alternative approaches are used. Given the scale of the spot INR/USD trading and the high level of information efficiency in foreign exchange markets one may be predisposed to favour the Fama (1998) view. One approach to the problem is to apply similar statistical methods but determine whether the return anomaly persists over different sample periods, or is specific to one or more subperiods.

Many authors have tested for long memory in asset returns, including both stocks and exchange rate returns. Lo (1991)[2] proposed robustifying the rescaled range statistics of Hurst (1951)[3] against short run dependence and tested for US stock indices. Jacobsen

[1] Fama, E. F. 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics* 49: 283-306.
[2] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.
[3] Hurst, H.E.(1951). "Long-Term Storage Capacity of Reservoirs," *Transactions of the American Society of Civil Engineers*, 116, 770-799.

(1996)[1] tested for long memory in US, Japanese and some West European stock index returns.

Fung and Lo's (1993)[2] long memory study analyzed the prices of two interest rate futures markets, Eurodollars and T-bills. The result from the classical R/S analysis and Lo's (1991) modified R/S analysis provide no evidence of the existence of long memory and support for the weak form efficient market hypothesis. However, Fung et al (1994) [3]examined long memory in stock index futures by using variance ratio, R/S and auroregressive fractally integrated moving average models. All three types of analyses concluded that no long memory exists in the data. Similar tests have been pursued by many academicians but the results are mixed, but all authors agreed the identification of long memory is very important and significant in two senses: (a) the time span and strength of long memory will be an important input for investment decisions regarding investment horizons and composition of portfolios; and (b) prediction of price movements will be improved. It is also noticeable that research methodologies have developed very fast. In the 1980's the classical R/S analysis was the major tool but in 1990's the methods are being diversified with the modified R/S analysis and the AFIMA model as new techniques.

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[1] Jacobsen, B. (1996) "*Long Term Dependence in Stock Returns*," Journal of Empirical Finance, 3, 393 -- 420.

[2] Fung, H. G. and Lo, W. C. (1993): ``Memory in interest rate futures", The Journal of Futures Markets 13, 865-872.

[3] Fung, H K, S Lai, and M Lai, 1994, "Fractal Structure in Currency Futures Price Dynamics" The Journal of Futures Markets, 169-181

Nath and Reddy (2003)[1] studied the long memory process in Indian foreign exchange market and found that the R/S analysis gives indications of long-term memory but with noise while Variance Ratio test showed mixed results.

IV.1.3 Long memory evidence in Volatilities in Equity and Forex Market

Ding, Granger and Engle (1993), de Lima and Crato (1993), Bollerslev and Mikkelsen (1996), Baillie, Bollerslev and Mikkelsen (1996) and Breidt, Crato, and de Lima (1998), among others, found compelling evidence that the volatility of financial markets displays a long-memory structure. As Engle (1982)[2], Bollerslev (1986)[3] and many other researchers have shown, the volatility of financial returns may display a strong autocorrelation structure while the level of the returns display no memory and a random-walk type behavior.

Ding, Granger and Engle (1993)[4], Baillie et al. (1996)[5] and Andersen et al. (2001)[6], have pointed out in their studies the importance of long memory in volatility. In particular, while standard stochastic volatility models capture the fact that the smile

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[1] Nath G C, Reddy Y V (2003), "Long Memory in Rupee-Dollar Exchange Rate – An Empirical Study" ICFAI Journal of Applied Finance, May 2003

[2] Engle, Robert F.: (1982) Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of the United Kingdom Inflation, *Econometrica*, Volume 50, p. 987-1007

[3] Bollerslev, Tim: (1986) Generalized Auto-Regressive Conditional Heteroskedasticity, *Journal of Econometrics*, Volume 31, p. 307-327

[4] Ding, Z., Granger, C.W. J., and Engle, R.F. (1993), A long memory property of stock market returns and a new model, Journal of Empirical Finance, 1, 83—106.

[5] Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 74, 3–30.

[6] Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001). The distribution of realized exchange rate volatility. Journal of the American Statistical Association, 96, 42–55.

decreases as the time to maturity increases, such effect is more pronounced than in the data. Volatility persistence provides a valid justification for this effect. Interestingly, long range dependence in stochastic volatility is consistent with continuous time no-arbitrage pricing. In particular, even though volatility is not a semimartingale in itself (as fractional Brownian is not a martingale), prices are (since volatility is not assumed to be a traded asset) and therefore admit an equivalent martingale measure (indeed more than one since markets are typically not complete).

Several classes of stochastic processes can mimic the properties of long memory: the long memory ARCH processes introduced by Robinson (1991)[1], the long memory stochastic volatility proposed by Harvey (1998) and Breidt, Crato and de Lima (1998)[2], the multifractal models of assets returns developed by Mandelbrot, Fisher and Vavlet (1997), the multi-factors models of Gallant, Hsu and Tauchen (1998)[3], and mixture of ARCH and IGARCH processes, mixing a transitory and permanent component, by Ding and Granger (1996)[4], and Engle and Lee (1999[5]).

Accordingly, more recent work has availed itself of the sizeable advances in autoregressive conditional heteroskedastic (ARCH) and generalised autoregressive

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[1] Robinson, P. M.(1991): Testing for Strong Serial Correlation and Dynamic Condition Heteroskedasticity, Journal of Econometrics, 47, 67-84.

[2] Breidt, F.J., N. Crato, and P. de Lima (1998), "On the Detection and Estimation of Long-Memory in Stochastic Volatility," *Journal of Econometrics*, 83, 325-348.

[3] Gallant, A. Ronald, Chien-Te Hsu, and George Tauchen (1998), "Using Daily Range Data to Calibrate Volatility Diffusions and Extract the Forward Integrated Variance," The Review of Economics and Statistics

[4] Ding, Z., and C. Granger (1996): "Varieties of Long Memory Models", Journal of Econometrics, 73, 61-77.

[5] Engle, R.F., and G. Lee, (1996), "*Estimating Diffusion Models of Stochastic Volatility*," in Modeling Stock Market Volatility, Academic Press, Inc.

conditional heteroskedastic (GARCH) models to study the conditional volatility of stock markets and ascertain the predictability of future stock return volatility conditional on past volatilities and return shocks [see, for instance, Tse and Zuo (1997)[1], Aggarwal et al. (1999), Adrangi et al. (1999) and Huang and Yang (2000)]. A few studies have even extended these to the multivariate case. However, relatively few studies have adopted an exclusively Asian regional perspective.

IV. 2. Market Interlinkages

There have been several reasons that the need for well-developed, efficient and integrated financial markets is being increasingly stressed in modern literature on economics and finance. In finance theory, this refers to a market condition that reduces arbitrage opportunities and also helps investors to diversify their portfolio across different markets (and hence reduce risk exposures). An economist considers one such development as a facilitator of savings, investment and consequent economic growth. Moreover, under such development, as impulses in one market get reflected quickly in other markets, transmission mechanism of monetary policy becomes smooth and speedy and thus policy intervention becomes more effective in bringing fruits in desired direction within specified time horizon. The development of deep and integrated financial markets, therefore, has been emphasised by monetary policy makers in modern days. In fact, this has been a precondition for 'inflation targeting approach', a new paradigm of monetary policy, to function credibly and effectively.

[1] Tse, Y.K. and X.L. Zuo (1997). Testing for conditional heteroscedasticity: Some Monte Carlo results, Journal of Statistical Computation and Simulation 58, 237—253.

Prior to 1990s, Indian financial system was full of substantial structural rigidities and was under sever administrative control. Administered interest rate structure, thin foreign exchange market and prevailing fixed exchange rate mechanism, under-developed secondary markets for government securities, lack of adequate depth of money and capital markets, and also inadequate institutional arrangements/framework are a few characteristics of the financial sector, which had resulted into substantial amount of segmentation of financial markets during those years. One of the major objectives of the economic reforms that have been initiated in India since 1991, therefore, has been development of financial markets into an integrated one. Accordingly, several policy measures have been taken, in phases, towards innovations of new financial instruments, improving market depth/conditions, strengthening institutional and regulatory framework and so on. Now, it is believed that Indian financial system has achieved the international standard in its market practices.

Some of the specific developments that have taken place during the reforms process and might have impacted on the extent of financial markets integration are[1] (i) dismantling of various price and non-price controls in financial markets; (ii) like other Asian emerging economies, Indian equity market has continued to grow and has seen the relaxation of foreign investment restrictions primarily through country deregulation; (ii) the issuance of ADR/GDRs has facilitated the trade of foreign securities on the NYSE, NASDAQ or on non-American exchanges; (iii) allowing Indian Rupee to be determined by market forces (though at times market intervention by Reserve Bank of India, the

[1] One may refer to Bhoi and Dhal (1998); Nag and Mitra (1999-2000), Nath and Samanta (2003), among others for discussion on related issues.

concerned authority, took place). Gradual move towards full convertibility of Indian Rupee has had an impact in the Indian capital market as international investors have invested substantial amount (about US $23 billion as of December 2003) in Indian capital market; (iv) the two-way fungibility of ADRs/GDRs allowed by RBI has also possibly strengthened the linkages between the stock and foreign exchange markets in India.

In view of above, the extent of financial markets integration in the liberalisation era needs to be scrutinized empirically. Though some recent studies have investigated related issues, further research on the subject is needed primarily because the Indian economy is still passing through a transition phase and impact of reform measures initiated in different phases during the liberalisation era might have not yet reflected fully in the economy. Thus, the extent of markets integration is perhaps changing over time – indicating the possibility of getting different conclusion on market integration for the period, which was not covered in previous studies. Moreover, a fresh investigation is needed for examining the robustness of empirical results on methodological choice. In this context, this study aims at assessing the changing level of integration between foreign exchange and capital markets in India during recent years.

The possible inter-linkage between stock prices and exchange rates are suggested by several arguments/hypotheses, particularly important are those identified in 'goods

market approaches' (Dornbusch and Fischer, 1980)[1] explaining likely impact of exchange rate on stock prices and the 'portfolio balance approaches' for justifying impact in reverse direction. The arguments provided in 'goods market approaches' flow from that as many companies borrow in foreign currencies to fund their operations, a change in exchange rate affects the cost of funds and value of earnings of many firms, which in turn affect the competitiveness of a firm and its stock prices – a depreciation (appreciation) of local currency makes exporting goods more (less) attractive to foreigners, resultant increase (decrease) of foreign demand of goods raises the revenue of firms, value of firms appreciates and thus stock prices increase. The sensitivity of an importing firm to a change in exchange rate is just opposite to that of an exporting firm. Therefore, on a macro basis, the impact of exchange rate fluctuations on stock market seems to depend on both the importance of a country's international trades in its economy and the degree of the trade imbalance.

To complete the linkage, influence in reverse direction can be justified by 'portfolio balance approaches' under the exchange rate regime that allows exchange rate to be determined by market mechanism (i.e., the demand and supply condition). A blooming stock market would attract capital flows from foreign investors, which may cause an increase in the demand for a country's currency. Thus, local currency appreciates. The reverse would happen in case of falling stock prices where the investors would try to sell their stocks to avoid further losses and would convert their money into foreign

[1] Dornbusch, R. and S. Fischer (1980), "Exchange Rates and Current Account," *American Economic Review* 70, 960-971.

currency to move out of the country. There would be demand for foreign currency in exchange of local currency. As a result, rising (declining) stock prices would lead to an appreciation (depreciation) in local currency. Moreover, foreign investment in domestic equities could increase over time due to benefits of international diversification that foreign investors would gain. Furthermore, movements in stock prices may influence exchange rates (and money demand) because investors' wealth (and liquidity demand) could depend on the performance of the stock market.

Although theories suggest causal relations between stock prices and exchange rates, existing empirical evidence on the issue provides mixed results. Consider first some studies based on micro level data. For example, Jorion (1990, 1991)[1], Bodnar and Gentry (1993)[2], and Bartov and Bodnar (1994)[3] all fail to find a significant relation between simultaneous dollar movements and stock returns for U.S. firms. He and Ng (1998)[4] find that only about 25 percent of their sample of 171 Japanese multinationals has significant exchange rate exposure on stock returns. Griffin and Stulz's (2001)[5] empirical results show that weekly exchange rate shocks have a negligible impact on the value of industry indexes across the world. However, Chamberlain, Howe, and

[1] Jorion, P. (1990), "The Exchange Rate Exposure of U.S. Multinationals," *Journal of Business* 63, 331-345. and Jorion, P. (1991), "The Pricing of Exchange Rate Risk in the Stock Market," *Journal of Financial and Quantitative Analysis* 26, 363-376.

[2] Bodnar, G. M. and W. M. Gentry (1993), "Exchange Rate Exposure and Industry Characteristics: Evidence from Canada, Japan, and the USA," *Journal of International Money and Finance* 12, 29-45.

[3] Bartov, E. and G. M. Bodnar (1994), "Firm Valuation, Earnings Expectations, and the Exchange-Rate Exposure Effect," *Journal of Finance* 49, 1755-1785.

[4] He, J. and L. K. Ng, (1998), "The Foreign Exchange Exposure of Japanese Multinational Corporations," *Journal of Finance* 53, 733-753.

[5] Griffin, J. M. and R. M. Stulz (2001), "International Competition and Exchange Rate Shocks: A Cross-Country Industry analysis of Stock Returns," *Review of Financial Studies* 14, 215-241.

Popper (1997)[1] find that the U.S. banking stock returns are very sensitive to exchange rate movements, but not for Japanese banking firms. While such findings are different from those reported in prior research, Chamberlain *et al.* attributed the contrast to the use of daily data in their study instead of monthly data as used in most prior studies.

On a macro level, several studies document relatively stronger relationship between stock price and exchange rate. Ma and Kao (1990)[2], for instance, find that a currency appreciation negatively affects the domestic stock market for an export-dominant country and positively affects the domestic stock market for an import-dominant country, which seems to be consistent with the goods market theory. Ajayi and Mougoue (1996)[3], using daily data for eight countries, show significant interactions between foreign exchange and stock markets, while Abdalla and Murinde (1997)[4] document that a country's monthly exchange rates tends to lead its stock prices but not the other way around. Pan, Fok & Lui (1999)[5] used daily market data to study the causal relationship between stock prices and exchange rates and found that the exchange rates Granger-cause stock prices with less significant causal relations from stock prices to exchange rate. They also find that the causal relationship have been stronger after the Asian crisis.

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[1] Chamberlain, S.; J. S. Howe, and H. Popper (1997), "The Exchange Rate Exposure of U. S. and Japanese Banking Institutions," *Journal of Banking and Finance* 21, 871-892.

[2] Ma, C. K. and G. W. Kao (1990), "On Exchange Rate Changes and Stock Price Reactions," *Journal of Business Finance & Accounting* 17, 441-449.

[3] Ajayi, R. A. and M. Mougoue (1996), "On the Dynamic Relation between Stock Prices and Exchange Rates," *Journal of Financial Research* 19, 193-207.

[4] Abdalla, I. S. A. and V. Murinde (1997), "Exchange Rate and Stock Price Interactions in Emerging Financial Markets: Evidence on India, Korea, Pakistan, and Philippines," *Applied Financial Economics* 7, 25-35.

[5] Pan, Fok & Lui (1999), Dynamic Linkages Between Exchange Rates and Stock Prices: Evidence from Pacific Rim Countries, Shippensburg University Working Papers.

In the context of Indian economy, a few recent studies have examined integration of forex and stock markets empirically using macro-level data for liberalisation era. For example, Nag and Mitra (1999-2000)[1] investigate the integration of three financial markets, viz., money market, forex market and stock market. Based on empirical results using daily data on call money rate, exchange rate (Indian Rupee/US Dollar) and stock price index (BSE Sensex) for the period October 1996 to July 1999, they arrive at two important conclusions. First, short-run money market and forex market are gradually getting integrated and prices in these markets are sensitive to price movements in other financial markets. Second, the capital market continues to be somewhat insular to the changes in the rate variables in other financial markets. The empirical study by Nath and Samanta (2003a, b)[2] tests whether returns in forex market are interrelated with returns in capital market. Employing daily data during March 1993 to December 2002, they conclude that causal link is generally absent though in recent years there has been a sign of causal influence, at least from capital market to forex market. Nath (2003)[3] conducted a study to test the interlinkages among global markets using 10 stock indices of developed and emerging markets and did not find long-term relationship with Indian market but found short term causal relationship among some of the Asian markets. Nath

[1] Nag, A. K. and Amit Mitra (1999-2000), "Integration of Financial Markets in India: An Empirical Investigation", *Prajnan*, Vol. XXVIII, No. 3, pp. 219-41.

[2] Nath G C, Samanta G P (2003a): "Dynamic Relation between Exchange Rate and Stock prices – A case for India", Paper at 39th Annual Conference of Indian Econometric Society, February 2003 and Nath G C, Samanta G P (2003b): "Integration Between Forex and Capital Markets in India: An Empirical Exploration" in ICFAI Journal of Applied Finance, September 2003

[3] Nath G C (2003): "Global Equity Markets – A Study of Cointegration" in Decision, Journal of IIM, Kolkata (July-December) 2003

and Verma (2003)[1] did a similar study using the stock market indices of India, Taiwan and Singapore and found these markets did not have long-term equilibrium relationship.

The literature on market interlnkages are tabulated in IV-1 below:

[1] Nath G C, Veram S (2003) : "Study of Common Trend and Integration in Emerging Markets – A case Study of India, Singapore and Taiwan" NSE Working Paper

TABLE IV-1: SUMMARY OF LITERATURE ON INTERLINKAGES					
STUDY	**MARKETS**	**TIME**	**METHOD**	**RESULTS**	COMMENTS
The international Crash of October 1987: Causality Tests A.G. Malliaris, Jorge L. Urrutia Journal of Financial and Quantitative Analysis. (1992)	New York S&P500 Tokyo Nikkei London FT-30 Hong Kong Hang Seng Singapore Strait-Times Australia All Ordinaries	May 1, 1987-March 31, 1988 Daily Closing Prices 5 lags (11 months)	Granger Causality, ADF test, Test of Cointegration, Error Correction. Wald Test: F-Statistic By pairs	No lead-lag relationship for the pre-crash and post-crash periods, for the crash month, causality increases. Tokyo played a passive role; Hong Kong played a leading role among Asian Markets. Crash probably started simultaneously in all the stock markets, seems to have been an international crisis of equity markets. FEEDBACK: NY-L, NY-HK, L-Sing, L-T, L-Sydney, HK-Syd, T-Syd. UNIDIRECTIONAL: NY-T, L-HK, HK-Sing, T-Sing, Syd-Sing, HK-T.	Market efficiency and information available then. Data synchronization due to time zone shift differences. European market indices today affect the US market in the same calendar day, but the Asian and Australian markets are impacted the following trading day. Activities in the New York market affects European, Asian and Australian markets the following trading day. Asian & Australian activities affect the European an American markets the same calendar day.
International Stock Market Efficiency and Integration. A study of Eighteen Nations Kam C. Chan, Benton E. Gup, Ming-Shiun Pan. Journal of Business Finance &	US Canada UK Germany Japan France Italy Belgium Denmark Netherlands Spain Norway Finland Sweden Switzerland India	January 1961-December 1992 Monthly data. Base year 1985 Dividends are not included. (32 years)	Cointegration Individually and collectively in regions to test for the weak form market efficiency. Unit Roots: Phillips & Perron test. Cross-country market Efficiency hypothesis with Johansen's	Unit Root tests: All the stock markets are individually weak form efficient. Cointegration: Only few markets (European Financial Center and Asian) show evidence of cointegration with others. The number of significant cointegrating vectors increases before the October 1987 Crash. Countries with common economic ties may not be cointegrated to each other. Less market segmentation leads to cointegration relationships among international stock markets. Stock markets don't have long-run co-movements. Contagion effect isn't very strong.	If two stock markets are collectively efficient in the long run, their stock prices cannot be cointegrated (Granger, MacDonald and Taylor have demonstrated it). If two markets are cointegrated, then possible arbitrage profits can be explored. Cointegration is suggested if the rank of *r* (parameter matrix) is between zero and the number of stock series. The rank of *r* equals the number of cointegrating vectors. 7 regions (North America, G7, Four Big European Community,

Accounting (1997)	Pakistan Australia		tests. Error correction for up to tenth-order lags.		European Community, Scandinavian, European Financial Centers, Asian)
A Causality Test of the October Crash of 1987: Evidence from Asian Stock Markets. Mohammad Najand Journal of Business Finance & Accounting (1996)	Hong Kong Hang Seng Singapore Strait Times Japan Nikkei	January, 1984-December 1989. Daily data. (6 years)	State Space Procedure with ARMA Models. Akaike Information Criterion (to determine k lags) Canonical correlation analysis to select the dimension of the state vector. Kalman filter to refine initial models.	A substantial interaction exists among Asian Markets. All Period: Japan influence on the Singapore and Hong Kong markets and plays the leading role on them. FEEDBACK: J-Sing, UNIDIRECTIONAL: HK-Sing, J-HK Pre-Crash: No lead-lag relation among them. Crash: Japan plays a leading role. Contemporaneous causality, suggesting simultaneous effects. Post-Crash: Asian markets seem to be much more interrelated after the crash.	A Causality Test of the October Crash of 1987: Evidence from Asian Stock Markets. Mohammad Najand Journal of Business Finance & Accounting (1996)
Modeling the Dynamic Interdependence of Mayor European Stock Markets Gregory Koutmos Journal of	London FT500 Share France CAC General Germany Commerzebank Italy BCI General	January 4, 1986-December 31, 1991 All Indices are value weighted and broadly based.	Multivariate VAR-EGARCH Model. (Error correction) Analysis for returns and volatility Kolmogorov-Smirnov Test for Normality of returns, Ljung-Box for	All returns are negatively skewed highly leptokurtic with respect to the Normal distribution. No Normality was found. Degree of Asymmetry is highest for Germany and UK. (Negative innovations increase volatility more than positive) France and Italy volatility is high and very close to 1. No market plays a major role as an information producer, UK is the only market whose lagged returns influence significantly the conditional means of the remaining three markets. Volatility interactions: Conditional	Leverage effect: whereby negative stock returns automatically produce a higher debt to equity ratio and hence higher volatility. Theodossiou and Lee (1995) find no evidence of volatility feedback in European stock returns. Most of the time, sample correlation coefficients are used with the implicit assumption that the return series involved are mean and variance stationary. Under

Business Finance & Accounting (1996)		(5 years, 11 months)	linear and nonlinear dependencies.	variance in each market is also affected by past innovations generated in the other markets with the exception of Italy is not affected by UK innovations, and vice-versa. Stock markets are integrated. The four markets are weak form efficient.	this assumption, conditional and unconditional estimates coincide. On average, a negative innovation in a given market increases volatility within and across markets twice more than positive innovation.
The Price Linkages Between Country Funds and National Stock Markets: Evidence from cointegration and Causality Tests of Germany, Japan and UK funds. Uri Ben-Zion, Jongmoo Jay Choi, Shmuel Hauser. Journal of B F & Ac (1996)	UK FTSE Germany DAX Japan Nikkei US S&P500 With each of the national country funds.	December 1, 1987-February 28, 1990. Daily closing prices in dollar terms. 5 lags (2 years, 3 months)	Unit Root test for stationarity with DF-statistic Cointegration test Engle-Granger regression. Granger Causality X^2 Statistic Error Correction Adjusting for synchronization due to trading time differences.	Unit root tests indicate that price levels of country funds and market indices are non-stationary. Their first differences are stationary. Cointegration tests show that pair of relations between country funds and national stock prices are not cointegrated. Causality tests show that pairs that show causal relations are not necessarily those that have cointegrating relations. The only market that's cointegrated with the US market is the German.	Cointegration defines a long-term stationary equilibrium. Data synchronization between New York trading time. Lack of cointegration between country fund and the US market price index indicates the existence of potential long-term portfolio gains. Presence of causality indicates joint market inefficiency and a potential for short-term arbitrage between the fund and the fund assets. Cointegration should proceed on price levels not returns, because their first differences are stationary.
Co-Movements in International Equity Markets Salim m. Darbar, Partha Deb	Canada Toronto 300 Share Japan Topix UK FTSE-100 share US S&P500	January 1, 1989-December 31, 1992 Daily data close-to-	Multivariate GARCH Model (1,1) Conditional and unconditional covariance	Significant transitory covariance. For 5 of the 6 pairs, there was find evidence of a permanent nonzero covariance. US-Jap shows no evidence of ZUC or permanent Cov. There are periods in which even returns for US and Japan are correlated, such correlations can be	Modeling time-varying characteristics of daily co-movements of international stock returns in a new multivariate GARACH framework and decompose the cross-country conditional

The Journal of Financial Research (1997)		close. (3 years)	Matrix, Flexible and parsimonious model Likelihood ratio test for ZUC and ZCC Lagrange Multipliers GARCH to estimate cross-country conditional correlations. By pairs. Standard errors 1000 simulations of cond. Correlations.	expected to revert to zero. Jap-Can, US-Jap, UK-US, have greater positive transitory effects than negative. UK-Can, US-Can, UK-Jap display the opposite characteristic. 5 of the 6 pairs have negative correlations, suggesting cross-country conditional correlations are typically nonnegative. There were find significant time variations. It takes 3 to 5 days for the estimated correlation to return to normal levels, except for US-Jap pair (1 day). A drop in the conditional correlation increases the probability the two markets will move in the opposite direction; an increase in the condit. Correl. Increases the probability the two markets will move in the same direction.	covariance into permanent and transitory components. Time-varying transitory component captures the fluctuations around constant permanent level. US-Japan shows no evidence of permanent correlation but it dos show evidence of significant transitory correlation. All other pairs display significant evidence of both transitory and permanent correlations.
Equity Market Integration: The Case of North America. William L. Atterberry, Peggy E. Swanson North American Journal of Economics & Finance (1997)	US S&P500 Canada TSE 300Comp Mexico IPC	January 1, 1985-December 31, 1994 Daily closing prices (10 years)	VAR, Granger Causality (bivariate & multivariate, Estimation with OLS), ECM for nonstationary series but cointegrated. Phillips-Perron Unit Root tests, Johansen Cointegration test, Akaike's Final	For the entire period, all pairs with bidirectional causality as well as contemporaneous determination. FEEDBACK: US and Canada in 1987 and 1994, and the overall period. UNIDIRECTIONAL: US-Can for 1993 Before 1987, neither short-term causal effects nor long-term equilibrium relationships are detected among North American markets. Simultaneous causality for all periods except for 1993. In 1987 Mexico is affected by both the US and Canada and affects US but not Canada. In 1988 long-term relationships emerge for the three countries, in 1993 long-term relationships between US and Mexico	Adjustments for differences in market closing time. Relationships involving Mexico have been more dependent on trade flows. Well-developed markets in countries with few capital flow restrictions display a high degree of comovement and a relatively low degree of unique variability of stock prices. Implementation of NAFTA at the beginning 1994 produced an effect similar to the post-crash effect of 1987. Potential benefits associated with diversification across equity markets with in North America

			Prediction Criterion	The short-term relationships weaken in 1989 and there are no short-term relationships with Mexico. US dominates in long-term and short-term effects. Contemporaneous determinations are consistent with weak-form efficiency. Short-term causal effects of the 1987 Crash are manifested immediately, followed by long-term equilibrium linkages.	system appear to be diminished during periods of economic uncertainty.

CHAPTER V

V.0 METHODOLOGY

V.1 Methodology in study of Long Memory Process

Two important and robust tests have been used to study the long memory process of stock and foreign exchange market. The basic constructions of these methodologies are explained below.

V.1.1 Variance Ratio Test

A variety of procedures have been developed to test for predictability over different time horizons. Two of the most popular are Lo and MacKinley's (1988)[1] variance ratio (VR) test and Classical rescaled range Analysis developed by hydrologist Hurst (1951). The classical rescaled range analysis was layer modified by Lo's (1991)[2] that is known as modified rescaled range (MRS) test. The former is primarily a test for short-range dependence and the latter a test for long-range dependence. Informally, short-range dependence occurs in a time series when there is some relationship between realizations at different dates, but the maximum dependence between realizations at any two dates becomes negligible as the time-span between the two dates increases. Long-range dependence exists when the dependence between realizations remains non-negligible as the time-span increases. Examples of short-range dependence include most classes of

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[1] Lo, A. and C. MacKinlay,(1988), "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies* 1, 41-66.
[2] Lo, A., (1991), "Long-Term Memory in Stock Market Prices," *Econometrica* 59, 1279-1313.

ARMA model which are integer-differenced to achieve stationarity. Long-range dependence occurs in fractionally-differenced processes.

When first applied to American data, the Variance Ratio test typically rejected the random walk hypothesis in favour of positive autocorrelations at short horizons (under one year) and negative autocorrelation at longer horizons, both for stock market indices and individual stocks. Positive autocorrelation in this context is often referred to as "mean *a*version" and negative autocorrelation as "mean *re*version". (See Poterba and Summers (1988)[1] and Lo and MacKinley (1988)[2]). Subsequent research on US data suggests that, when allowance is made for various possible biases in the VR statistic, the results are far less clear. Richardson and Stock (1989)[3] argued that the Poterba and Summers data, which cover 1926-1985, actually provide only relatively weak evidence against the random walk hypothesis. Using related techniques, Kim, Nelson and Startz (1991)[4] found that mean reversion is a phenomenon which is confined almost entirely to the inter-war period in the US. The post-war data appear to be more consistent with either the random walk model, or with positive autocorrelation (mean aversion) at both short and long horizons. Jegadeesh (1990)[5] also found evidence of positive autocorrelation in US data, particularly in the January returns.

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[1] Poterba, J., and L Summers (1987): "Mean Reversion in Stock Returns: Evidence and Implications," forthcoming in *Journal of Financial Economics*

[2] Lo, A. and C. MacKinlay,(1988), "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies* 1, 41-66.

[3] Richardson, M., and Stock, J. (1989), *Drawing Inferences from Statistics Based on Multi-Year Asset Returns*, Journal of Financial Economics 25, 323348. 49

[4] Kim, Nelson, and Startz, 1991, "Mean Reversion in Stock Prices? A Reappraisal of the Empirical Evidence," Review of Economic Studies 58, pp. 515-528

[5] Jegadecsh, N., 1990, Evidence of Predictable Behavior of Security Returns," Journal of Finance 45, 881-898.

Evidence from non-US data is almost equally ambiguous. Frennberg and Hansson (1993)[1] found that Swedish stock index data covering 1919-1990 exhibit essentially the same features as that of Poterba and Summers; ie: mean aversion at short horizons and mean reversion at longer horizons. MacDonald and Power (1993)[2] report similar evidence for a sample of individual stocks in the United Kingdom. However, neither of these papers take account of the criticisms and suggested amendments to the VR test procedures which were proposed by Richardson and Stock (1989)[3]. Accordingly it is not clear whether their results are as robust as they appear at first sight. Claessens, Dasgupta, and Glen (1993)[4] examined the stock market indices of 20 emerging markets and found departures from the random walk at short horizons in 11 of these markets, but, like the preceeding authors, they did not take account of the Richardson-Stock criticisms. Huang (1995)[5] studied 9 Asian stock market indices, and found that only Malaysia and Korea departed significantly from the random walk. Moreover, the VR tests suggested that the returns were mostly positively autocorrelated, irrespective of the return horizon. On the other hand, Mills (1991)[6] found that the United Kingdom *Financial Times/Actuaries* All-Share index was predictable at horizons of one year or more (and therefore did depart significantly from the random walk), but like Huang, he found that the returns were positively autocorrelated, irrespective of the horizon.

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[1] Frennberg, P. and B. Hansson (1993): Testing the Random Walk Hypothesis on Swedish Stock Prices 1919-1990 *Journal of Banking and Finance* Vol. 17, No. 1, 175-191.

[2] MacDonald, R. and Power, D.M. (1993), "*Persistence in UK share returns: some evidence from disaggregated data*", Applied Financial Economics, Vol. 3, pp. 27-38.

[3] Richardson, M., and Stock, J. (1989), *Drawing Inferences from Statistics Based on Multi-Year Asset Returns*, Journal of Financial Economics 25, 323348. 49

[4] Claessens, S., S. Dasgupta, and J. Glen (1995), "Return Behavior in Emerging Stock Markets", *World Bank Economic Review* 9(1):131-151.

[5] Huang, Bwo-Nuang (1995), "Do Asian Stock Market Prices Follow Random Walks? Evidence from the Variance Ratio Test," *Applied Financial Economics*, 5 : 251-256.

[6] Mills, T.C. (1991), "Assessing the predictability of UK stock market returns using statistics based on multiperiod returns", *Applied Financial Economics*, Vol. 1, pp. 241-245.

The VR test exploits the property of an IID random walk (in log prices) that the variance of the return increases linearly with the time horizon (Q) over which the return is calculated. The test involves a comparison between the variance of the one period return (here, one month) and the variance of the Q-period return. However, if Q is large, and non-overlapping observations are used, the test will have little power. Therefore, we follow Lo and Mackinley (1988)[1], and define the VR statistic ($M(Q)$) for overlapping data as:

$$M(Q) = \sigma_Q^2 / \sigma_1^2 - 1 \qquad \text{...(1)}$$

with: $$\sigma_Q^2 = \sum_{t=Q}^{T} (R_{Qt} - Q\mu)^2 / QT$$

and: $$R_{Qt} = \sum_{i=1}^{Q} R_{t-i+1}$$ = the continuously compounded Q-period return.

$$\mu = \sum_{t=1}^{T} R_{1t} / T$$

T = the total number of observations.

Under the null of IID returns, then, as T→∞ with Q fixed, $M(Q)$ has an approximate limiting normal distribution; and a standardized VR statistic is given by:

$$Z_1(Q) = \sqrt{T} M(Q)[2(2Q-1)(Q-1)/3Q]^{-0.5} \overset{a}{\sim} N(0,1) \qquad \text{...(2)}$$

It can be shown that the finite sample performance of this test is substantially improved by using instead of σ_Q^2, the unbiased estimate of the variance (v_Q):

$$v_Q = \sigma_Q^2 T^2 / (T-Q+1)(T-Q) \qquad \text{...(3)}$$

[1] Lo, A. and C. MacKinlay,(1988), "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies* 1, 41-66.

Since stock return series typically display time-varying variances, it is possible to develop a robust (heteroscedasticity-consistent) version of the VR statistic, which is given by:

$$Z_2(Q) = \sqrt{T}M(Q)/s(Q) \overset{a}{\sim} N(0,1) \qquad \text{...(4)}$$

with: $$s^2(Q) = 4\sum_{j=1}^{Q-1}(1 - j/Q)^2\theta(j)$$

and: $$\theta(j) = \frac{T\sum_{t=j+1}^{T}(R_t - \mu)^2(R_{t-j} - \mu)^2}{\left(T\sigma_1^2\right)^2}$$

In their seminal contributions, Lo and MacKinley (1988)[1] worked with a sample size which was much larger than ours, particularly in relation to the maximum return horizon; and they pointed out that the normal approximation for *M(Q)* is likely to be unsatisfactory for large *Q/T* because the empirical distribution becomes increasingly skewed as *Q/T* increases. Accordingly, we follow Lo and MacKinley (1989)[2], and Poterba and Summers (1988)[3], and report Monte Carlo estimates of the empirical distribution of *M(Q)* for comparison with the results for the $Z_1(Q)$ and $Z_2(Q)$ statistics. Moreover, in deriving the limiting distribution, Lo and MacKinley (1988)[4] assumed that Q is fixed, so that $Q/T \rightarrow 0$ as $T \rightarrow \infty$. Richardson and Stock (1989) argued one could equally well assume that $Q/T \rightarrow$

[1] Lo, A. and C. MacKinlay,(1988), "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies* 1, 41-66.

[2] Lo, A.W. and MacKinley, C. (1989), "The size and power of the Variance Ratio test in finite samples: A Monte Carlo investigation", *Journal of Econometrics*, Vol. 40, pp. 203-238.

[3] Poterba, J., and L Summers (1987): "Mean Reversion in Stock Returns: Evidence and Implications," forthcoming in *Journal of Financial Economics*

[4] Lo, A.W. and MacKinley, C. (1988), "Stock market prices do not follow random walks: evidence from a simple specification test", *Review of Financial Studies*, Vol. 1, pp. 41-66.

z, where z is a fixed, non-zero fraction. This produces a different (non-normal) limiting distribution which, they argue, is a closer approximation to the small sample distribution of *M(Q)*. However, Mills (1991)[1] simulated the empirical distribution of *M(Q)* under each of these assumptions and found relatively little difference between the two.

We have used the Variance Ratio Test popularized by Cochrane (1988)[2], and used by MacDonald and Power (1992)[3] etc. The same is stated as

$$Z(k) = (1/k) * \{ \mathrm{Var}(X_{t-k}) / \mathrm{Var}(X_t) \} \qquad \ldots(5)$$

where X_t denotes a one period return, obtained from the first difference of the natural logarithmic of the exchange rate, and X_{t-k} denotes the *k*-period return calculated using the *k*th difference of the exchange rate. The possibilities are as follows:

1. If the price series follows a random walk, this ratio should equal unity.
2. If the series is stationary, the ratio will tend to zero.
3. If price exhibit mean reversion, Z (*k*) should lie between zero and one.
4. Values of Z (*k*) above one indicate that a current increase in the value of the price will be reinforced in the future by further positive increases.

Variance ratio tests have been applied extensively over the past decade, both in macroeconomics and finance. Examples include Campbell and Mankiw (1987) and

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[1] Mills, T.C. (1991), "Assessing the predictability of UK stock market returns using statistics based on multiperiod returns", *Applied Financial Economics*, Vol. 1, pp. 241-245.

[2] Cochrane, J.H., 1988. How big is the random walk in GNP? Journal of Political Economy 96, 893-920.

[3] MacDonald, R. and Power, D.M. (1993), "*Persistence in UK share returns: some evidence from disaggregated data*", Applied Financial Economics, Vol. 3, pp. 27-38.

Cochrane (1988) on output fluctuations, Fama and French (1988), Lo and MacKinlay (1988), Poterba and Summers (1988), Richardson and Stock (1989), Chow and Denning (1993), and Richardson (1993) on stock returns, and Huizinga (1987), Liu and He (1991), and Fong et al. (1997) on foreign exchange rate returns. Variance ratio tests are especially good at detecting linear dependence in the returns, see Faust (1992)[1].

V.1.2 Classical R S Analysis (Rescaled Range)

Hurst (1900-1978) was an English hydrologist, who worked in the early 20th century on the Nile River Dam project. When designing a dam, the yearly changes in water level are of particular concern in order to adapt the dam's storage capacity according to the natural environment. Studying an Egyptian 847-year record of the Nile River's overflows, Hurst observed that flood occurrences could be characterized as persistent, i.e. heavier floods were accompanied by above average flood occurrences, while below average occurrences were followed by minor floods. In the process of these findings he developed the Rescaled Range (R/S) Analysis.

Standard autocorrelation tests detect long-term dependency in stock market prices if dependent behaviour is periodic and if the periodicity is consistent over time. Fundamental historical changes however alter the period of cycles. Mandelbrot (1972)[2]

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[1] Faust J (1992): When are Variance Ratio Tests for Serial Dependence Optimal? Econometrica, 60, 1215-1226

[2] Mandelbrot, B. (1972) "Statistical Methodology for Non-period Cycles: From the Covariance to R/S analysis," *Annals of Economic and Social Measurement* 1, 1972.

proposes a statistic to measure the degree of long-term dependency, in particular, "non periodic cycles". The rescaled range, or R/S statistic, is formed by measuring the range between the maximum and minimum distances that the cumulative sum of a stochastic random variable has strayed from its mean and then dividing this by its standard deviation. An unusually small R/S measure would be consistent with mean reversion, for instance, while an unusually large one would be consistent with return persistence. To construct this statistic, consider a sample of returns $X_1, X_2, \ldots, X_n$ and let $\overline{X_n}$ denote the sample mean and equation is given by the following:

$$Q_n = 1/(\sigma_n . \sqrt{n}) \left[\max \sum_{j=1}^{n} (X_j - \overline{X_n}) - \min \sum_{j=1}^{n} (X_j - \overline{X_n}) \right] \qquad \ldots(6)$$

In his original work, Mandelbrot suggested using the sample standard deviation estimator for the scaling factor, σ_n

We have used this as the second technique to judge persistence in stock market returns. Peters (1994)[1] has discussed this method in a simpler and neater way. Let us take a series of data $X_1, X_2, \ldots, X_n$ and let $\overline{X_n}$ denote the sample mean. Let σ_n again be the standard deviation. The rescaled range was calculated by first rescaling or "normalizing" the data by subtracting the sample mean:

$$Z_r = X_r - \overline{X_n} \qquad r = 1,2\ldots\ldots n$$

The resulting series, Z, now has a mean of zero. The next step creates a cumulative time series Y:

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[1] Peters E., *Fractal Market Hypothesis: Applying Chaos Theory to Investment and Economics,* John Wiley, 1994.

$$Y_1 = Z_1 + Z_r \qquad r = 2,3.....n$$

Note that by definition the last value of Y (Y_n) will always be zero because Z has a mean of zero.

The adjusted range, R_n is the maximum minus the minimum value of the Y_r:

$$R_n = \max(Y_1, ..., Y_n) - \min(Y_1, ..., Y_n) \qquad ...(7)$$

The subscript n for R_n now signifies that this is the adjusted range for $X_1, X_2, ..., X_n$. Because Y has been adjusted to a mean of zero, the maximum value of Y will always be greater than or equal to zero, and the minimum will always be less than or equal to zero. Hence, the adjusted range R_n will always be non-negative. This adjusted range R_n is the distance that the system travels for time index n. If we set n = T, then we can apply the general Brownian motion equation $R = T^{0.50}$ where R is the distance covered and T is a time index. In fact, Einstein studied the properties of the Brownian motion and found that the distance R covered by a particle undergoing random collisions is directly proportional to the square-root of time T:

$$R = c^* T^{0.50}$$

where c is a constant which depends on the time-series. The generalization proposed by Hurst was: $R = c^* T^H$ where H is the Hurst exponent. If H=0.5, the behaviour of the time-series is similar to a random walk; if H<0.5, the time-series covers less "distance" than a random walk (i.e., if the time-series increases, it is more probable that then it will decrease, and *vice-versa*); if H>0.5, the time-series covers more "distance" than a random walk (if the time-series increases, it is more probable that it will continue to increase).

This equation applies only to time series in Brownian motion: that have mean zero and variance equal to one. To apply to any time series (like stock returns), we need to generalize the equation. Hurst found that the following was a more general form of equation:

$$R/\sigma = c * T^{H} \qquad \ldots(8)$$

The R/S (or R/σ) value is referred to as the rescaled range analysis because it has mean zero and is expressed in terms of local standard deviation. In general, the R/S value scales as we increase the time increment, T, by a "power–law "value equal to H, generally called the Hurst exponent. Hurst (1951) also gave a formula for estimating the value of H from a single R/S value (as quoted in Peters, 1996):

$$H = \log (R/S) / \log (T/2) \qquad \ldots(9)$$

where T = number of observations.

Hurst originally performed this operation so he could compare diverse phenomena. Rescaling would allow us to compare the period of time that may be many years apart. By rescaling the data to mean zero and a standard deviation of 1 allows us to compare diverse phenomena and time periods. If the system is independently distributed (random walk) then H = 0.50. Feder (1988)[1] shows that the empirical law tends to overstate H when it is greater than 0.70 and understate it when it is less than or equal to 0.40. However for short data sets, where regression is not possible, the empirical law can be used as a reasonable estimate.

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[1] J. Feder, Fractals, Plenum, *New York*, (1988).

There are 3 distinct classifications for the Hurst exponent (H):

1. $H = 0.5$

H equal to 0.5 denotes a random series.

2. $0 <= H < 0.5$

This type of system is anti persistent or mean reverting. That means if the system has been up in the previous period, it is likely to be down in the next period. The strength of anti-persistent behaviour will depend on how close H is to 0.

3. $0.5 < H < 1.0$

Here we have a persistent or trend reinforcing series. That means, if the series has been up (down) in the last period, hence the chances are that it will continue to be positive (negative) in the next period. Trends are apparent. The strength of the trend-reinforcing behaviour, or persistence, increases as H approaches 1. The closer H is to 0.5, the noisier it will be and the trend would be less defined. Persistent series are fractional Brownian motion, or biased random walks. The strength of the bias depends on how far H is above 0.50. The step by step guide to calculate R/S statistics is given in Appendix – I.

In summary, according to statistical mechanics, H should equal to 0.5 if the series is a random walk. In other words, the range of cumulative deviations should increase with the square root of time, T. When H is different from 0.5, the observations were not independent. Each observation carried a memory of all the events that preceded it. This memory is long term and it lasts for ever. More recent events have a greater impact than distant events, but there was still residual influence. On a broader scale, a system that

exhibits Hurst statistics is the possible result of a long stream of interconnected events. That implies what happens today influences the future. The impact of the present on the future can be expressed as a correlation given by the following relationship (Peter (1994) pg-64)[1]: $C = 2^{(2H-1)} - 1$ where C is the correlation measure and H being the Hurst coefficient. The above relationship implies that if H is closer to 0, the correlation moves towards -0.50, negative correlation implying frequent reversals or volatile than a random series. And as H increases towards 1, the correlation approaches 100%. The close H is to 0.5, the noisier it will be, and less defined its trend will be. Persistent time series are more interesting class because, as Hurst found, they are plentiful in nature.

V.2 Methodology used in the Study of Market Interlinkages

V.2.1 Johansen's Cointegration Methodology

Let $y_1, y_2, \ldots, y_k$ be a set of variables which we are interested in. Suppose that each variable is I(1) and therefore needs differencing in order for us to obtain a set of stationary random variables. If Y_t is the (k,1) vector with ith element equal to the value of y_i at time t then Y_t is a vector of I(1) variables. In general any (non-trivial) linear combination of the elements of this vector will be I(1). Thus

$$\beta' Y_t = \begin{bmatrix} \beta_1 \\ \beta_2 \\ . \\ . \\ \beta_k \end{bmatrix}' \begin{bmatrix} y_{1t} \\ y_{2t} \\ . \\ . \\ y_{kt} \end{bmatrix} = \sum_{i=1}^{i=k} \beta_i y_{it}$$

[1] Peters E., *Fractal Market Hypothesis: Applying Chaos Theory to Investment and Economics,* John Wiley, 1994.

(where we exclude the zero vector for β) is generally I(1). However, there may exist linear combination(s), resulting from particular β vectors, which are I(0).

We note the following points

(i) A β vector which leads to $\beta'Y_t$ being a stationary random variable will have at least two non-zero elements. This is because we exclude the zero vector, and any β vector with a single non-zero element will result in a non-zero multiple of a single element of Y_t, which must be I(1), (ii) If we find an β vector such that $\beta'Y_t$ is I(0) then any non-trivial scalar multiple of the β vector will also lead to a stationary linear combination of the elements of Y_t , (iii) We may be able to find a second linear combination of the elements of Y_t which is stationary and which is not related to the initial linear combination in the manner outlined in (ii). Thus the two β vectors which we find will be linearly independent. In fact we may find up to k-1 linearly independent β vectors (β_1, β_2 , ..., β_{k-1}, say) such that $(\beta_i)'Y_t$ is stationary (for i = 1,2,...,k-1). We can exclude the possibility of finding k linearly independent β vectors, each giving a stationary linear combination of the elements of Y_t, since this would imply that Y_t is a stationary vector.

In general suppose that β_i, i = 1,2,...r ($0<r\leq k-1$), are linearly independent vectors such that $(\beta_i)'Y_t$ is stationary. It follows that the (k,r) matrix

$$\beta = [\beta_1, \beta_2, \ldots, \beta_r] \tag{10}$$

will have full column rank and that the (r,1) vector

$$\beta' Y_t = \begin{bmatrix} \beta_1' Y_t \\ \beta_2' Y_t \\ . \\ . \\ \beta_r' Y_t \end{bmatrix}$$

will be a vector of stationary variables. For the moment we shall leave the question of how we might determine r to one side and take it as a known constant.

We now consider an important result concerning the representation of I(1) vectors which have stationary linear combinations, or which, to use the common terminology, cointegrate. The various columns of the β matrix in (10) are called cointegrating vectors. This will allow us to arrive at a natural interpretation of the cointegrating relationships. The result, the Granger Representation Theorem, establishes the existence of an ecm representation for such vectors which can be written in the form

$$A(L)\Delta Y_t = -\alpha\beta' Y_{t-1} + d(L)\varepsilon_t \qquad (11)$$

where ε_t is a (n,1) vector white noise process, such that $E(\varepsilon_t) = 0$ and

$$E\left(\varepsilon_t \varepsilon_s'\right) = \begin{matrix} G & t = s \\ 0 & t \neq s \end{matrix}$$

In (11) A(L) is a matrix polynomial in the lag operator and d(L) is a scalar polynomial in the lag operator. The first matrix in A(L) can be taken to be an identity matrix, so that the left-hand side in (11) can be written as

$$\Delta Y_t - A_1 \Delta Y_{t-1} - \ldots - A_p \Delta Y_{t-p}$$

assuming that A(L) is of finite order (p), and

$$d(L) = 1 + d_1 L + d_2 L^2 + d_3 L^3 + \ldots$$

where $d_1, d_2, \ldots$ are scalars. This polynomial in L is applied to each element of the ε_t vector in (11). If d(L) were 1 we would have $d(L)\varepsilon_t = \varepsilon_t$ in (11), a well behaved disturbance vector.

The matrix β in (11) has already been defined. The matrix α is (k,r) and is full column rank. In fact there is an element of arbitrariness about the β and α matrices in that we can replace β by $\beta\Lambda$, as long as Λ is a non-singular matrix of size (r,r), and α by $\alpha(\Lambda')^{-1}$ and leave the matrix multiplying Y_{t-1} in (11) unchanged. Replacing β by $\beta\Lambda$ involves replacing the original r columns of β with a set of r linearly independent linear combinations of those columns. This is permissible and implies (via $\alpha(\Delta')^{-1}$ replacing α) a replacing of the r original columns of α by r linearly independent linear combinations of those original columns. This observation will be important when we discuss hypothesis testing.

Equation (11), suggests that we should think of

$$\beta_i' Y_t = 0 \quad i = 1,2,\ldots,r \quad [\Leftrightarrow \beta' Y_t = 0]$$

as a set of r equilibrium conditions which guide the evolution of Y_t over time and

$$\mu_{it} = \beta_i' Y_t \quad i = 1,2,\ldots,r$$

as the set of r disequilibrium measures which, again as in the error correction mechanism as we initially discussed it, are required in order to obtain a convincing explanation of the change in the elements of Y_t over time. Each of these r disequilibrium measures will be involved in the explanation of each element of ΔY_t. In particular $\alpha\beta' Y_{t-1}$ will contribute

$$\alpha_{11}(\beta_1' Y_{t-1}) + \alpha_{12}(\beta_2' Y_{t-1}) + \ldots + \alpha_{1r}(\beta_r' Y_{t-1})$$

to the explanation of Δy_{1t}. In addition to this variable (11) implies that lagged differences in all the variables ($y_1, y_2, \ldots, y_k$) are required in explaining Δy_{1t}.

The linear combinations of Y_t which are stationary will have zero expected values and finite variances so that not only will zero be the expected value of these terms but it will also be meaningful in that there will be a non-trivial probability of being "close" to it. In contrast if the variance were to go to infinity as the sample size increased, as occurs with a non-stationary linear combination, then the expected value would become increasingly unimportant. If the equilibrium concept is to have any relevance for the specification of econometric models, the economy should appear to prefer a small value for $\beta' X_t$ rather than a large value and translate this into a requirement that the disequilibrium measures should be zero mean and stationary.

The argument above suggests the stationary linear combinations of the Y_t vector should be thought of as the equilibrium relationships amongst the variables because of the way in which they appear in the ecm representation. An alternative way of arriving at the same association between the stationary linear combinations and the equilibrium conditions connecting variables might be as follows: Suppose y_{1t} and y_{2t} are both I(1) variables and that they both increase with time. If they are cointegrated it follows that there exists some linear combination of these variables (y_{1t}-βy_{2t}, say) which is stationary. But this suggests that the two individual series must be related since there can be no tendency for the series y_{1t}-βy_{2t} to increase with time.

Cointegrating regression

Assume there is a single equilibrium relationship connecting the elements of Y_t (r=1). The disequilibrium measure is $\beta' Y_t = \mu_t$, a stationary random variable. Given that we can multiply β (a vector here) by an arbitrary non-zero constant we can take any element of it we choose to be 1 (we "normalise" β so that the chosen element is 1), and obtain something that looks like a regression model. Suppose we choose to think of the first element of β as 1 and write

$$\beta' Y_t = y_{1t} + \beta_2 y_{2t} + \dots + \beta_k y_{kt} = \mu_t$$

or

$$y_{1t} = - \beta_2 y_{2t} - \dots - \beta_k y_{kt} + \mu_t$$

This is certainly an equation we can consider estimating the parameters of by OLS, and is usually called the cointegrating regression. It has shown that the asymptotics for the OLS estimators in this equation are non-standard

Testing for cointegration

If we return to the case where r = 1 and regress y_1 on $y_2, \dots, y_k$ we can consider the question of deciding whether or not there is a cointegrating relationship between the variable. This involves examining the residuals from the cointegrating regression and in particular testing a null hypothesis that assumes the residual series has a unit root against an alternative that the series is stationary (so that the null hypothesis is non cointegration

and the alternative hypothesis is cointegration). We are thus asking the same type of question concerning the residuals from the cointegrating regression as we consider when we ask whether the basic variables ($y_1, y_2, \ldots, y_k$) have a unit root, so that Dickey Fuller and augmented Dickey Fuller tests seem obvious procedures to consider. Engle and Granger consider these tests amongst others.

Johansen procedure

The work we have considered above leaves two basic questions unanswered: How can we test hypotheses concerning the β matrix and is it possible to test hypotheses concerning the number of equilibrium relationships? An advantage of the Johansen approach is that it shows how such tests can be carried out.

The approach taken to estimation is described as Maximum Likelihood and is based on an assumption of multivariate normality. In the sense that the asymptotic arguments do not depend on normality it appears that the assumption is not particularly important but Phillips (1991) suggests it will be important as far as establishing optimality results is concerned. Johansen worked with the ecm directly and adopts a framework that is based on the assumption that introducing sufficient lags will allow for a well behaved disturbance term. ΔY_t is assumed to be an I(1) vector and the initial specification of the process involves writing

$$\Delta Y_t = \iota + \Gamma_1 \Delta Y_{t-1} + \ldots + \Gamma_{p-1} \Delta Y_{t-p-1} + \Gamma_p Y_{t-p} + \varepsilon_t \qquad (12)$$

where the (k,1) vectors ε_t are assumed to be independently distributed as $N(0,\Lambda)$ The existence of r equilibrium relationships allows us to write

$\Gamma_p = -\alpha\beta'$

and we need to consider the estimation of the following parameter matrices

$\iota \quad \Gamma_1 \ldots \Gamma_{p-1} \quad \alpha \quad \beta \quad \Lambda$

The vector ι is a vector of intercepts. Its inclusion implies that there will be drift terms (π_i, i=1,2,...,k , below) when one rearranges (12) into a form that resembles the relationships considered in unit root testing

$$y_{it} = \pi_i + y_{i,t-1} + e_{it} \quad , \quad i = 1,2,\ldots,k$$

or, collectively

$$Y_t = \pi + Y_{t-1} + e_t$$

Johansen shows how the π vector is related to ι. It is of interest to consider when π is a zero vector, so that there are no drift terms allowed in the implied expression for Y_t. It turns out that $\pi = 0$ is equivalent to ι being in the range space of the α matrix (i.e. $\iota = \alpha v$, for some vector v) and if we impose this in estimation we can combine the ι and A_pX_{t-p} terms as follows

$$\iota + \Gamma_p Y_{t-p} = \alpha v - \alpha\beta' Y_{t-p} = \alpha\left[v, -\beta'\right]\begin{bmatrix} 1 \\ Y_{t-p} \end{bmatrix}$$

which has the implication that the equilibrium relationships (at time t-p) are given by

$$\left[v, -\beta'\right]\begin{bmatrix} 1 \\ Y_{t-p} \end{bmatrix} = v - \beta' Y_{t-p} = 0$$

and thus an intercept is included in these relationships. The restriction that $\iota = \gamma v$ (Π=0) might be imposed in estimation if no drift terms are found in the unit root tests for the individual variables.

As far as estimation is concerned it is straightforward to obtain expressions for the ML estimators of $\Gamma_1, \Gamma_2, \ldots, \Gamma_{p-1}$, α, ι and Λ in terms of an ML estimator of β. Johansen also shows how to obtain an estimate of β which is subject to a quite natural mathematical normalisation. The procedure is based on a given value for r, but by considering the maximised log-likelihood function (which will depend on the value of r chosen) it becomes possible to test hypotheses concerning the value of this parameter.

There are various types of hypothesis that can be tested involving the cointegrating vectors. The hypotheses can be tested using a likelihood ratio test (comparing restricted and unrestricted estimations) and it turns out that the limiting distribution under the null hypothesis is chi-square, as in a conventional asymptotic analysis. It will be useful to have an example in mind, so assume there are n=4 variables and r=3 equilibrium relationships. We can thus write the β matrix in the form

$$\beta = \begin{vmatrix} \beta 1,1 & \beta 2,1 & \beta 3,1 \\ \beta 1,2 & \beta 2,2 & \beta 3,2 \\ \beta 1,3 & \beta 2,3 & \beta 3,3 \\ \beta 1,4 & \beta 2,4 & \beta 3,4 \end{vmatrix}$$

so that the three equilibrium relationships are given by

$$\beta_{1,1}y_{1t}+\beta_{1,2}y_{2t}+\ \beta_{1,3}y_{3t}+\beta_{1,4}y_{4t}$$
$$=\beta_{2,1}y_{1t}+\beta_{2,2}y_{2t}+\ \beta_{2,3}y_{3t}+\beta_{2,4}y_{4t}$$
$$=\beta_{3,1}y_{1t}+\beta_{3,2}y_{2t}+\ \beta_{3,3}y_{3t}+\beta_{3,4}y_{4t}=0$$

One approach to hypothesis testing involves imposing the same linear restrictions on each cointegrating vector. For example, suppose that we wish to evaluate the validity of a unit coefficient for the variable y_2 in a relationship that is normalised so that y_1 appears with a coefficient of 1, so that we wish to consider the acceptability of an equilibrium relationship of the form

$$y_{it}=\beta y_{2t}+\chi y_{3t}+\delta y_{4t} \qquad \text{....(13)}$$

In fact it will always be possible to select a linear combination of the three columns of the β matrix which gives an equilibrium relationship of this type, but what we might wish to test is whether all equilibrium relationships are of this type. This requires that we impose a suitable restriction on each of the three cointegrating vectors. The restriction will set the coefficient multiplying y_2 equal to the negative of the coefficient multiplying y_1. This restriction imposed on each cointegrating vector gives a total of three restrictions,

$$\beta_{1,1}=-\beta_{1,2}\quad,\quad \beta_{2,1}=-\beta_{2,2}\quad \beta_{3,1}=-\beta_{3,2}$$

and these restrictions will imply that any cointegrating vector has the property that the coefficient multiplying y_1 is the negative of the coefficient multiplying y_2, so that we get all cointegrating relationships being of the form in (13) with β=1 when we normalise by setting the coefficient multiplying y_1 to one.

The likelihood ratio test, since the same restriction is imposed on each of the three cointegrating vectors, will have three degrees of freedom in this case. In general if a set of q linear restrictions are imposed on each of the r cointegrating vectors, so as to ensure any cointegrating vector satisfies the same q linear restrictions, then the likelihood ratio test will have qr degrees of freedom.

The above approach to hypothesis testing might be useful if we have no idea what the equilibrium relationships might be (in which case it is not obvious where hypotheses that we wish to test might come from). In practice, however, one might have some idea concerning the nature of the equilibrium relationships. Thus Johansen and Julieus (1990)[1] find evidence that suggests the presence of three equilibrium relationships in a four variable data set where the variables are a money stock variable, an income variable, and two interest rates (m,y,i_1,i_2). We might speculate that these variables will be related in equilibrium by (i) a demand for money function, $m=f(y,i_1,i_2)$, (ii) an interest rate condition, $i_1 = i_2$ and (iii) an income determination equation, $y=g(m)$. Assuming relationships (i) and (iii) are linear we can write

$$m = \beta y + \chi i_1 + \delta i_2 \qquad \text{(i)}$$

where we might wish to test whether or not β can be set at 1,

$$i_1 = i_2 \qquad \text{(ii)}$$

and

$$y=\theta m \qquad \text{(iii)}$$

[1] Johansen, S., Julieus, K., 1990. Maximum Likelihood Estimation and Inference on Cointegration – with Application to the Demand for Money. Oxford Bulletin of Economics and Statistics 52, 169-210.

If this speculation happened to be true then we should be able to find an β matrix of the form

$$\beta = \begin{array}{c} m \\ y \\ i_1 \\ i_2 \end{array} \begin{bmatrix} \alpha_{11} & 0 & \alpha_{31} \\ \alpha_{12} & 0 & \alpha_{32} \\ \alpha_{13} & \alpha_{23} & 0 \\ \alpha_{14} & -\alpha_{23} & 0 \end{bmatrix}$$

where the equilibrium relationships are fed into the columns of β in an unnormalised form. We want to be able to test hypotheses concerning the estimated β matrix that allow us to assess the validity of the above speculation. Notice that if there is a unit coefficient attached to y when the money demand function (in the first column of β) is normalised so that m has a coefficient of 1, then two of three cointegrating vectors in the above matrix will satisfy the restriction we previously considered imposing on all three cointegrating vectors.

Testing for the existence of potential cointegrating relationships among the variables in X_t involves testing for statistically significant eigenvalues (λ_i). The eigenvector (v_i) corresponding to the statistically significant eigenvalues (λ_i) are the coefficient of the variables in the cointegrating relationship. Johansen (1988)[1] suggests the following two likelihood ratio tests, depending on the null and alternative hypotheses considered.

Trace Test:

[1] Johansen, S. (1988), Statistical analysis of cointegrating vectors, Journal of Economic Dynamics and Control 12, 231-254.

Null hypthesis (Ho): There are at most p cointegrating relations ($r \leq p$)

Alternative hypothesis (H1): $r = n$

Test Statistic:

$$\lambda_{tr} = - T \sum \ln (1 - \hat{\lambda}_i) \qquad \{15\}$$

The empirical distributions of the test have been calculated and reported in Johansen and Juselius (1990)[1] for values of (n-r) from 1 to 5. The test is performed sequentially with r = 0,1,2,.....,n. If the null hypothesis of r = 0 at the most is accepted, then testing stops and one concludes that there is no cointegration. Otherwise, the testing procedure continues until for some value p we accept the null hypothesis of r = p at the most. This means there are p cointegrating vectors.

Maximum Eigenvalue Test:

Null hypothesis (Ho): there are at most p cointegrating relations ($r \leq p$)

Alternative hypothesis (Ha): $r = p + 1$

Test Statistic:[2]

$$\lambda_{max} = - T \ln (1 - \hat{\lambda}_{p+1}) \qquad \{16\}$$

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[1] S. Johansen and K. Juselius, "Maximum Likelihood Estimation and Inference on Cointegration - with Applications to the Demand for Money", OXFORD BULLETIN OF ECONOMICS AND STATISTICS, Vol 52, 1990, pp. 169-210.

[2] S. Johansen and K. Juselius, "Maximum Likelihood Estimation and Inference on Cointegration - with Applications to the Demand for Money", OXFORD BULLETIN OF ECONOMICS AND STATISTICS, Vol 52, 1990, pp. 169-210.

the testing procedure is similar to the one explained above for the trace test, and the critical values could be found in Johansen and Juselius (1990)[1].

Between Johansen's two likelihood ratio tests for cointegration, the trace test shows more robustness to both skewness and kurtosis (i.e., normality) in residuals than the maximum eigenvalue test (Cheung and Lai 1993)[2]: therefore we have employed the trace test to perform the cointegration tests. However, we have also shown the results of the Maxeigen value test wherever it was relevant.

Vector Autoregressive Analysis

Two decades ago, Sims (1980)[3] provided a new macroeconometric a simple and parsimonious framework: vector autoregressions (VARs). A univariate autoregression is a single equation; single variable linear model in which the current value of a variable is explained by its own lagged values. A VAR is a *n*-equation, *n*-variable linear model in which each variable is in turn explained by its own lagged values, plus current and past values of remaining *n-1* variables. This simple framework provides a systematic way to capture dynamics in multiple time series. The VAR is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The mathematical representation of a VAR is

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[1] Johansen, Soren and Katarina Juselius, (1990), *Maximum Likelihood Estimation and Inference on Cointegration - with Applications to the Demand for Money*", Oxford Bulletin of Economics and Statistics, 52, pp.169-210.

[2] Cheung, Y. and K.S. Lai (1993), "Do Gold Market Returns Have Long Memory?" -*Financial Review*, 28, 2, 181-202.

[3] Sims, C.A. (1980): *Macroeconomics and reality*. Econometrica 48, 1-48

$$Y_t = A_1 Y_{t-1} + ... + A_p Y_{t-p} + BX_t + \varepsilon_t \qquad (17)$$

where Y_t is a k vector of endogenous variables, X_t is a d vector of exogenous variables, $A_1....A_p$ and B matrices of coefficients to be estimated, and ε_t is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right hand side variables.

The VAR analysis enables us to analyze the variance decomposition of the forecast errors, providing insight information on unexpected variation in one variable with shocks from the other variables in the system. We can use VAR to decompose forecast error variance to measure the effect of each variable on itself and the other variables over different time horizons and also to provide information on dynamic responses to shocks in the system.

V.2.2 Granger Causality Test

The dynamic linkage may simply be examined using the concept of Granger's (1969) causality. Formally, a time series X_t Granger-causes another time series Y_t if series Y_t can be predicted better by using past values of (X_t, Y_t) than by using only the historical values of Y_t. In other words, X_t fails to Granger-cause Y_t if for all $m > 0$ the conditional probability distribution of Y_{t+m} given $(Y_t, Y_{t-1},...)$ is the same as the conditional probability distribution of Y_{t+m} given both $(Y_t, Y_{t-1}, ...)$ and $(X_t, X_{t-1}, ...)$. That is, X_t does not Granger-cause Y_t if

$$\Pr(Y_{t+m} \mid \Psi_t) = \Pr(Y_{t+m} \mid \Omega_t) \qquad (18)$$

where $Pr(\bullet)$ denotes conditional probability, ψ_t is the information set at time t on past values of Y_t, and Ω_t is the information set containing values of both X_t and Y_t upto time point t.

Testing causal relations between two stationary series X_t and Y_t can be based on the following bivariate autoregression (Granger, 1969)[1]

$$Y_t = \alpha_0 + \sum_{k=1}^{p} a_k Y_{t-k} + \sum_{k=1}^{p} \beta_k X_{t-k} + u_t \qquad (19)$$

$$X_t = \varphi_0 + \sum_{k=1}^{p} \varphi_k Y_{t-k} + \sum_{k=1}^{p} \Phi_k X_{t-k} + v_t \qquad (20)$$

where p is a suitably chosen positive integer; α_k's and β_k's, k = 0,1, ...,p are constants; and u_t and v_t usual disturbance terms with zero means and finite variances. The null hypothesis that X_t does not Granger-cause Y_t is rejected if the β_k's, k>0 in equation (2) are jointly significantly different from zero using a standard joint test (e.g., an F test). Similarly, Y_t Granger-causes X_t if the ϕ_k's, k>0 coefficients in equation (3) are jointly different from zero. A bi-directional causality (or feedback) relation exists if both β_k's and ϕ_k's, k>0 are jointly different from zero.

It may be mentioned that the above test is applicable to stationary series. In reality, however, underlying series may be non-stationary. In such cases, one has to transformed

[1] Granger, C. W. J. (1969), "Investigating Causal Relations by Econometrics Models and Cross Spectral Methods," *Econometrica* 37, 424-438.

the original series into stationary series and causality tests would be performed based on transformed-stationary series. A special class of non-stationary process is the I(1) process (i.e. the process possessing a unit root). An I(1) process may be transformed to a stationary one by taking first order differencing. Thus, while dealing with two I(1) process for causality, equations (2) and (3) must be expressed in terms of differenced-series. However, if underlying I(1) processes are cointegrated, the specifications so obtained must be modified by inserting the lagged-value of the cointegration relation (i.e. error-correction term) as an additional explanatory variable. In other words, equations (2) and (3) should be modified as

$$\Delta Y_t = \alpha_0 + \sum_{k=1}^{p} \alpha_k \Delta Y_{t-k} + \sum_{k=1}^{p} \beta_k \Delta X_{t-k} + \delta \; ECT_{t-1} + u_t \qquad (21)$$

$$\Delta X_t = \phi_0 + \sum_{k=1}^{p} \phi_k \Delta Y_{t-k} + \sum_{k=1}^{p} \Phi_k \Delta X_{t-k} + \eta \; ECT_{t-1} + v_t \qquad (22)$$

where Δ is the difference operator and ECT_{t-1} represents an error correction term derived from the long-run cointegrating relationship between the I(1) processes X_t and Y_t. This term can be estimated by using the residual from a cointegrating regression.

V.2.3 Geweke Feedback

In many empirical studies (for instance, Nath and Samanta, 2003)[1] p and q are assumed to be equal and estimation is carried out in single-equation framework (i.e. each equation is estimated separately). It may be noted that such an estimation strategy inherently

[1] Nath G C, Reddy Y V (2003), "Long Memory in Rupee-Dollar Exchange Rate – An Empirical Study" ICFAI Journal of Applied Finance, May 2003

assumes that residuals u_t and v_t are uncorrelated (and hence X_t and Y_t are not contemporaneously related). In this simple case, the null hypothesis H_{02} that X_t does not Granger-cause Y_t (or in other words X_t does not lead Y_t) is accepted if $(\beta_1, \beta_2, \ldots, \beta_p) = (0, 0, \ldots, 0)$. The F-statistics can be used to test this hypothesis. Similarly, the null hypothesis H_{03} that Y_t does not Granger-cause X_t if the γ_k's, k>0 in equation (2) are all statistically zero. But the residual series may, in general, be correlated and estimation of these equations, therefore, needs to be performed simultaneously. In so doing, when p=q, one may estimate Eqs. (1)-(2) using ordinary least-square (OLS) technique in Vector Auto-Regression (VAR) framework. Thus, dynamic relationship between X_t and Y_t can be modelled under the general set-up

$$\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} \alpha_0 \\ \gamma_0 \end{pmatrix} + \sum_{k=1}^{p} \begin{bmatrix} \alpha_k & \beta_k \\ \gamma_k & \delta_k \end{bmatrix} \begin{pmatrix} Y_{t-k} \\ X_{t-k} \end{pmatrix} + \begin{pmatrix} u_t \\ v_t \end{pmatrix} \qquad \text{..... (23)}$$

$$\text{with } Cov\begin{pmatrix} u_t \\ v_t \end{pmatrix} = \begin{bmatrix} \sigma_u^2 & \sigma_{uv} \\ \sigma_{uv} & \sigma_v^2 \end{bmatrix}$$

Relationship between contemporaneous X_t and Y_t may be examined based on correlation coefficient between u_t and v_t, which is asymptotically normally distributed with mean zero and variance 1/n (n being the number of observations used for estimating the correlation coefficient) under the null hypothesis H_{01}. The correlation coefficient is estimated as $r_{uv} = \hat{\sigma}_{uv} / (\hat{\sigma}_u * \hat{\sigma}_v)$, where the symbol ^ is used to indicate an estimated value. As r_{uv} is asymptotically N(0,1/n) under H_{01} the statistics (nr_{uv}^2) follows a χ_1^2 distribution under H_{01}. Null hypotheses H_{02} and H_{03} can be tested based on, say block F-

tests (which examine the significance of the block of lags associated with each of the variables in each equation). But the block F-statistics is useful only to examine whether the null hypothesis would be accepted or not. It cannot compare the test statistics across different periods to reveal how the extent of causal influence varies over time for a pair of variables because the distribution of test statistics under alternative hypothesis is not known. In this context, Geweke's(1978, 1982)[1] feedback measures are particularly important (see Bracker, et al., 1999[2] for a discussion and application of these measures for assessing the evolution in international stock market integration).

In order to estimate Geweke's feedback measures, Eqs. above need to be re rewritten in a more general set-up as follows:

$$Y_t = \alpha_0 + \sum_{k=1}^{p} a_k Y_{t-k} + \sum_{k=1}^{q} \beta_k X_{t-k} + u_t \qquad \text{..... (24)}$$

$$X_t = \gamma_0 + \sum_{k=1}^{q} \gamma_k Y_{t-k} + \sum_{k=1}^{p} \delta_k X_{t-k} + v_t \qquad \text{..... (25)}$$

with $Cov\begin{pmatrix} u_t \\ v_t \end{pmatrix} = \begin{bmatrix} \sigma_u^2 & \sigma_{uv} \\ \sigma_{uv} & \sigma_v^2 \end{bmatrix} = \Sigma$, say.

[1] Geweke, J. (1978), "Testing the Exogeneity Specification in the Complete Dynamic Simultaneous Equations Model", *Journal of Econometrics*, Vol. 6, pp. 163-85 and Geweke, J. (1982), "Measurement of Linear Dependence and Feedback Between Multiple Time Series", *Journal of American Statistical Association*, Vol. 77, pp. 304-13.

[2] Bracker, Kevin; Diane Scott Docking and Paul D. Koch (1999), "Economic Determinants of Evolution in International Stock Market Integration", *Journal of Empirical Finance*, Vol. 6, No. 1, pp. 1-27.

where p, q are suitably chosen positive integers; ($\alpha_0, \alpha_1, \ldots, \alpha_p$), ($\beta_1, \beta_2, \ldots, \beta_q$), ($\gamma_0, \gamma_1, \ldots, \gamma_q$) and ($\delta_1, \delta_2, \ldots, \delta_p$) are constants; and u_t and v_t are usual disturbances and Cov(.) represents variance-covariance matrix.

Under the joint null hypothesis H_{04}: H_{01}, H_{02} and H_{03}, the system represented by Eqs. (24)-(25) becomes:

$$Y_t = \alpha_0' + \sum_{k=1}^{p} a_k' Y_{t-k} + u_t', \quad Var(u_t') = \sigma_1^2, \qquad \text{..... (26)}$$

$$X_t = \gamma_0' + \sum_{k=1}^{p} \delta_k' X_{t-k} + v_t', \quad Var(v_t') = \sigma_2^2 \quad with\ Cov(u_t', v_t') = 0 \qquad \text{..... (27)}$$

In above, Eqs. (24) and (25) represent a Near-VAR system and may be estimated as a system of seemingly unrelated regressions (see Doan, 1990; Filardo, 1997; Judge et al. 1988). However, Eqs. (26) and (27) can be estimated with OLS. Based on these estimated equations, Geweke (1982)[1] derives following three feedback measures

(i) $$n\,\hat{F}_{X.Y} = n \ln\left[\frac{\hat{\sigma}_u^2 * \hat{\sigma}_v^2}{\det(\hat{\Sigma})}\right] \xrightarrow{a} \chi_1^2 \quad under\ H_{01}$$

(ii) $$n\,\hat{F}_{X\to Y} = n \ln\left[\frac{\hat{\sigma}_u^2}{\sigma_1^2}\right] \xrightarrow{a} \chi_q^2 \quad under\ H_{02}$$

(iii) $$n\,\hat{F}_{Y\to X} = n \ln\left[\frac{\hat{\sigma}_v^2}{\sigma_2^2}\right] \xrightarrow{a} \chi_q^2 \quad under\ H_{03}$$

[1] Geweke, J. (1982), "Measurement of Linear Dependence and Feedback Between Multiple Time Series", *Journal of American Statistical Association*, Vol. 77, pp. 304-13.

where n is the sample size, symbol ^ is used to indicate estimates (for example, in above $\hat{\Sigma}$ indicates estimate of Σ), det($\hat{\Sigma}$) indicates determinant of $\hat{\Sigma}$, and the symbol $\xrightarrow{a}$ indicates asymptotic distribution.

For estimating above feedback measures, choice of p and q is very crucial. As argues by Geweke (1978)[1], a larger value of p in each equation helps to ensure that errors are not autocorrelated, while a smaller value of q increases the power of the tests. In their empirical analysis based on daily data, Bracker et al. (1999)[2] set p=10 and q=5.

The advantage of using Geweke (1982)[3] measures of feedback over traditional F-statistics (for testing null hypotheses H_{01} through H_{03}) is that asymptotic distribution of each Geweke feedback measure is also known under the alternative hypothesis (to H_{01} through H_{03}) that feedback is present. Thus Geweke feedback measures represent cardinal measures of the degree of dependence present in given sample (Geweke, 1982[4]; Bracker et al., 1999[5]). Observing this advantage, Bracker et al. (1999) compare unidirectional feedback measures (i.e. $n\,\hat{F}_{X\to Y}$ and $n\,\hat{F}_{Y\to X}$) for different yearly samples to observe how a leader/follower relationship between pairs of international stock markets changes over

[1] Geweke, J. (1978), "Testing the Exogeneity Specification in the Complete Dynamic Simultaneous Equations Model", *Journal of Econometrics*, Vol. 6, pp. 163-85.
[2] Bracker, D.S. Docking, P.D. Koch (1999) .Economic Determinants of Evolution in International Stock Market Integration. *Journal of Empirical Finance*, **6**, 1-27.
[3] Geweke, J. (1982), "Measurement of Linear Dependence and Feedback Between Multiple Time Series", *Journal of American Statistical Association*, Vol. 77, pp. 304-13.
[4] Geweke, J. (1982), "Measurement of Linear Dependence and Feedback Between Multiple Time Series", *Journal of American Statistical Association*, Vol. 77, pp. 304-13.
[5] Bracker, D.S. Docking, P.D. Koch (1999) .Economic Determinants of Evolution in International Stock Market Integration. *Journal of Empirical Finance*, **6**, 1-27.

time. In our study, we also use Geweke feedback measures to assess the extent of market integration in different years.

CHAPTER VI

VI.0 DATA AND DATA CHARACTERISTICS

VI.1. STOCK MARKET DATA

For the study we have used the stock market data for the period from July 1990 to September 2003 - about 14 years data. The procedures for collecting and transforming data affect any serious statistical modeling. The daily closing values of the index S&P CNX NIFTY for the period from July 1990 to September 2003 is considered for the study. From July 1990 to October 1995, the S&P CNX NIFTY values used here is the simulated values maintained by IISL (a subsidiary of NSEIL which looks into the Index products of NSEIL). From November 1995 to September 2003, the actual close values of S&P CNX NIFTY have been taken for the purpose of the study. The index consists of underlying stocks whose closing prices determine the closing values of S&P CNX NIFTY. S&P CNX Nifty is a well diversified 50 stock index accounting for 23 sectors of the economy. It is used for a variety of purposes such as benchmarking fund portfolios, index based derivatives and index funds. S&P CNX Nifty is owned and managed by India Index Services and Products Ltd. (IISL), which is a joint venture between NSE and CRISIL. IISL is India's first specialised company focussed upon the index as a core product. IISL have a consulting and licensing agreement with Standard & Poor's (S&P), who are world leaders in index services. The total traded value of all Nifty stocks is approximately 70% of the traded value of all stocks on the NSE, Nifty stocks represent about 59% of the total market capitalization, Impact cost of the S&P CNX Nifty for a

portfolio size of Rs.5 million is 0.10%, S&P CNX Nifty is professionally maintained and is ideal for derivatives trading. S&P CNX Nifty is computed using market capitalisation weighted method, wherein the level of the index reflects the total market value of all the stocks in the index relative to a particular base period. The method also takes into account constituent changes in the index and importantly corporate actions such as stock splits, rights, etc without affecting the index value. The base period selected for S&P CNX Nifty index is the close of prices on November 3, 1995, which marks the completion of one year of operations of NSE's Capital Market Segment. The base value of the index has been set at 1000 and a base capital of Rs.2.06 trillion. The constituents and the criteria for the selection judge the effectiveness of the index. S&P CNX Nifty is unique in this respect. Selection of the index set is based on 3 criteria: (1) Liquidity (Impact Cost) For inclusion in the index, the security should have traded at an average impact cost of 0.75% or less during the last six months for 90% of the observations (instead of the earlier criteria of 1.5% or less during the last one year for 85% of the observations). (2) Market Capitalisation: Companies eligible for inclusion in Nifty must have a six monthly average market capitalisation of Rs.500crores or more during the last six months. And (3) Floating Stock: Companies eligible for inclusion in S&P CNX Nifty should have at least 12% floating stock. For this purpose, floating stock shall mean stocks which are not held by the promoters and associated entities (where identifiable) of such companies. The Table VI-0 gives the present composition of S&P CNX NIFTY as of November 2003.

Table VI-0: S&P CNX NIFTY COMPOSITION

Sr. No.	Industry	Market Capitalisation as on 28-Nov-2003 (Rs.crores)	Weightage (%)
1	**Aluminium**		
	Hindalco Industries Ltd.	11459	2.1
	National Aluminium Company Ltd.	9887	1.81
	Industry Total	21346	3.91
2	**Automohiles - 2 and 3 wheelers**		
	Bajaj Auto Ltd.	9935	1.82
	Hero Honda Motors Ltd.	7479	1.37
	Industry Total	17414	3.19
3	**Automobile - 4 wheelers**		
	Mahindra and Mahindra Ltd	4092	0.75
	Tata Engineering and Locomotive Co. Ltd.	13098	2.4
	Industry Total	17190	3.15
4	**Banks**		
	HDFC Bank Ltd	8591	1.58
	ICICI Bank Ltd.	15357	2.82
	Oriental Bank of Commerce	4470	0.82
	State Bank of India	24752	4.54
	Industry Total	53170	9.76
5	**Cement & Cement Products**		
	Associated Cement Co. Ltd.	3872	0.71
	Grasim Industries Ltd.	8243	1.51
	Gujarat Ambuja Cements Ltd.	4354	0.8
	Industry Total	16469	3.02
6	**Cigarettes**		
	ITC Ltd.	21224	3.9
	Industry Total	21224	3.9
7	**Computers - Software**		
	Digital Globalsoft Ltd.	2169	0.4
	Infosys Technologies Ltd.	32634	5.99
	HCL Technologies Ltd.	7960	1.46
	NIIT Ltd.	835	0.15
	Satyam Computer Services Ltd.	10375	1.9
	Wipro Ltd.	35768	6.57
	Industry Total	89741	16.47
8	**Diversified**		
	Larsen & Toubro Ltd.	9969	1.83
	Hindustan Lever Ltd.	39237	7.2
	Tata Chemicals Ltd.	2298	0.42

	Industry Total	51504	9.45
9	**Electrical Equipment**		
	Asea Brown Boveri Ltd	2248	0.41
	Bharat Heavy Electricals Ltd.	10884	2
	Industry Total	13133	2.41
10	**Finance - Housing**		
	Housing Development Finance Corporation Ltd.	13571	2.49
	Industry Total	13571	2.49
11	**Foods and Food Processing**		
	Britannia Industries Ltd.	1335	0.25
	GlaxoSmithkline Consumer Healthcare Ltd.	1417	0.26
	Industry Total	2752	0.51
12	**Gas**		
	Gas Authority of India Ltd.	14824	2.72
	Industry Total	14824	2.72
13	**Hotels**		
	Indian Hotels Co. Ltd.	1710	0.31
	Industry Total	1710	0.31
14	**Media & Entertainment**		
	Zee Telefilms Ltd.	5356	0.98
	Industry Total	5356	0.98
15	**Personal Care**		
	Colgate Palmolive (India) Ltd.	1892	0.35
	Dabur India Ltd.	1940	0.36
	Industry Total	3832	0.71
16	**Petrochemicals**		
	Indian Petrochemicals Corp. Ltd.	5296	0.97
	Reliance Industries Ltd.	68011	12.48
	Industry Total	73306	13.45
17	**Pharmaceuticals**		
	Cipla Ltd.	7213	1.32
	Dr. Reddy's Laboratories Ltd.	9723	1.78
	Glaxosmithkline Pharmaceuticals Ltd.	3658	0.67
	Ranbaxy Laboratories Ltd.	18966	3.48
	Sun Pharmaceutical Industries Ltd.	5557	1.02
	Industry Total	45117	8.27
18	**Power**		
	BSES Ltd.	6276	1.15
	Tata Power Co. Ltd.	5309	0.97
	Industry Total	11585	2.12
19	**Refineries**		
	Bharat Petroleum Corporation Ltd.	10745	1.97
	Hindustan Petroleum Corporation Ltd.	12445	2.28
	Industry Total	23189	4.25
20	**Shipping**		

	Shipping Corporation of India Ltd.	4726	0.87
	Industry Total	4726	0.87
21	**Steel & Steel Products**		
	Steel Authority of India Ltd.	17389	3.19
	Tata Iron and Steel Co. Ltd.	13317	2.44
	Industry Total	30706	5.63
22	**Tea & Coffee**		
	Tata Tea Ltd.	1456	0.27
	Industry Total	1456	0.27
23	**Telecommunication - Services**		
	Mahanagar Telephone Nigam Ltd.	7582	1.39
	Videsh Sanchar Nigam Ltd.	3853	0.71
	Industry Total	11435	2.1
	Total	**544,756**	**100%**

Source: NSEIL

But using daily prices often encounters one problem; the limits for daily price changes, based on the closing price of the previous day. Therefore the series are truncated and that might distort non-linear modeling. Due to earlier provision of price bands, many times the stocks hit a circuit breaker and hence the series gets distorted. What we have today is not only the price bands on most of the individual stocks, but there is a band for the index. However, the analysis of daily price data is necessary to understand any findings. Daily logarithmic returns have been calculated and analysis has been carried out for various time lags like 2 weeks, 1 month, 3 months, 6 months, 9 months, 1 year, 2 years and 5 years to understand to what extent, the long memory process exists, if it exists at all.

VI.1.1.Descriptive Statistics

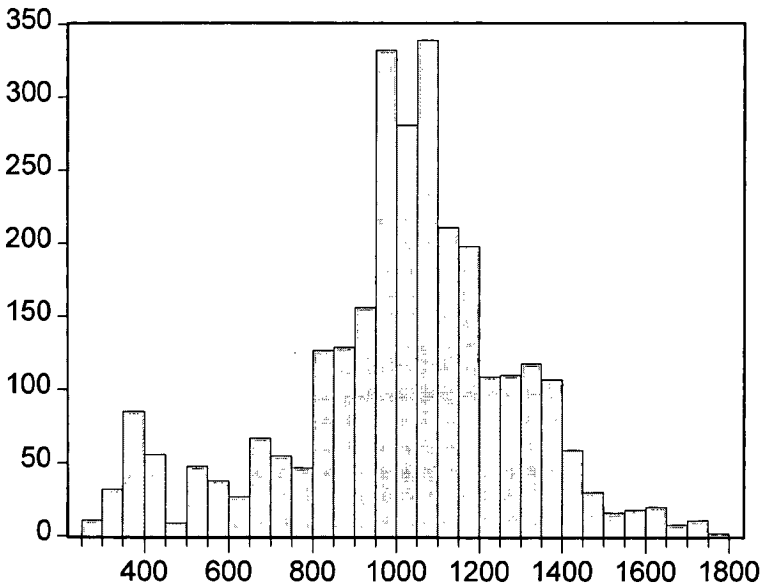
The Table-VI-1 summarises the findings for the dataset that was divided into various time buckets according to their relevance in order to understand the structural changes happening in India due to economic reforms since 1991: The daily returns were

calculated using the equation 1. We have more than 2800 data points that is quite large for any analysis of time series behaviour. We have calculated logarithmic returns of the closing values of index.

$$R_t = LN(P_t / P_{t-1}) * 100$$

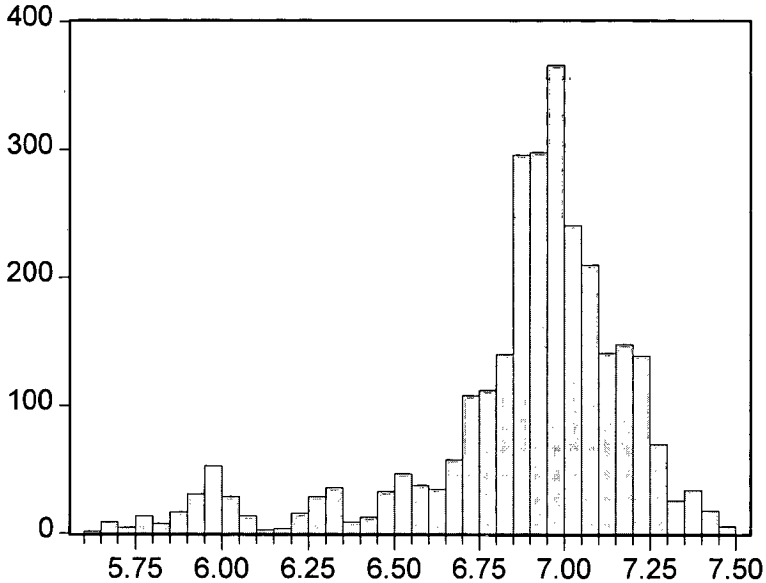
where R_t is the return of day *t*, P_t is the price of the asset in day t and P_{t-1} is the price of the asset in day *t-1*. The histograms of S&P CNX NIFTY values, log values of S&P CNX NIFTY as well as the logarithmic returns of S&P CNX NIFTY has been plotted in Chart VI-1, VI-2, VI-3.

Chart VI-1: Histogram of S&P CNX NIFTY



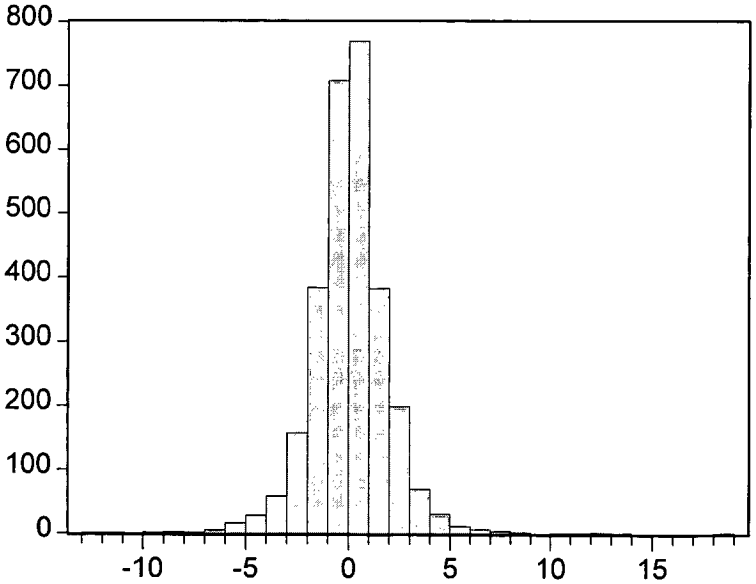
Series: NIFTY	
Sample 1 2856	
Observations 2856	
Mean	1013.238
Median	1036.390
Maximum	1756.000
Minimum	279.0200
Std. Dev.	273.9803
Skewness	-0.490615
Kurtosis	3.442019
Jarque-Bera	137.8252
Probability	0.000000

Chart VI-2: Histogram of Log Values of S&P CNX NIFTY



Series: LNIFTY	
Sample 1 2856	
Observations 2856	
Mean	6.873710
Median	6.943500
Maximum	7.470800
Minimum	5.631300
Std. Dev.	0.332572
Skewness	-1.512874
Kurtosis	5.336670
Jarque-Bera	1739.207
Probability	0.000000

Chart VI-3: Histogram of Log returns of S&P CNX NIFTY



Series: DLNIFTY	
Sample 1 2856	
Observations 2856	
Mean	0.061233
Median	0.045652
Maximum	18.90058
Minimum	-12.52194
Std. Dev.	1.941445
Skewness	0.394883
Kurtosis	11.65810
Jarque-Bera	8994.776
Probability	0.000000

The daily returns have been plotted in Chart–VI-3 that looks very close to a normal distribution but surely not a normal distribution. The Kurtosis is higher than 3 indicating

excess kurtosis and the returns are positively skewed. The Jarque-Bera statistics surely rejects normality condition. We have plotted the S&P NIFTY close values (Chart VI-4), their log values (Chart-VI-5) as well as their return series (Chart-VI-6) against the backdrop of the normal distribution.

Chart-VI-4 : Normal Distribution plot of S&P NIFTY

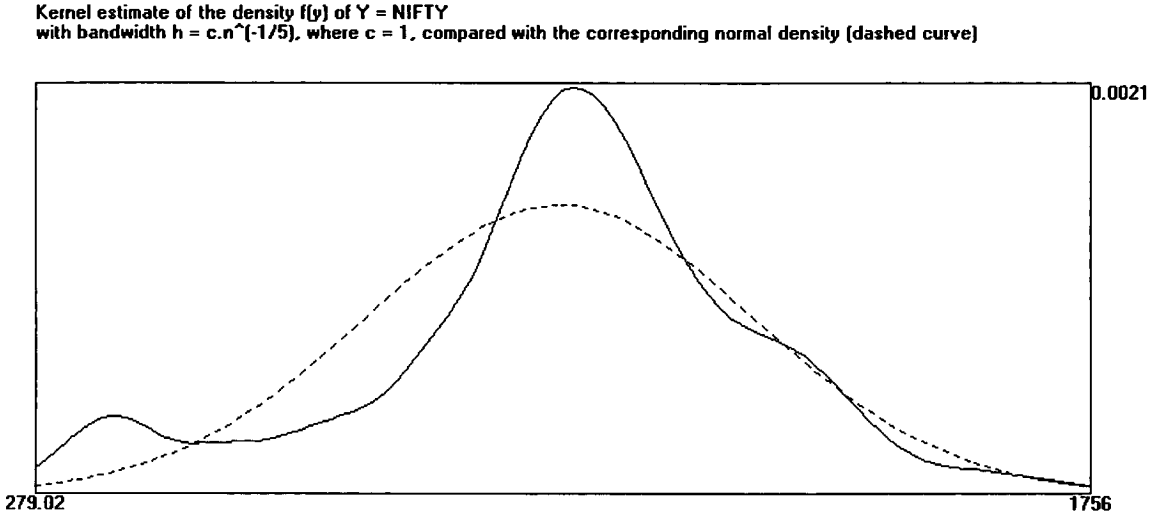


Chart-VI-5 : Normal Distribution plot of Log values of S&P NIFTY

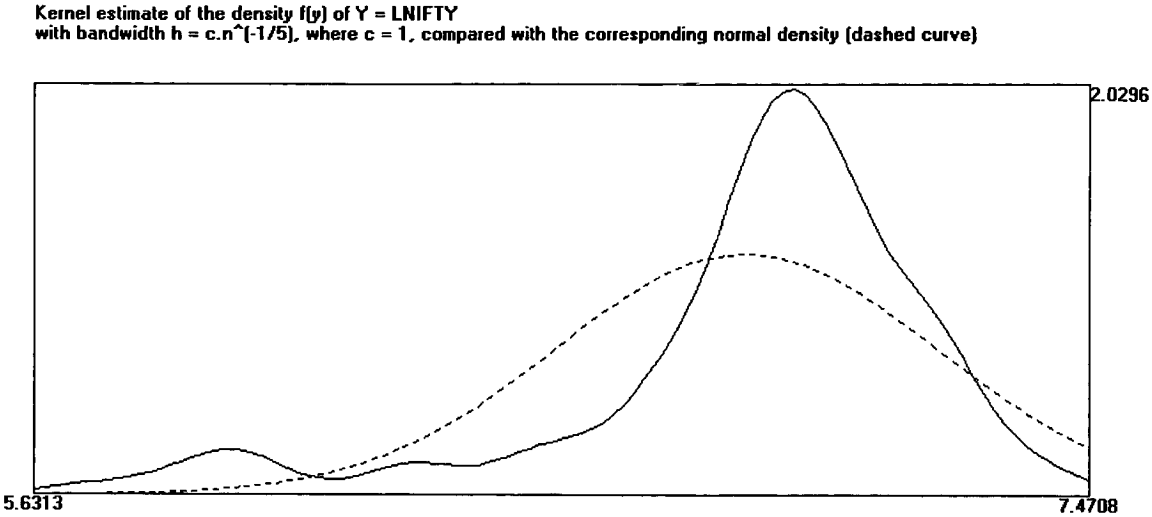
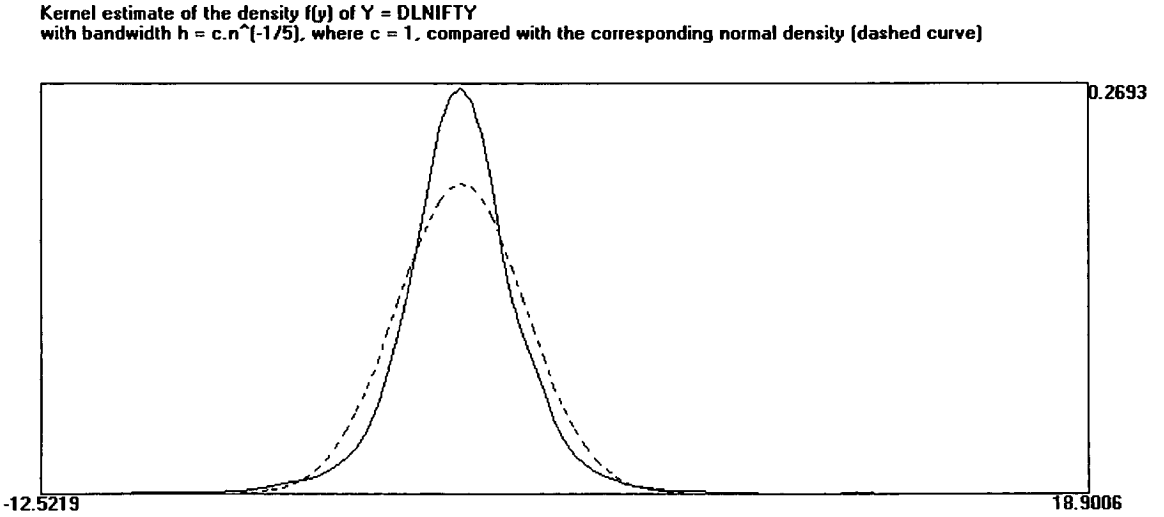


Chart-VI-6 : Normal Distribution plot of Log Returns of S&P NIFTY



The respective series have been plotted as well to give a clear picture of their distribution. Chart-VI-7 gives the plot of NIFTY, Chart-VI-8 gives the plot of log of NIFTY and Chart-VI-9 gives plot of returns.

Chart-VI-7: Plot of S&P CNX NIFTY MOVEMENT

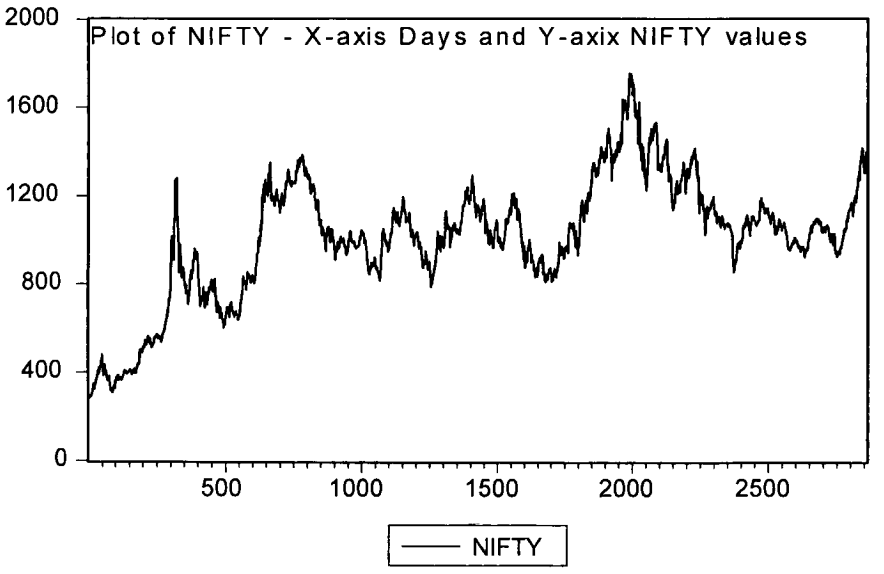


Chart-VI-8: Plot of log values of S&P CNX NIFTY

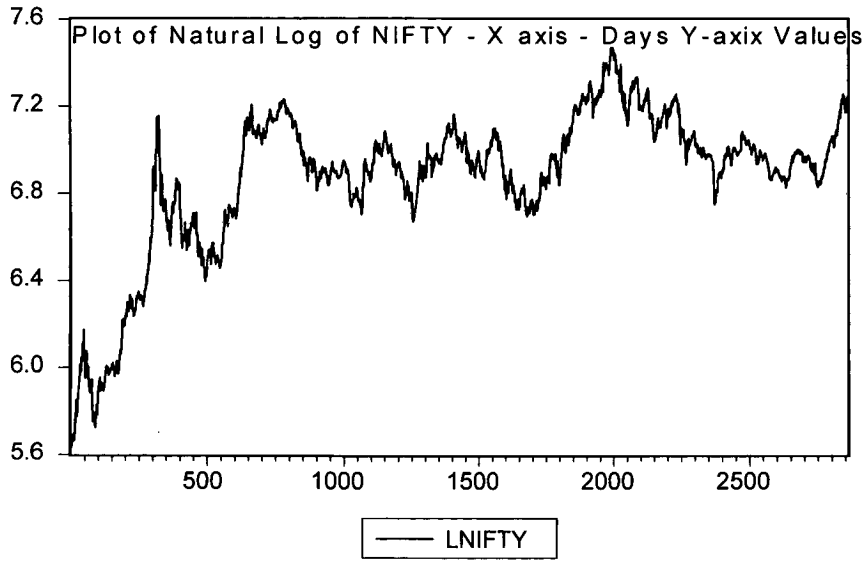
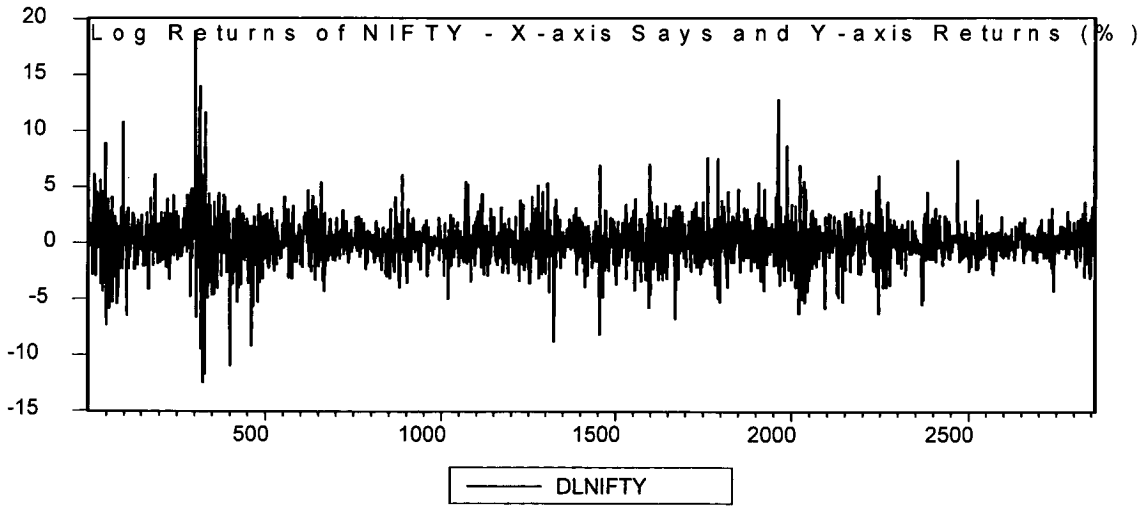


Chart-VI-9: Plot of Log Returns Movement of S&P CNX NIFTY



The table VI-1 gives the descriptive statistics of the log returns of S&P CNX NIFTY for various time buckets.

Table-VI-1: Descriptive Statistics of Daily Returns of S&P CNX NIFTY

Period	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations
1990-03	0.061	0.046	18.901	-12.522	1.941	0.395	11.658	8994.77	2856
1990-94	0.172	0.142	18.901	-12.522	2.448	0.385	11.822	2741.59	839
1995-03	0.015	0.022	12.773	-8.840	1.685	0.274	7.090	1430.88	2017
1996-03	0.031	0.036	12.773	-8.840	1.714	0.270	7.117	1298.23	1807
1997-03	0.037	0.063	12.773	-8.840	1.728	0.223	7.457	1324.87	1585
1998-03	0.029	0.045	12.773	-6.766	1.708	0.374	7.466	1162.04	1360
1999-03	0.053	0.088	12.773	-6.333	1.678	0.502	8.400	1420.38	1130
2000-03	0.010	0.072	12.773	-6.333	1.632	0.480	9.694	1705.10	895
2001-03	0.023	0.065	7.361	-6.310	1.351	-0.055	6.706	376.871	658
2002-03	0.066	0.093	7.361	-4.337	1.151	0.525	7.127	318.939	422
2003-03	0.136	0.252	3.638	-4.337	1.233	-0.225	3.852	6.992	181

From the descriptive statistics, we can infer some of major implications of microstructure changes at various periods of regime shifts. If we look at the overall market, we see that the relative risk as measured by standard deviation of daily returns has come down steadily over reforms period and the same is substantially low after introduction of derivatives and T+2 settlement system. The incidence of large losses have also significantly come down as we see from the Min values in the table. We can say that the policy changes introduced during last few years had a positive impact on the market as the relative risk has come down steadily.

VI.1.2 Understanding Behaviour of Stock Market Volatility

Impact of derivatives trading on the volatility of the cash market in India has been studied by Thenmozhi (2002)[1], Shenbagaraman (2003)[2], Gupta and Kumar (2002)[3] and Raju and Karande (2003)[4], Nath (2003)[5]. Gupta and Kumar(2002) did find that the overall volatility of underlying market declined after introduction of derivatives contracts on indices. Thenmozhi (2002) reported lower level volatility in cash market after introduction of derivative contracts. Shenbagaraman (2003) reported that there was no significant fall in cash market volatility due to introduction of derivatives contracts in Indian market. Raju and Karande (2003) reported a decline in volatility of the cash market after derivatives introduction in Indian market. All these studies have been done using the market index and not individual stocks. These studies were conducted using data for a smaller period and when the notional trading volume in the market was not significant and before tremendous success of futures on individual stocks. Nath (2003) found that the volatility has come down after the introduction of derivatives but there was no conclusive proof that the same is due to introduction of derivatives trading in Indian market. Today derivatives market in India is more successful and we have more than 3 years of derivatives market.

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[1] Thenmozhi M (2002) : Futures Trading, Information and Spot Price Volatility of NSE-50 Index Futures Contract, NSE Working Paper, 2002, http://www.nseindia.com/content/research/Paper59.pdf

[2] Shenbagaraman P: Do Futures and Options trading increase stock market volatility?, NSE Working Papers, 2003, http://www.nseindia.com/content/research/Paper60.pdf

[3] Gupta O P, Kumar M (2002): Impact of Introduction of Index Futures on Stock Market Volatility: The Indian Experience, 2002, (http://www.pbfea2002.ntu.edu.sg/papers/2070.pdf).

[4] Raju M T, Karande K (2003) : Price discovery and volatility of NSE futures market, SEBI Bulletin, Vol 1(3) p. 5-15

[5] Nath G C (2003): Behaviour of Stock Market Volatility after derivatives, NSE News, November 2003.

We have used the daily stock market data from January 1999 (for IGARCH we have used the data from January 1998 to get the initial estimate of conditional volatility) to October 2003 to study the behaviour of volatility. The period has been chosen because derivatives have been introduced in Indian market from June 2000. We have calculated daily returns using the following equation:

$$R_t = LN(P_t / P_{t-1}) * 100 \qquad (30)$$

where R_t is the daily return, P_t is the value of the security on day t and P_{t-1} is the value of the security on day $t-1$.

We have calculated the standard deviation of returns using the following methods:

$$\sigma^2 = \sum_{t=1}^{n} (R_t - \overline{R})^2 / (n-1) \qquad (31)$$

where $\overline{R}$ is the average return over the period. We have calculated the rolling standard deviation for 1 year window as well as for a 6 month window to capture the conditional dynamics. Next we have calculated the volatility using RiskMetrics[1] method with λ = 0.94 (IGARCH) and the initial volatility was computed using one year data from January 1998 to December 1998. Then we have used a GARCH model to estimate the daily volatility. In the linear ARCH(q) model originally introduced by Engle (1982), the conditional variance h_t is postulated to be a linear function of the past q squared innovations:

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

[1] Riskmetrics@™

$$h_t = \alpha_o + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 , \tag{32}$$

with: $\alpha_0 > 0$ and $\alpha_i \geq 0$, i = 1, ..., q,

where ψ_{t-1} is the set of information available at time t-1.

In empirical applications of ARCH(q) models a long lag length and a large number of parameters are often called for. An alternative and more flexible lag structure is often provided by the generalized ARCH, or GARCH(p,q) model proposed independently by Bollerslev (1986)[1] and Taylor (1986):

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

$$h_t = \alpha_o + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} . \tag{33}$$

Nelson, Cao (1992)[2] and Drost, Nijman (1993)[3] give necessary and sufficient conditions to ensure nonnegativity of conditional variance in (33).The process is covariance stationary if and only if $\alpha_1 + \alpha_2 + ... + \alpha_q + \beta_1 + \beta_2 + ... + \beta_p < 1$. In empirical applications GARCH(1,1) is the most frequently used model:

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

[1] Bollerslev, Tim: (1986) Generalized Auto-Regressive Conditional Heteroskedasticity, *Journal of Econometrics*, Volume 31, p. 307-327

[2] Nelson, D. B., Cao C. Q., (1992) Inequality Constraints in the Univariate GARCH Model, Journal of Business and Economic Statistics, 10, 1992, 229-35.

[3] Drost F.C., Nijman T. E.(1993) Temporal Aggregation of GARCH Processes, Econometrica 61, 909-927.

$$h_t = \alpha_o + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}, \tag{34}$$

where: $\alpha_0 > 0, \alpha_1 \geq 0, \beta_1 \geq 0$.

If $\alpha_1 + \beta_1 < 1$, than unconditional variance of ε_t is given by:

$$\text{var}(\varepsilon_t) = \alpha_0 \cdot (1 - \alpha_1 - \beta_1)^{-1}. \tag{35}$$

In many applications especially with daily frequency financial data the estimate for $\alpha_1 + \alpha_2 + ... + \alpha_q + \beta_1 + \beta_2 + ... + \beta_p$ turns out to be very close to unity. Engle and Bollerslev (1986)[1] were the first to consider GARCH processes with $\alpha_1 + \alpha_2 + ... + \alpha_q + \beta_1 + \beta_2 + ... + \beta_p = 1$ as a distinct class of models, which they termed integrated GARCH (IGARCH). In the IGARCH class of models a shock to the conditional variance is persistent in the sense that it remains important for future forecasts of all horizons. Lamoureux and Lastrapes (1990)[2] argued that large persistence may actually represent mis-specification of the variance and result from structural changes in the unconditional variance of the process. They have shown that occasional discrete shift in the mean level of volatility causes substantial upward bias in estimates of the volatility persistence.

We have used the two benchmark indices: S&P CNX NIFTY and S&P CNX NIFTY JUNIOR along with selected few stocks for studying the volatility behaviour during the

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[1] Bollerslev, Tim: (1986) Generalized Auto-Regressive Conditional Heteroskedasticity, *Journal of Econometrics*, Volume 31, p. 307-327

[2] Lamoureux C. G., Lastrapes W. D. (1990) , Persistence in Variance, Structural Change and the GARCH Model, Journal of Business and Economic Statistics, 8, 1990, 225-234.

period January 1999 to October 2003. We have considered 20 stocks as given in the Annexure VI-1. Out of these 20 stocks, 13 have single stock futures and options while 7 do not have the same. Futures and options are available on S&P CNX NIFTY but not on S&P CNX NIFTY Junior. We have divided the entire period into the following blocks:

- Full period from January 1, 1999 to October 31, 2003 – PD1
- First Sample period from January 1, 1999 to May 31, 2000 – PD2
- Second sample period from June 1, 2000 to November 30, 2001 – PD3
- Third Sample period from December 1, 2001 to October 31, 2003 – PD4
- Fourth Sample period from June 1, 2002 to October 31, 2003 – PD5
- Fifth Sample period from November 1, 2002 to October 2003 – PD6

The justification for sub-periods is that we have given 6 months time after introduction of all available four products (futures on individual stocks and indices, options on individual stocks and indices) to settle down. We have also tried to study the behaviour during last one year (November 2002 to October 2003). We have taken the period from June 2000 to November 2001 as the intervening period during which various derivative products were introduced in the market. However, one may experiment with different time time/buckets.

It is observed that the volatility as measured by standard deviation for the period blocks have come down for most of the stocks. It can be seen that for almost all stocks as well as the benchmark indices, the static volatility for the period before introduction of derivatives was higher. The descriptive statistics for various periods for benchmark

indices is given in Table-VI-2. Annexure–VI-2 gives the descriptive statistics of the returns for various periods for all the 20stocks selected in the sample. We have not provided the finer details of the 20 securities like, their average trading volume, market capitalization, weight in the benchmark index, percentage to total trading volume and market capitalization, etc. The same data can be easily made available on request from the authors or looking at the NSE publications and websites (http://nseindia.com)

Table:VI-2 Descriptive Statistics of NIFTY and NIFTY Junior Daily Returns

	PD1	*PD2*	*PD3*	*PD4*	*PD5*	*PD6*
	NIFTY	**NIFTY**	**NIFTY**	**NIFTY**	**NIFTY**	**NIFTY**
Mean	0.0465	0.1251	-0.0683	0.0782	0.1159	0.1952
Median	0.1168	0.1320	0.0261	0.1429	0.1731	0.3514
Maximum	7.5394	7.5394	5.9960	3.8453	3.6385	3.6385
Minimum	-7.7099	-7.7099	-6.3095	-4.3371	-4.3371	-4.3371
Std. Dev.	1.6065	2.0507	1.6262	1.1518	1.1288	1.1914
Skewness	-0.1620	0.0208	-0.5417	-0.1002	-0.2402	-0.3690
Kurtosis	5.6096	4.6646	4.7027	3.8256	3.6655	3.6884
Jarque-Bera	350.0764	41.1250	63.9834	14.4948	10.0206	10.6948
Probability	0	0	0	0.0007	0.0067	0.0048
Observations	1215	356	377	482	357	252
	JUNIOR	**JUNIOR**	**JUNIOR**	**JUNIOR**	**JUNIOR**	**JUNIOR**
Mean	0.0460	0.1341	-0.1611	0.1429	0.1606	0.2974
Median	0.1559	0.3530	0.0388	0.1649	0.1712	0.3419
Maximum	7.3724	7.3724	4.7632	5.7327	4.3458	4.3458
Minimum	-9.0327	-9.0327	-8.3465	-5.1571	-5.0714	-3.1343
Std. Dev.	2.0532	2.6950	2.0566	1.3873	1.3489	1.3480
Skewness	-0.5277	-0.4255	-0.7401	-0.1039	-0.1857	-0.2067
Kurtosis	4.9004	3.5569	4.5146	4.1838	3.6028	3.2050
Jarque-Bera	239.2232	15.3416	70.4518	29.0132	7.4566	2.2351
Probability	0	0.0005	0	0	0.0240	0.3271
Observations	1215	356	377	482	357	252

As can be seen in the above table, the daily static standard deviation has fallen from 2.0507% (annual volatility of 32.54%) in pre-derivatives period to 1.1914% (annual volatility of 18.91%) in last 12 months for NIFTY while for NIFTY JUNIOR, the fall comparable fall is from 2.6950% (annual 42.78%) to 1.3480% (annual 21.40%). While calculating annual volatility, we have used square root of 252 trading days, though

strictly it may not be correct if the data series does not fit a standard normal distribution.(J B statistics are significant for all time blocks except the last one year). This has been done for simplicity as annualized volatility is not the main these of this paper.

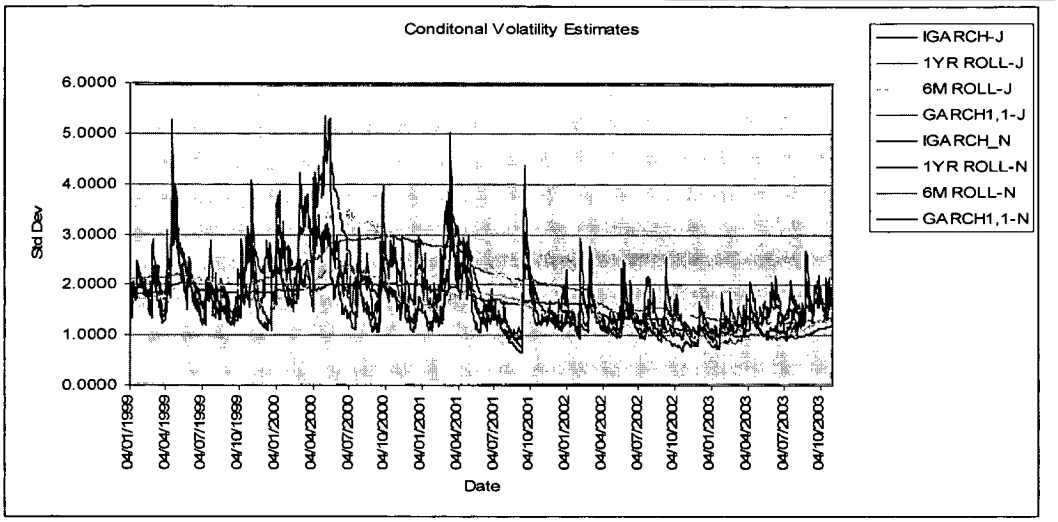
We have found the log return series is stationary while the log series is non-stationary at 99% confidence level by conducting an Augmented Dickey Fuller test and Phillip Peron Test with proper lag length on the basis of SIC. The result of the same is available on request from the authors. We used GARCH(1,1) to find out the conditional volatility of the benchmark indices as well as the stocks in question. Table-VI-3 gives the GARCH coefficients for the same.

Table –VI-3: GARCH(1,1) coefficients for the period 1999-2003

Category	C	ARCH	GARCH	AR(1)	MA(1)
JUNIOR	0.1866	0.1965	0.7677	-0.3316	0.4768
NIFTY	0.1201	0.1423	0.8162	-0.2006	0.3018
RELIANCE	0.8602	0.2291	0.6466	-0.6295	0.6713
BHEL	0.0348	0.0429	0.9541	-0.7379	0.7902
DRREDDY	0.1560	0.0433	0.9368	-0.9382	0.9596
ICICIBANK	0.5896	0.1344	0.8191	-0.0500	0.1333
GLAXO	0.4129	0.1434	0.7932	0.5943	-0.5758
HDFC	0.0952	0.0680	0.9175	-0.2444	0.2715
HINDLEVER	0.1390	0.0904	0.8852	-0.8947	0.9196
L&T	0.0342	0.0462	0.9491	-0.6403	0.6860
ITC	0.0730	0.0713	0.9178	0.9740	-0.9899
RANBAXY	0.1670	0.1116	0.8695	-0.3435	0.4056
SAIL	0.2946	0.1166	0.8831	-0.8609	0.8958
SBIN	0.1012	0.0991	0.8889	-0.9405	0.9596
WIPRO	1.3212	0.1719	0.7619	0.2293	-0.1259
ASHOKLEY	0.2971	0.0790	0.8991	-0.9061	0.9401
BOB	0.6808	0.2110	0.7481	-0.3809	0.4927
BEL	0.9776	0.1237	0.8227	-0.3700	0.4393
IDBI	0.9312	0.1249	0.7907	-0.4745	0.5613
CORPBANK	0.6219	0.2174	0.7485	-0.2175	0.2665
VYASYA	1.2339	0.1840	0.7072	0.9575	-0.9730
ASIANPAINT	1.1467	0.3972	0.3781	-0.9629	0.9553

The different forms of conditional volatility estimates are calculated for the period from January 1999 to October 2003 and have been plotted. For individual stocks the plots are given in Annexure–VI-3 while the plots of conditional volatility estimates for benchmark indices are plotted in Chart –VI-10.

Chart VI-10 Conditional Volatility of S&P CNX NIFTY and NIFTY JUNIOR



We can see from the above chart that the conditional volatility has been steadily going down for benchmark indices over time. It is clearly evident that the volatility estimates of pre-derivatives period is higher than the post derivatives period. In the chart above, J indicates S&P CNX NIFTY JUNIOR while N indicates S&P CNX NIFTY.

When we compare the performance of stocks for whom derivatives are available with those for whom the same is not available, we see that generally the static volatility has come down for almost all stocks while for a few the same has increased. For example, Bank of Baroda has witnessed higher level of volatility in recent months. This is only one

stock from the sample under study which witnessed higher level of static volatility during last one year period compared to pre-derivatives period.

The volatility of the market ahs come down in recent months, specifically in the post derivatives period. The reduction may be due to many reasons – the microstructure changes, robust risk management practices followed by exchanges to contain volatility, introduction of derivatives on indices as well as on individual stocks. In order to ascertain the impact of derivatives on the cash market volatility, we have run a GARCH(1,1) estimation using dummy variable. We have identified 4 relevant dates of event to control the dummy variable. The dummy variable is given a value of zero before the new derivatives product was introduced and 1 after the event date. We have 4 event dates: (1) June 12, 2000; (2) June 4, 2001; (3) July 2, 2001 and (4) November 9, 2001. In order to study the impact of each event, we took the help of dummy variable to ascertain their coefficients and find its statistical significance. The results are given in Table-VI-4.

Table–VI-4: Event Analysis

	C	ARCH	GARCH	DUMMY Coefficient	AR(1)	MA(1)
Event 1	0.1181	0.1434	0.8158	-0.2330	-0.2018	0.3030
P-Values	0	0	0	0.0104	0.4663	0.2658
Event 2	0.1220	0.1463	0.8118	-0.1312	-0.2021	0.3040
P-Values	0	0	0	0.1127	0.4624	0.2601
Event 3	0.1218	0.1457	0.8125	-0.1083	-0.1987	0.3010
P-Values	0	0	0	0.1933	0.4692	0.264
Event 4	0.1207	0.1437	0.8147	-0.0460	-0.1994	0.3011
P-Values	0	0	0	0.5793	0.4706	0.2673

We find that the event 1 (introduction of index futures on June 12, 2000) is significant at 1% level with a negative coefficient of 0.23 that indicates the introduction of index futures might have made a difference in the volatility of the market as measured through

S&P CNX NIFTY. The negative sign of the dummy variable coefficient suggests reduction in volatility. This result is preliminary and needs to be studied in great detail with more robust tests. However, to understand the impact of index futures on volatility and to make out if the index futures has been the only factor instrumental that played important role in reducing the volatility, we incorporated another benchmark index into our equation along with the dummy variable and estimated the GARCH coefficients. The report of the same is produced in Table-VI-5.

Table –VI-5: Effect of Other Market Factors in Volatility

	C	ARCH	GARCH	DUMMY Coeff	Junior	AR(1)	MA(1)
Event 1	0.0187	0.0562	0.9224	-0.0061	0.6520	0.2488	-0.1789
P-Values	0.0005	0	0	0.9247	0.0000	0.5639	0.6840

Here we find that the dummy variable has retained its sign indicating the fall in volatility but the value is not statistically significant and the results indicate that other market effects might have helped in reducing the volatility. All these result are preliminary and needs to be studied in great detail with more robust tests.

We have studied the behaviour of volatility in equity market in pre and post derivatives period in India using static and conditional variance. We modeled conditional volatility using 4 different method: GARCH(1,1), IGARCH with $\lambda = 0.94$, one year rolling window of standard deviation and a 6 month rolling standard deviation. We have considered 20 stocks randomly from the NIFTY and Junior NIFTY basket as well as benchmark indices itself. We also used static point volatility analysis dividing the period under study among various time buckets and justified the creation of such time buckets. While studying conditional volatility we observed that for most of the stocks, the

volatility has come down in the post derivative period while for only few stocks in the sample (details are in Annexure VI-II and Chart VI-11) the volatility in the post derivatives has either remained more or less same or has increased marginally. All these methods suggested that the volatility of the market as measured by benchmark indices like S&P CNX NIFTY and S&P CNX NIFTY JUNIOR have fallen after in the post derivatives period. The finding is in line with the earlier findings of Thenmozhi (2002), Shenbagaraman (2003), Gupta and Kumar (2002) and Raju and Karande (2003). The earlier studies used shorter period of data and pre single stock futures and options period data while we have used data for a longer period that has taken into account various cyclical trends into consideration.

Annexure – VI-1: LIST OF STOCKS IN THE SAMPLE

NO	NAME OF THE STOCK	DERIVATIVES FLAG*
1	ASHOK LEYLAND LTD	N
2	ASIAN PAINTS INDIA LTD	N
3	BANK OF BARODA	Y
4	BHARAT ELECTRONICS LTD	Y
5	BHARAT HEAVY ELECTRICALS LTD	Y
6	CORPORATION BANK	N
7	DR. REDDY'S LABORATORIES LTD.	Y
8	GLAXOSMITHKLINE PHARMACEUTICALS LIMITED	N
9	HINDUSTAN LEVER LTD.	Y
10	HOUSING DEVELOPMENT FINANCE CORPORATION LTD.	Y
11	ICICI BANK	Y
12	IDBI	N
13	ITC LTD	Y
14	LARSEN & TUBRO LTD	Y
15	RANBAXY LTD	Y
16	RELIANCE INDUSTRIESLTD	Y
17	STATE BANK OF INDIA	Y
18	STEEL AUTHORITY OF INDIA LTD	N
19	VYSYA BANK LTD	N
20	WIPRO LTD	Y

* - Y indicates derivatives trading allowed in the stocks and N indicates reverse

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Annexure – VI-2: Descriptive Statistics of Selected Stocks

	PD1	PD2	PD3	PD4	PD5	PD6	PD1	PD2	PD3	PD4	PD5	PD6
Observations	1215	356	377	482	357	252	1215	356	377	482	357	252
	ASHOK	ASHOK	ASHOK	ASHOK	ASHOK	ASHOK	BOB	BOB	BOB	BOB	BOB	BOB
Mean	0.1357	0.1281	0.0600	0.2006	0.2360	0.3532	0.1110	-0.0923	0.0415	0.3154	0.3842	0.5744
Median	-0.1264	-0.2985	-0.1281	-0.0533	0.0475	0.2152	0.0000	-0.3567	0.0000	0.0000	0.0000	0.2962
Maximum	14.9075	10.7532	14.9075	14.7771	11.7051	8.8830	15.4151	7.7823	14.3766	15.4151	15.4151	15.4151
Minimum	-13.6983	-8.3502	-13.6983	-9.9279	-9.9279	-9.9279	-14.7237	-8.2938	-14.7237	-10.5134	-10.0996	-10.0996
Std. Dev.	3.6626	4.5971	3.6512	2.7983	2.4761	2.4782	3.1811	3.4078	3.0757	3.0821	3.2942	3.6184
Skewness	0.3428	0.1619	0.5093	0.5822	0.3747	0.0709	0.2936	0.4290	0.0194	0.4045	0.4131	0.3068
Kurtosis	3.9681	2.2040	5.5041	5.1655	4.9000	4.1191	5.3948	3.3938	8.2655	5.2817	4.7447	4.0708
Jarque-Bera	71.2386	10.9552	114.7983	121.4083	62.0553	13.3619	307.7890	13.2220	435.5369	117.6974	55.4338	15.9942
Probability	0	0.0042	0	0	0	0.0013	0	0.0013	0	0	0	0.0003
	ASIAN	ASIAN	ASIAN	ASIAN	ASIAN	ASIAN	CORPBNK	CORPBNK	CORPBNK	CORPBNK	CORPBNK	CORPBNK
Mean	0.0881	0.1134	0.0661	0.0867	0.0961	0.0931	0.0778	-0.0824	0.1779	0.1178	0.2006	0.3332
Median	-0.0200	-0.0425	-0.0370	-0.0065	0.0265	0.0151	-0.0479	-0.3219	-0.0388	-0.0424	0.0000	0.1843
Maximum	15.9432	10.2147	15.9432	7.9806	7.9806	7.9806	14.8634	7.7546	14.8634	11.0167	10.4452	10.4452
Minimum	-8.3382	-8.3382	-5.7172	-4.0857	-4.0857	-4.0857	-11.5845	-11.584	-10.7012	-8.3081	-8.2230	-8.2230
Std. Dev.	1.9913	2.7321	1.7660	1.4353	1.3891	1.4023	3.2431	3.9857	3.0416	2.7498	2.6428	3.0291
Skewness	1.1067	0.6179	2.3550	0.8076	1.0103	1.2348	0.4124	0.0321	1.0548	0.6440	0.6139	0.4985
Kurtosis	9.3915	4.3904	21.5323	6.8512	8.1044	9.4535	5.1665	2.9066	8.7438	5.3507	5.1037	4.0019
Jarque-Bera	2316.114	51.3252	5743.471	350.2751	448.3073	501.3480	272.0546	0.1904	588.1540	144.2862	88.2510	20.9790
Probability	0	0	0	0	0	0	0	0.9092	0	0	0	0
	BEL	BEL	BEL	BEL	BEL	BEL	DRREDDY	DRREDDY	DRREDDY	DRREDDY	DRREDDY	DRREDDY
Mean	0.2565	0.3301	0.0099	0.3950	0.2926	0.4430	0.1308	0.2949	0.0822	0.0477	0.0642	0.2141
Median	0.0000	0.0000	-0.1550	0.0619	0.1063	0.2311	0.0306	-0.0126	0.0044	0.0569	0.0579	0.0625
Maximum	18.2585	15.2989	18.2585	16.9043	14.2648	14.2648	11.2799	9.8075	11.2799	8.9421	8.9421	8.9421
Minimum	-17.0670	-12.743	-17.0670	-12.4327	-7.7940	-5.6506	-14.1919	-12.774	-10.9399	-14.1919	-14.1919	-7.5855
Std. Dev.	4.2404	5.5462	3.7311	3.4245	2.8321	2.5489	3.0139	4.1709	2.7690	2.0162	2.0836	2.0467
Skewness	0.3053	0.0725	0.3826	0.8043	0.6762	0.9228	0.0021	-0.0170	0.0413	-0.4961	-0.6595	0.3941
Kurtosis	3.7164	1.8600	6.2808	5.6446	5.2952	6.4638	5.0734	2.8019	5.5346	10.6137	10.9334	6.1388
Jarque-Bera	44.8545	19.5893	178.2759	192.4181	105.5676	161.7454	217.6279	0.5991	101.0177	1183.972	962.0992	109.9730

Probability	0	0.0001	0	0	0	0	0	0.7412	0	0	0	0
	BHEL	BHEL	BHEL	BHEL	BHEL	BHEL	GLAXO	GLAXO	GLAXO	GLAXO	GLAXO	GLAXO
Mean	0.0503	-0.2150	0.0483	0.2478	0.3224	0.4640	-0.0201	-0.1636	-0.0284	0.0922	0.0767	0.1563
Median	0.0178	-0.3227	0.0000	0.1497	0.1689	0.3166	-0.1106	-0.2695	-0.1719	0.0066	0.0000	0.0275
Maximum	13.8444	8.5888	13.8444	9.5393	8.1954	8.1954	11.3408	7.6989	11.3408	7.7641	7.6777	7.6777
Minimum	-11.8114	-8.3370	-11.8114	-10.0862	-4.8790	-3.5982	-10.3012	-8.3374	-10.3012	-7.4814	-4.6086	-3.5922
Std. Dev.	3.2031	3.8505	3.5548	2.2325	1.9022	2.0353	2.4278	3.1856	2.3839	1.7078	1.5278	1.5565
Skewness	0.0483	0.1623	0.0163	0.2178	0.6127	0.6069	0.2313	0.1017	0.4827	0.6370	0.6856	0.8941
Kurtosis	4.4078	2.7166	4.7538	5.5840	4.0415	3.6282	5.8839	3.5718	7.7164	5.8314	5.0533	5.3221
Jarque-Bera	100.8103	2.7545	48.3302	137.9136	38.4735	19.6126	431.8738	5.4638	364.0718	193.6063	90.6836	90.1908
Probability	0	0.2523	0	0	0	0.0001	0	0.0651	0	0	0	0

Annexure –VI-2: Descriptive Statistics of Selected Stocks (contd...)

	PD1	PD2	PD3	PD4	PD5	PD6	PD1	PD2	PD3	PD4	PD5	PD6
Observations	1215	356	377	482	357	252	1215	356	377	482	357	252
	HDFC	HDFC	HDFC	HDFC	HDFC	HDFC	WIPRO	WIPRO	WIPRO	WIPRO	WIPRO	WIPRO
Mean	0.1282	0.2194	0.0967	0.0855	0.1539	0.2005	0.1061	0.4548	-0.0686	-0.0149	-0.0350	-0.0093
Median	-0.0303	-0.0132	-0.0109	-0.0363	0.0000	0.0000	-0.0442	0.2910	-0.2336	-0.1000	-0.0785	-0.0536
Maximum	11.3336	11.3336	9.7375	8.2218	8.2218	8.2218	17.7101	10.8809	17.7101	17.1344	17.1344	9.0662
Minimum	-13.3766	-12.7754	-13.3766	-5.9475	-5.9475	-5.9475	-20.0707	-12.7832	-17.4334	-20.0707	-20.0707	-20.0707
Std. Dev.	2.4926	3.3069	2.3663	1.7956	1.9200	2.0621	4.4079	5.0659	5.1035	3.0999	2.9901	3.0154
Skewness	0.2123	0.2196	-0.1135	0.3863	0.3063	0.3708	-0.1928	-0.2417	-0.1314	-0.3548	-0.3872	-1.1871
Kurtosis	5.9797	3.8436	7.7667	4.9736	4.5660	4.4216	4.7052	2.5467	4.5076	9.3353	11.3888	10.7134
Jarque-Bera	458.5993	13.4193	357.7231	90.2184	42.0588	26.9924	154.7292	6.5145	36.7893	816.1652	1055.708	683.9048
Probability	0	0.0012	0	0	0	0	0	0.0385	0	0	0	0
	HINDLEV	HINDLEV	HINDLEV	HINDLEV	HINDLEV	HINDLEV	VYASYA	VYASYA	VYASYA	VYASYA	VYASYA	VYASYA
Mean	0.0038	0.1229	-0.0542	-0.0388	-0.0171	0.0337	0.0862	-0.1056	0.0025	0.2933	0.1659	0.2911
Median	0.0000	0.0265	0.0000	-0.0260	0.0278	0.0576	-0.0916	-0.5644	0.0000	-0.0386	-0.1320	-0.0903
Maximum	11.2690	11.2690	10.8170	5.5570	4.8350	4.8350	18.2483	7.7306	11.5171	18.2483	16.7389	16.7389
Minimum	-9.2196	-9.2196	-7.9666	-5.6554	-4.9133	-4.7134	-9.4438	-8.3382	-8.3397	-9.4438	-9.1498	-9.1498
Std. Dev.	2.2858	2.7955	2.3473	1.7598	1.7678	1.7813	3.1619	3.6053	2.7738	3.0902	2.5800	2.6739
Skewness	0.3966	0.5109	0.2433	0.0643	0.0141	-0.0280	0.8170	0.3499	0.2271	1.7091	1.3511	1.4859
Kurtosis	5.6414	5.0802	5.1210	3.6471	3.3488	3.1284	6.6576	2.9340	5.1428	11.4276	9.3286	9.8660
Jarque-Bera	385.0523	79.6774	74.3809	8.7415	1.8213	0.2062	812.4379	7.3300	75.3659	1661.055	704.3773	587.7286

Probability	0	0	0	0.0126	0.4023	0.9021	0	0.0256	0	0	0	0
	ICICIBNK	ICICIBNK	ICICIBNK	ICICIBNK	ICICIBNK	ICICIBNK	SBIN	SBIN	SBIN	SBIN	SBIN	SBIN
Mean	0.1989	0.6350	-0.1957	0.1853	0.1626	0.2400	0.0924	0.0722	0.0059	0.1749	0.2213	0.2960
Median	-0.0338	0.1811	-0.2505	-0.0707	-0.0334	0.0397	-0.0218	-0.1178	-0.0487	0.0588	0.0902	0.3474
Maximum	14.8603	7.8545	14.8603	12.9734	12.9734	12.9734	9.5352	7.7151	9.4781	9.5352	4.8772	4.8772
Minimum	-17.5869	-8.3392	-17.5869	-7.0505	-7.0505	-7.0505	-10.5229	-8.3341	-10.5009	-10.5229	-5.2843	-5.2843
Std. Dev.	3.6047	4.2445	4.1074	2.4592	2.2875	2.2745	2.6207	3.5259	2.3835	1.9249	1.6526	1.8142
Skewness	0.1851	0.0860	0.0341	0.9173	0.7443	0.9439	0.1473	0.2652	-0.2504	0.2184	0.0082	-0.0923
Kurtosis	5.2124	2.4647	6.2273	5.9273	6.2092	7.3641	4.8320	3.1187	5.1179	6.5816	3.3871	3.0128
Jarque-Bera	254.7261	4.6897	163.6843	239.6969	186.1628	237.3957	174.2986	4.3820	74.4000	261.4550	2.2335	0.3594
Probability	0	0.0959	0	0	0	0	0	0.1118	0	0	0.3274	0.8355
	IDBI	IDBI	IDBI	IDBI	IDBI	IDBI	SAIL	SAIL	SAIL	SAIL	SAIL	SAIL
Mean	0.0678	-0.0035	-0.0733	0.2307	0.3067	0.4622	0.1696	0.0412	-0.0736	0.4547	0.4686	0.7362
Median	-0.2006	-0.3240	-0.1857	0.0000	0.0000	0.0000	0.0000	-0.7875	0.0000	0.0000	0.0000	0.5155
Maximum	17.6063	7.8655	14.8464	17.6063	17.6063	17.6063	29.1910	29.1910	17.0818	26.3045	26.3045	26.3045
Minimum	-19.9046	-19.9046	-11.3543	-11.9935	-11.9935	-11.9935	-27.2178	-27.2178	-15.1685	-17.3613	-17.3613	-17.3613
Std. Dev.	3.2572	3.6766	2.5543	3.4140	3.6713	3.7322	4.5226	6.1127	2.9583	4.1312	4.2020	4.3300
Skewness	0.7013	-0.1228	1.1429	1.2418	1.1639	1.2046	0.9261	0.7040	0.3815	1.2908	0.9894	0.9743
Kurtosis	7.4457	5.3742	9.8672	7.6391	6.9565	7.2504	10.7472	7.7057	9.5409	9.6432	9.0782	9.7425
Jarque-Bera	1100.130	84.5099	822.8577	556.0969	313.4427	250.6353	3212.1420	357.8771	681.1939	1020.167	607.7966	517.2122
Probability	0	0	0	0	0	0	0	0	0	0	0	0

Annexure –VI-2: Descriptive Statistics of Selected Stocks (Contd...)

	PD1	PD2	PD3	PD4	PD5	PD6	PD1	PD2	PD3	PD4	PD5	PD6
Observations	1215	356	377	482	357	252	1215	356	377	482	357	252
	RELIANC	RELIANC	RELIANC	RELIANC	RELIANC	RELIANC	JUNIOR	JUNIOR	JUNIOR	JUNIOR	JUNIOR	JUNIOR
Mean	0.1155	0.2967	-0.0453	0.1074	0.1717	0.2403	0.0460	0.1341	-0.1611	0.1429	0.1606	0.2974
Median	0.0333	-0.0833	0.0304	0.0958	0.1511	0.2571	0.1559	0.3530	0.0388	0.1649	0.1712	0.3419
Maximum	12.4586	7.7264	12.2256	12.4586	12.4586	4.4091	7.3724	7.3724	4.7632	5.7327	4.3458	4.3458
Minimum	-10.5246	-8.3266	-10.5246	-5.6518	-4.3101	-4.0192	-9.0327	-9.0327	-8.3465	-5.1571	-5.0714	-3.1343
Std. Dev.	2.5802	3.4163	2.4612	1.8465	1.8078	1.6894	2.0532	2.6950	2.0566	1.3873	1.3489	1.3480
Skewness	0.3730	0.2982	0.0220	0.7680	0.8219	-0.0393	-0.5277	-0.4255	-0.7401	-0.1039	-0.1857	-0.2067
Kurtosis	5.7296	3.2125	7.7707	7.5524	8.0931	2.5686	4.9004	3.5569	4.5146	4.1838	3.6028	3.2050
Jarque-Bera	405.3624	5.9462	357.5453	463.5888	426.0352	2.0194	239.2232	15.3416	70.4518	29.0132	7.4566	2.2351
Probability	0	0.0511	0	0	0	0.3643	0	0.0005	0	0	0.0240	0.3271

	RANBAXY	RANBAXY	RANBAXY	RANBAXY	RANBAXY	RANBAXY	NIFTY	NIFTY	NIFTY	NIFTY	NIFTY	NIFTY
Mean	0.1482	0.2009	0.0841	0.1594	0.2090	0.2498	0.0465	0.1251	-0.0683	0.0782	0.1159	0.1952
Median	0.0670	-0.1454	-0.0334	0.1649	0.2757	0.3099	0.1168	0.1320	0.0261	0.1429	0.1731	0.3514
Maximum	11.4485	8.2536	11.4485	9.5365	6.2139	5.1345	7.5394	7.5394	5.9960	3.8453	3.6385	3.6385
Minimum	-12.7826	-12.7826	-11.8838	-6.0466	-5.1203	-5.1203	-7.7099	-7.7099	-6.3095	-4.3371	-4.3371	-4.3371
Std. Dev.	2.8401	3.9102	2.7880	1.7298	1.5528	1.5664	1.6065	2.0507	1.6262	1.1518	1.1288	1.1914
Skewness	0.1320	0.0599	0.0926	0.5241	0.0861	-0.0332	-0.1620	0.0208	-0.5417	-0.1002	-0.2402	-0.3690
Kurtosis	4.9638	2.8615	5.5794	6.5682	4.4150	4.3528	5.6096	4.6646	4.7027	3.8256	3.6655	3.6884
Jarque-Bera	198.7566	0.4974	105.0500	277.7740	30.2244	19.2616	350.0764	41.1250	63.9834	14.4948	10.0206	10.6948
Probability	0	0.7798	0	0	0	0.0001	0	0	0	0.0007	0.0067	0.0048
	ITC	ITC	ITC	ITC	ITC	ITC						
Mean	0.0118	-0.0097	-0.0222	0.0543	0.0989	0.1367						
Median	-0.0357	-0.1145	-0.0064	-0.0330	-0.0385	-0.0189						
Maximum	9.7477	9.7477	8.6842	5.3264	4.9663	4.1237						
Minimum	-10.7116	-8.3378	-10.712	-6.2695	-4.6352	-4.3555						
Std. Dev.	2.5337	3.5556	2.3699	1.5746	1.5172	1.4279						
Skewness	-0.0176	0.1022	-0.3342	0.0247	0.2237	0.1275						
Kurtosis	5.5297	3.4252	6.0085	3.8815	3.5421	3.2312						
Jarque-Bera	324.0418	3.3012	149.191	15.6550	7.3490	1.2442						
Probability	0	0.1919	0	0.0004	0.0254	0.5368						
	L_T01	L_T01	L_T01	L_T01	L_T01	L_T01						
Mean	0.0762	0.0454	0.0212	0.1421	0.2384	0.3049						
Median	0.0291	-0.2047	0.2492	0.0768	0.1375	0.1925						
Maximum	10.6771	7.7200	10.6771	5.8386	5.8386	5.8386						
Minimum	-14.6860	-12.5988	-14.6860	-7.0651	-7.0651	-3.9020						
Std. Dev.	2.9454	3.8604	3.1820	1.7249	1.6516	1.7478						
Skewness	-0.0670	0.0775	-0.2605	0.1336	0.2155	0.3200						
Kurtosis	5.0380	3.0562	5.2448	4.0772	4.4368	3.2555						
Jarque-Bera	211.1747	0.4030	83.4178	24.7358	33.4707	4.9855						
Probability	0	0.8175	0	0	0	0.0827						

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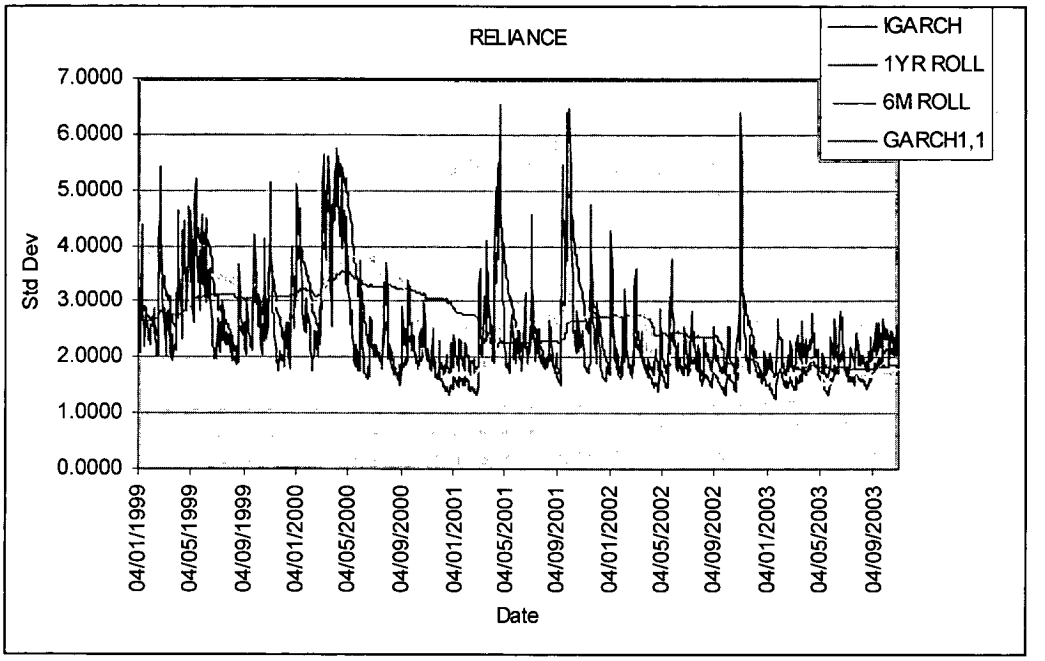
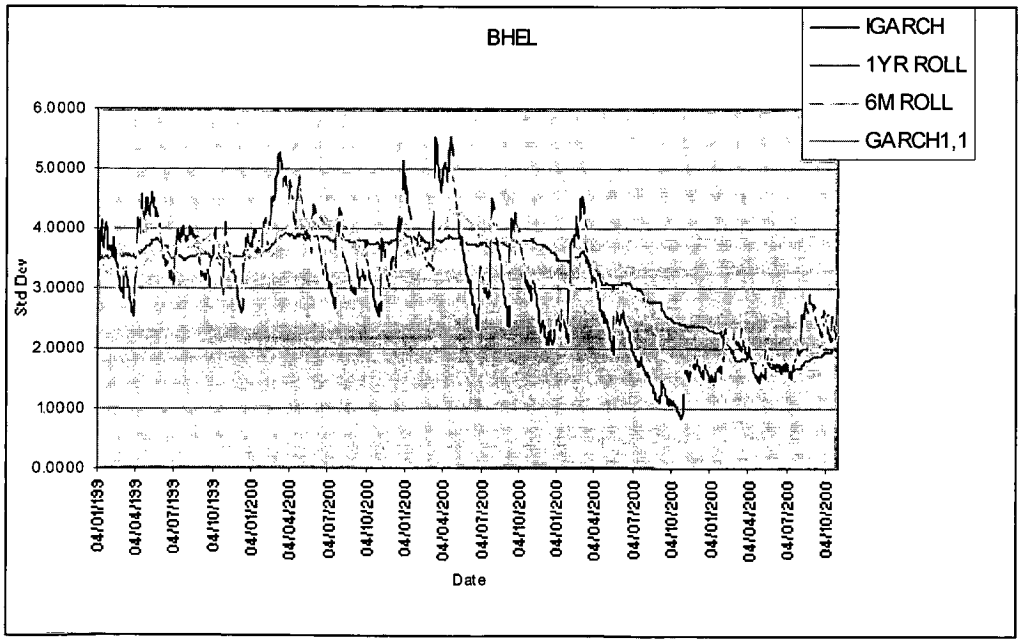
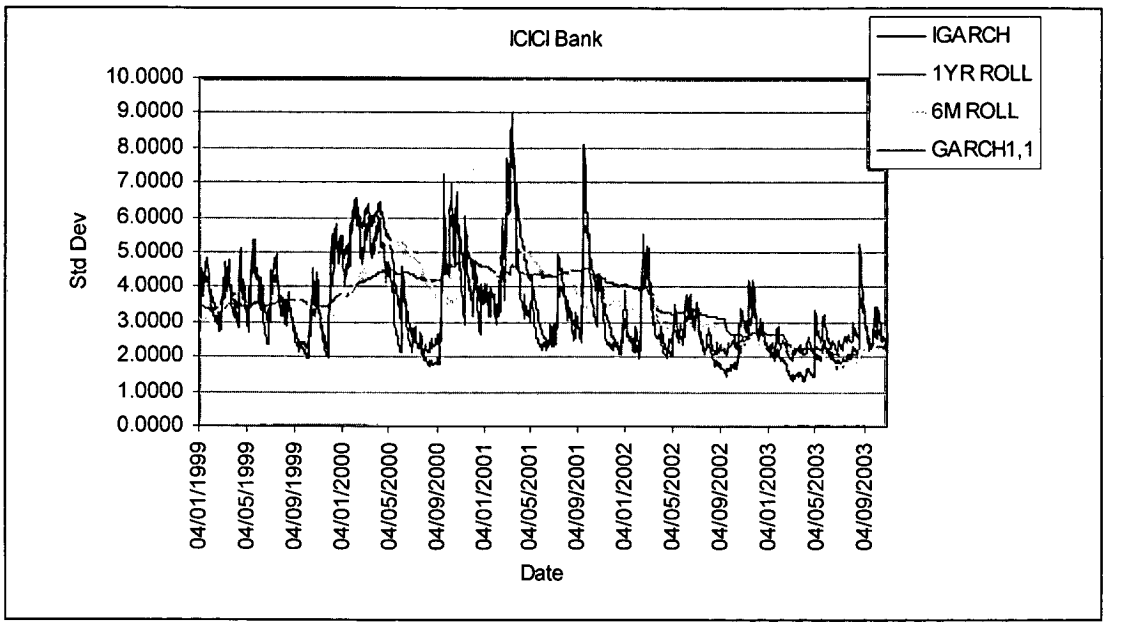
Chart-VI-11 – Plot of Conditional Vitality of Stocks (1999-2003)



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6M ROLL
GARCH1,1
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4.0000
3.0000
2.0000
1.0000
0.0000
04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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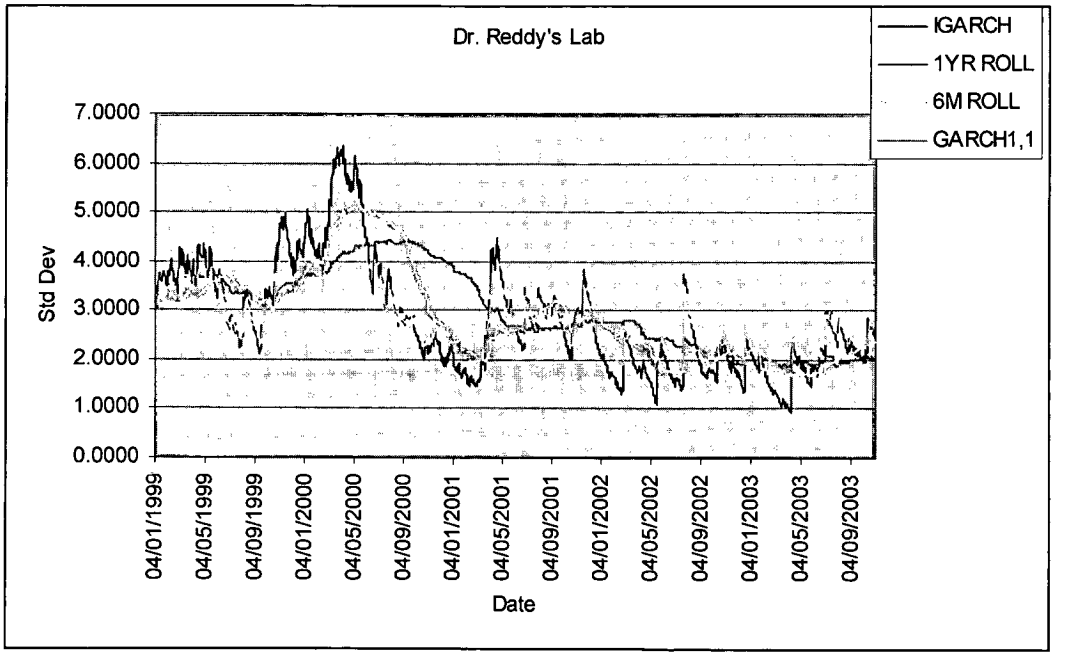
04/01/2002
04/05/2002
04/09/2002
04/01/2003
04/05/2003
04/09/2003
Date


Dr. Reddy's Lab
IGARCH
1YR ROLL
6M ROLL
GARCH1,1
Std Dev
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4.0000
3.0000
2.0000
1.0000
0.0000
04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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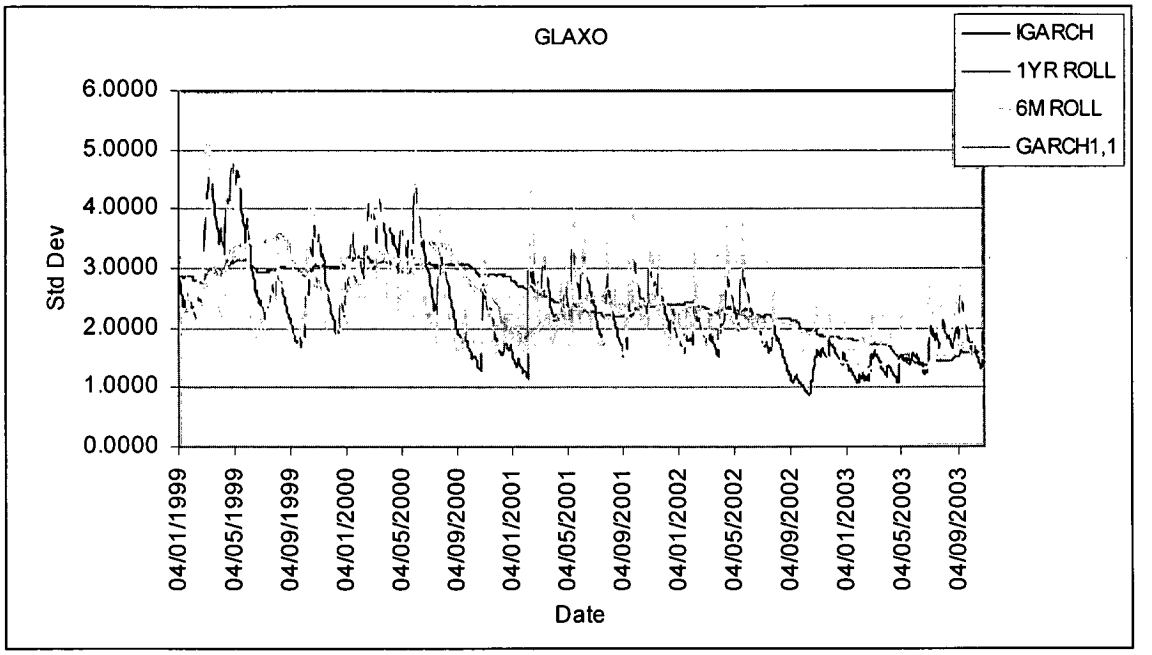
04/01/2002
04/05/2002
04/09/2002
04/01/2003
04/05/2003
04/09/2003
Date


GLAXO
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1YR ROLL
6M ROLL
GARCH1,1
Std Dev
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3.0000
2.0000
1.0000
0.0000
04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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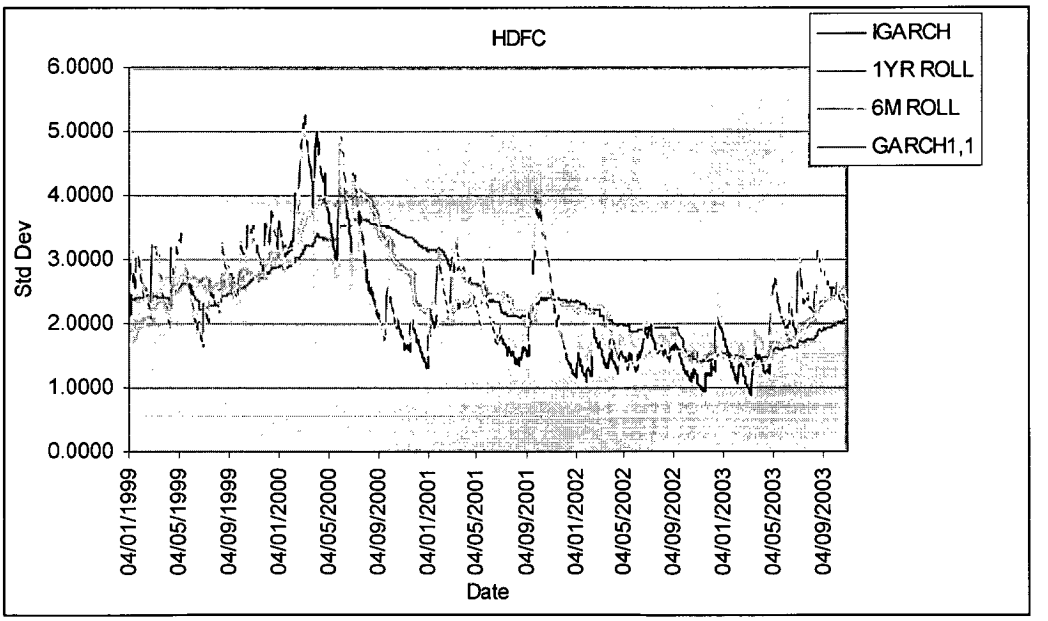
04/05/2002
04/09/2002
04/01/2003
04/05/2003
04/09/2003
Date


HDFC
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1YR ROLL
6M ROLL
GARCH1,1
Std Dev
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4.0000
3.0000
2.0000
1.0000
0.0000
04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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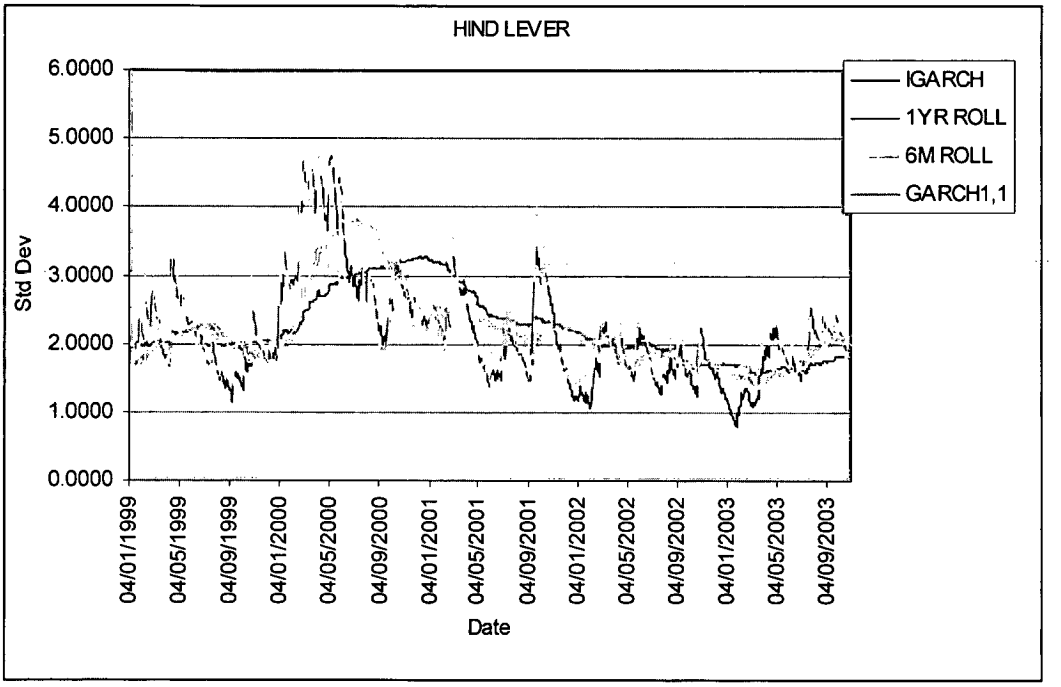
04/05/2002
04/09/2002
04/01/2003
04/05/2003
04/09/2003
Date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1YR ROLL
6M ROLL
GARCH1,1
Std Dev
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3.0000
2.0000
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0.0000
04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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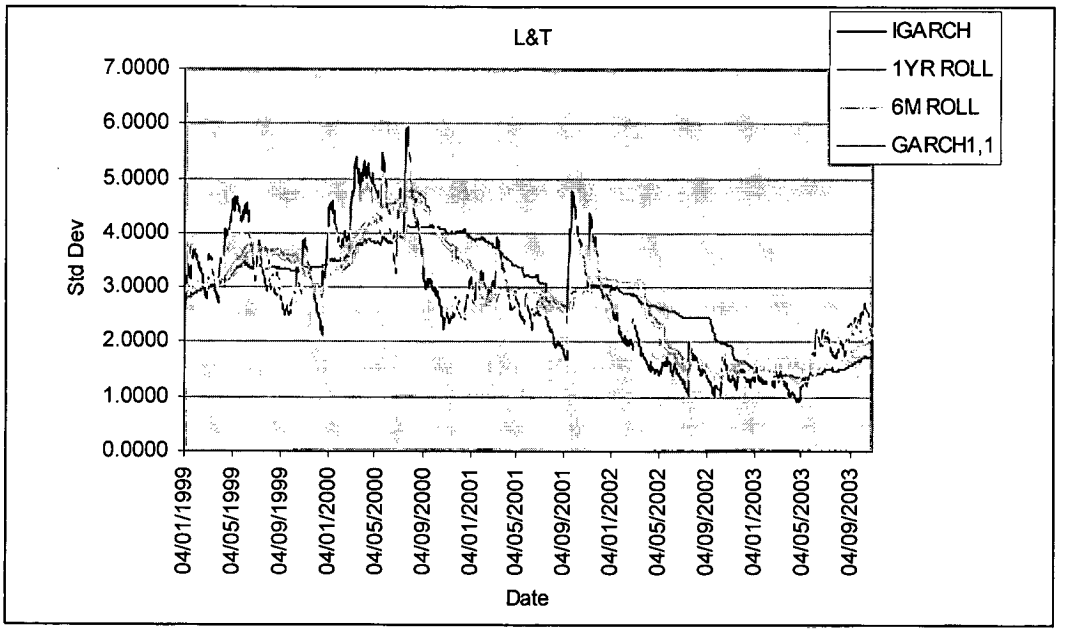
04/09/2002
04/01/2003
04/05/2003
04/09/2003
Date


L&T
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1YR ROLL
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GARCH1,1
Std Dev
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4.0000
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1.0000
0.0000
04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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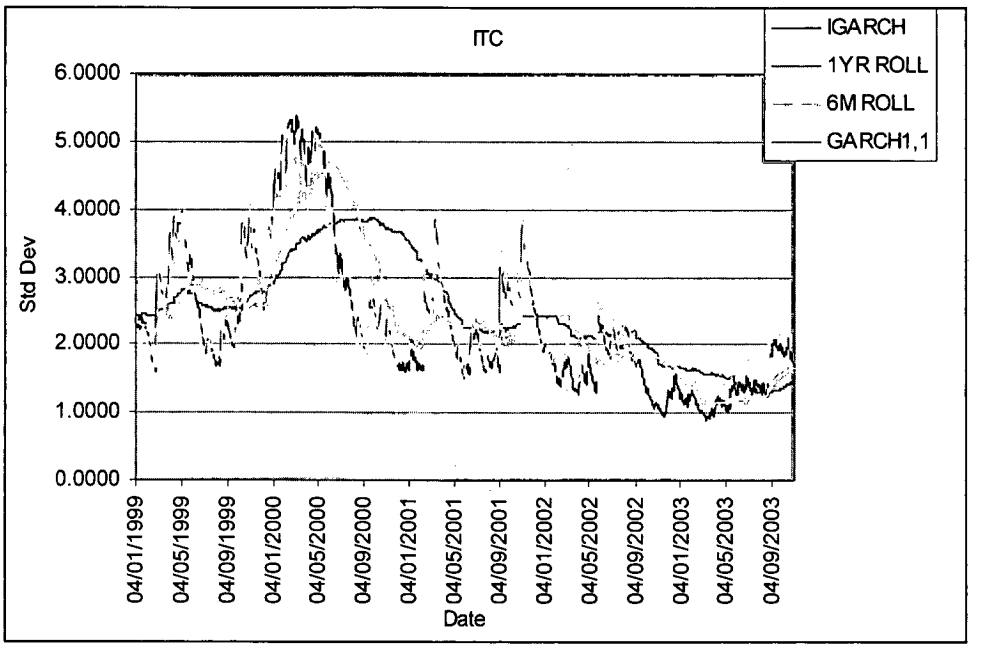
04/09/2002
04/01/2003
04/05/2003
04/09/2003
Date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6M ROLL
GARCH1,1
Std Dev
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04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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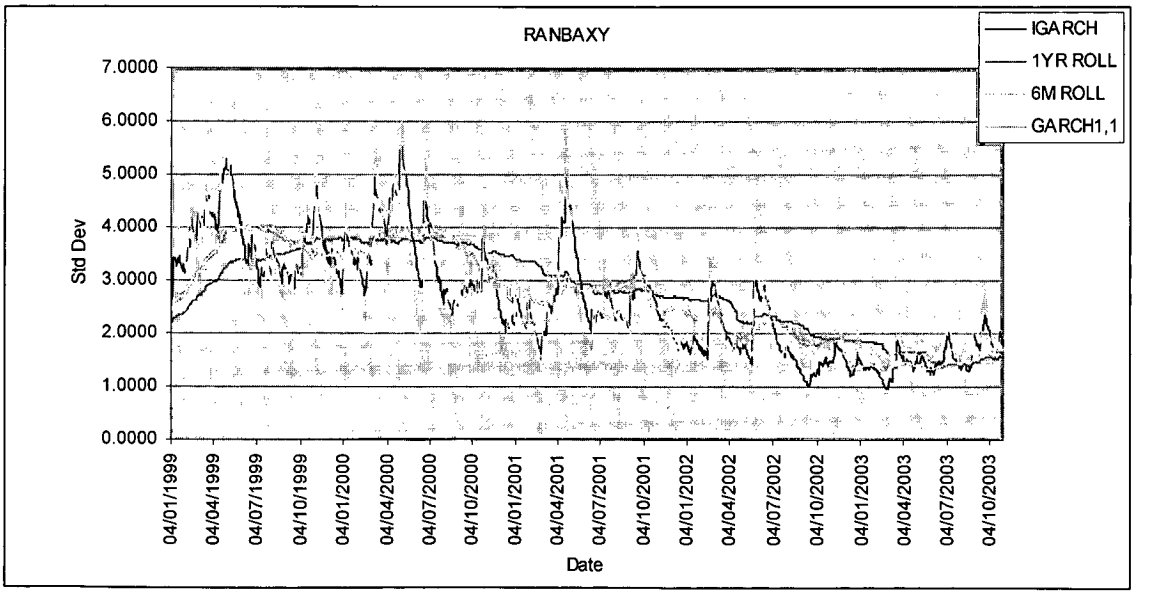
04/01/2002
04/05/2002
04/09/2002
04/01/2003
04/05/2003
04/09/2003
Date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6M ROLL
GARCH1,1
Std Dev
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1.0000
0.0000
04/01/1999
04/04/1999
04/07/1999
04/10/1999
04/01/2000
04/04/2000
04/07/2000
04/10/2000
04/01/2001
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04/07/2001
04/10/2001
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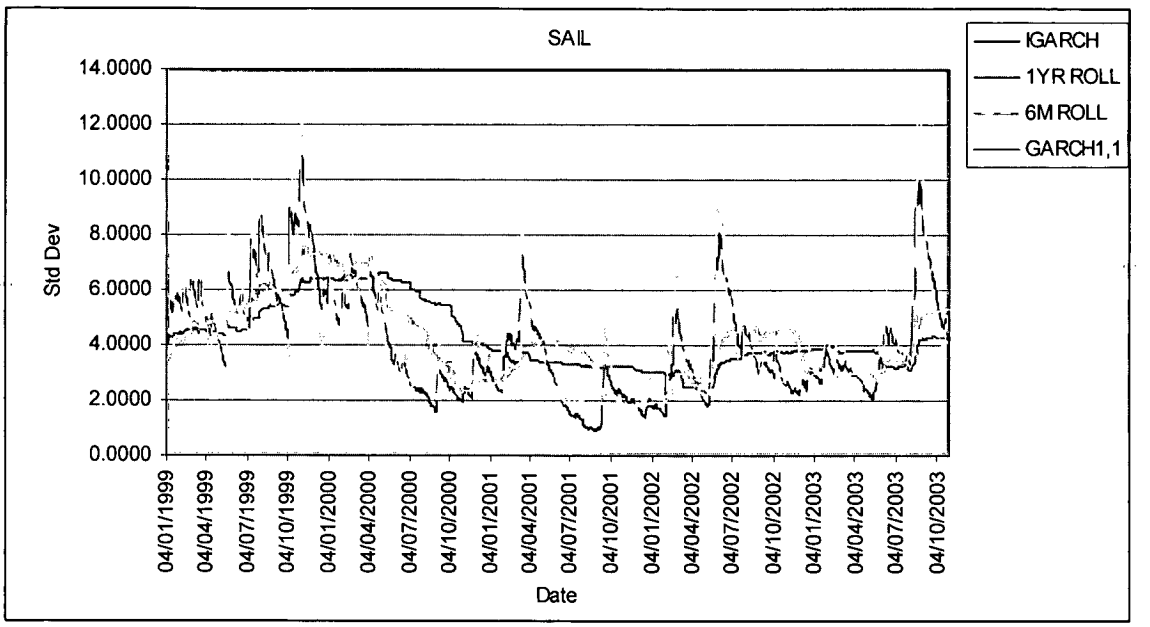
04/01/2003
04/04/2003
04/07/2003
04/10/2003
Date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6M ROLL
GARCH1,1
Std Dev
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04/04/1999
04/07/1999
04/10/1999
04/01/2000
04/04/2000
04/07/2000
04/10/2000
04/01/2001
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04/07/2001
04/10/2001
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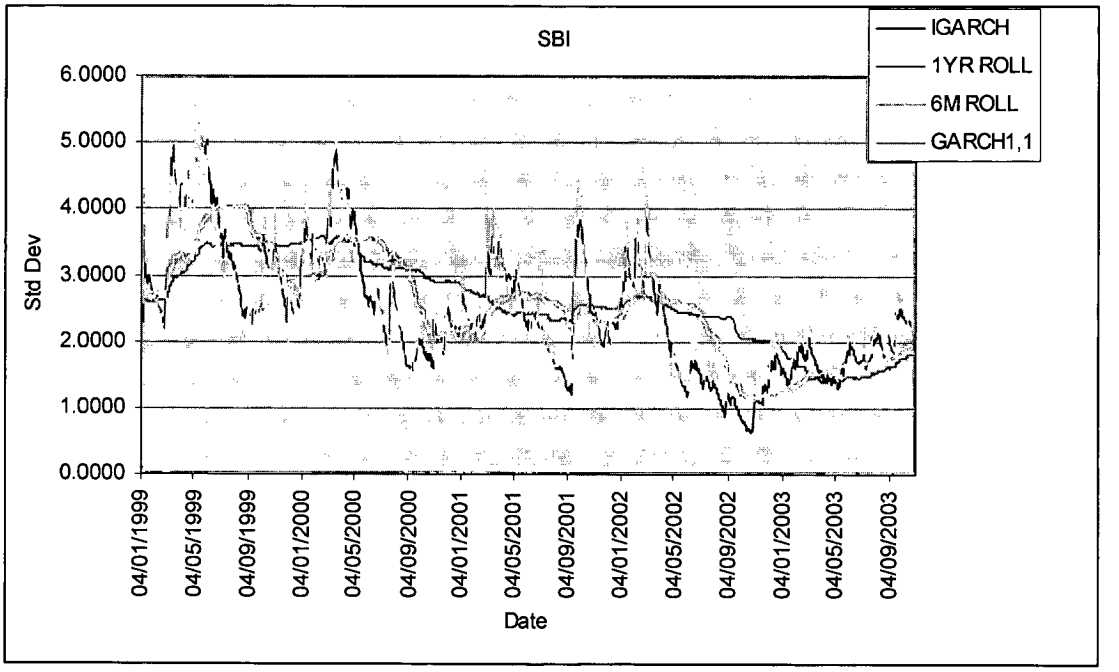
04/04/2003
04/07/2003
04/10/2003
Date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6M ROLL
GARCH1,1
Std Dev
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04/05/1999
04/09/1999
04/01/2000
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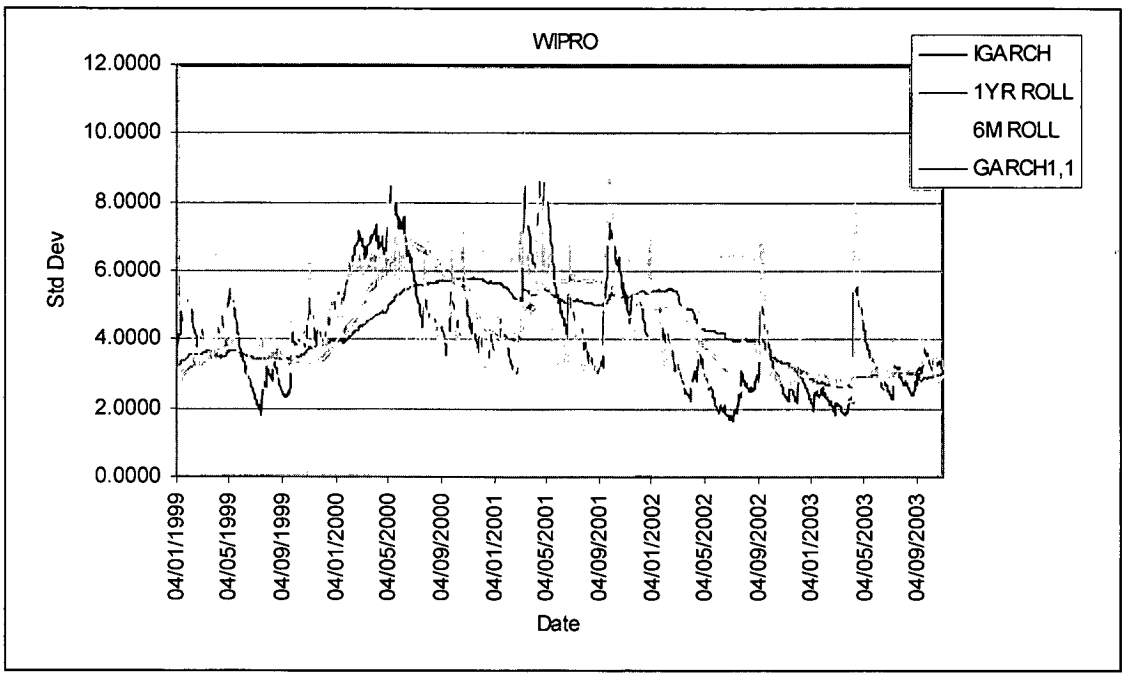
04/09/2003
Date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GARCH1,1
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04/09/1999
04/01/2000
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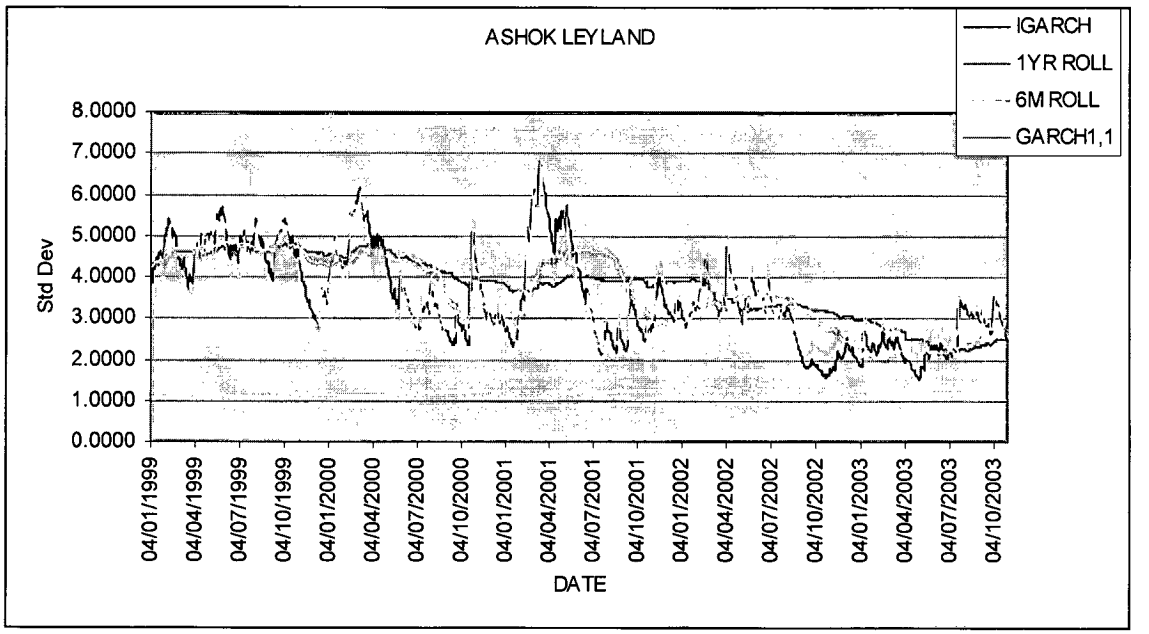
Date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1.0000
0.0000
04/01/1999
04/04/1999
04/07/1999
04/10/1999
04/01/2000
04/04/2000
04/07/2000
04/10/2000
04/01/2001
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04/10/2003
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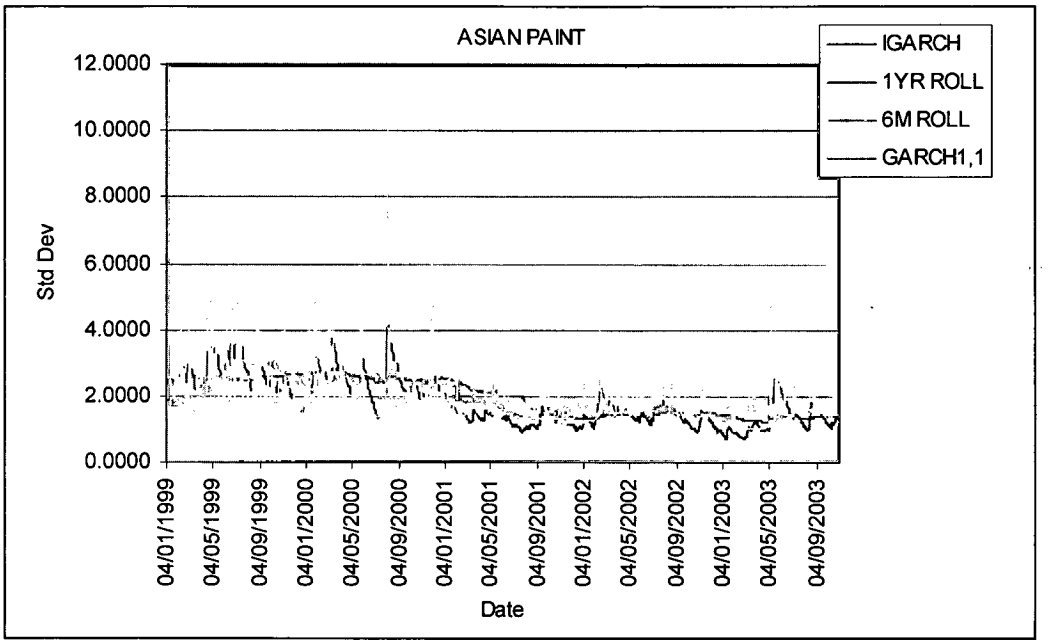
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6M ROLL
GARCH1,1
Std Dev
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04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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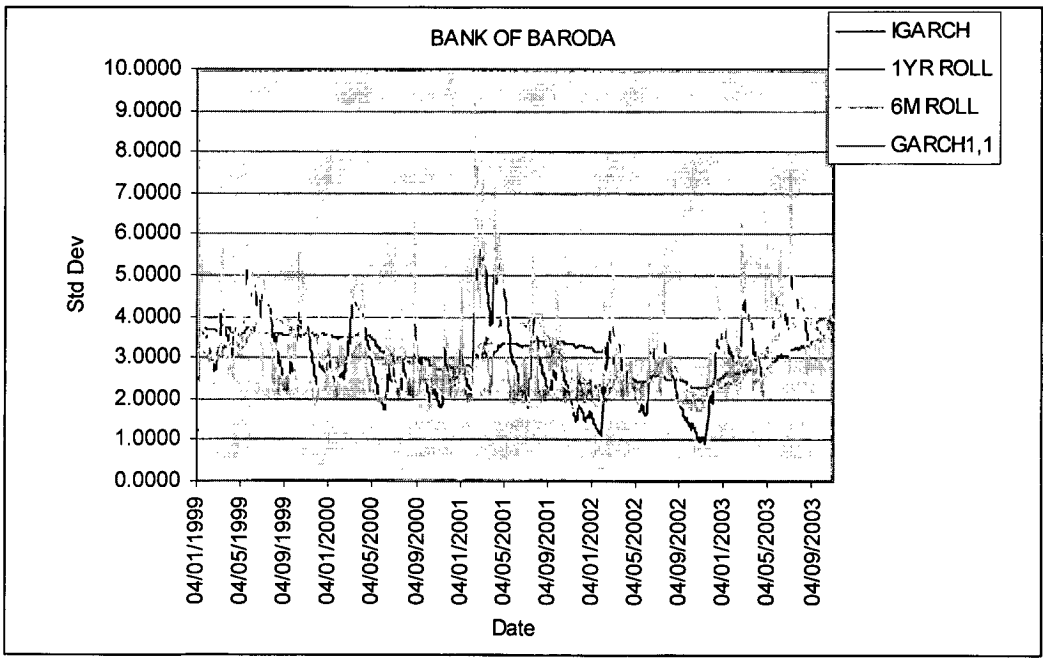
04/09/2003
Date


BANK OF BARODA
IGARCH
1YR ROLL
6M ROLL
GARCH1,1
Std Dev
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7.0000
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5.0000
4.0000
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2.0000
1.0000
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04/01/1999
04/05/1999
04/09/1999
04/01/2000
04/05/2000
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04/01/2001
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04/05/2003
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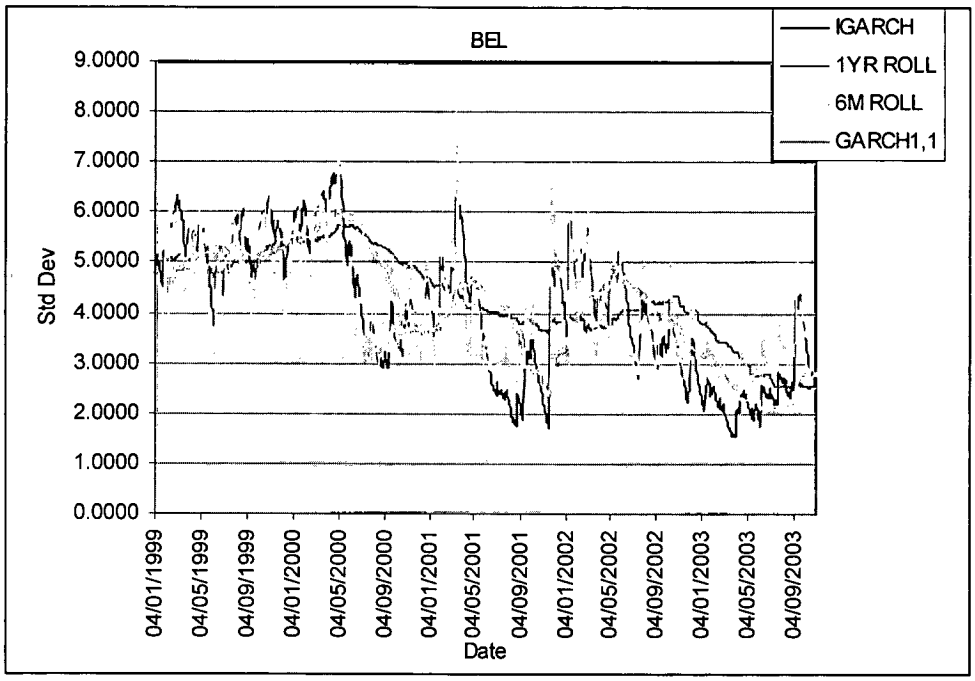
Date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1.0000
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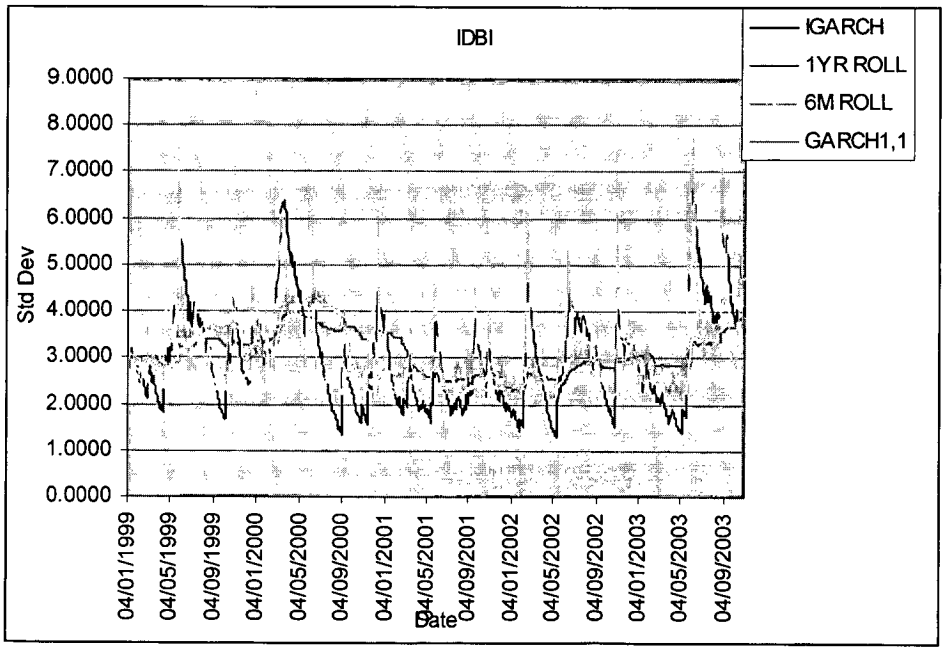
04/05/2003
04/09/2003
Date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1.0000
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04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
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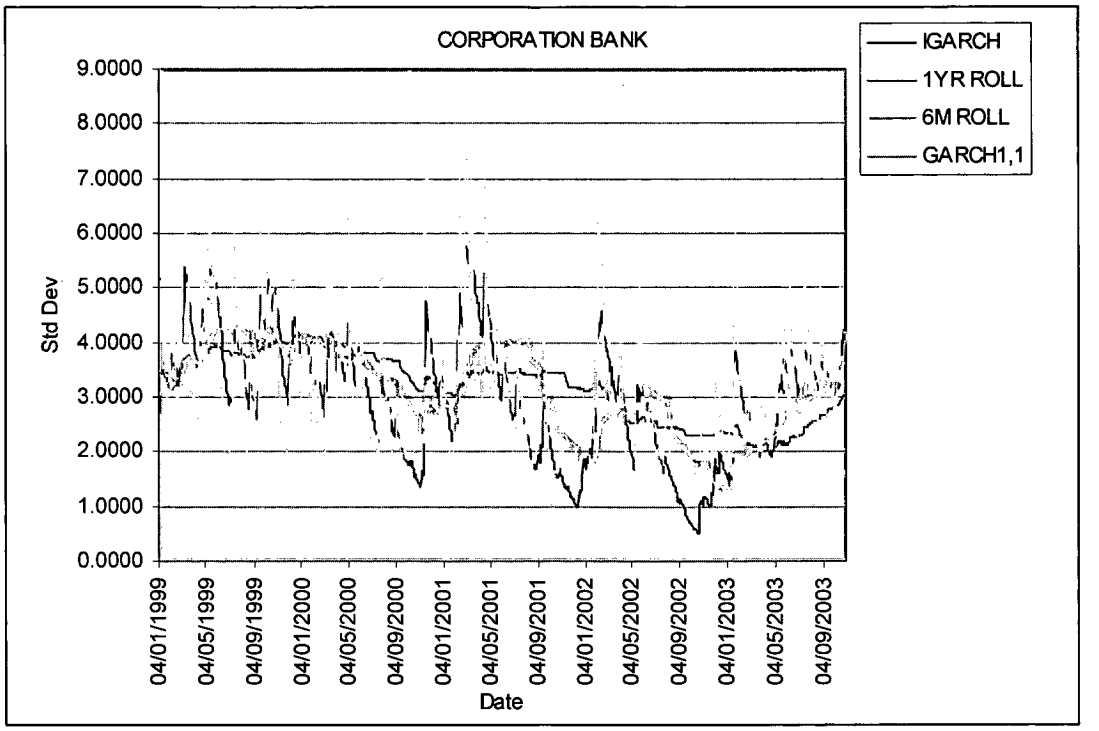
04/05/2003
04/09/2003
Date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GARCH1,1
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1.0000
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04/05/1999
04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
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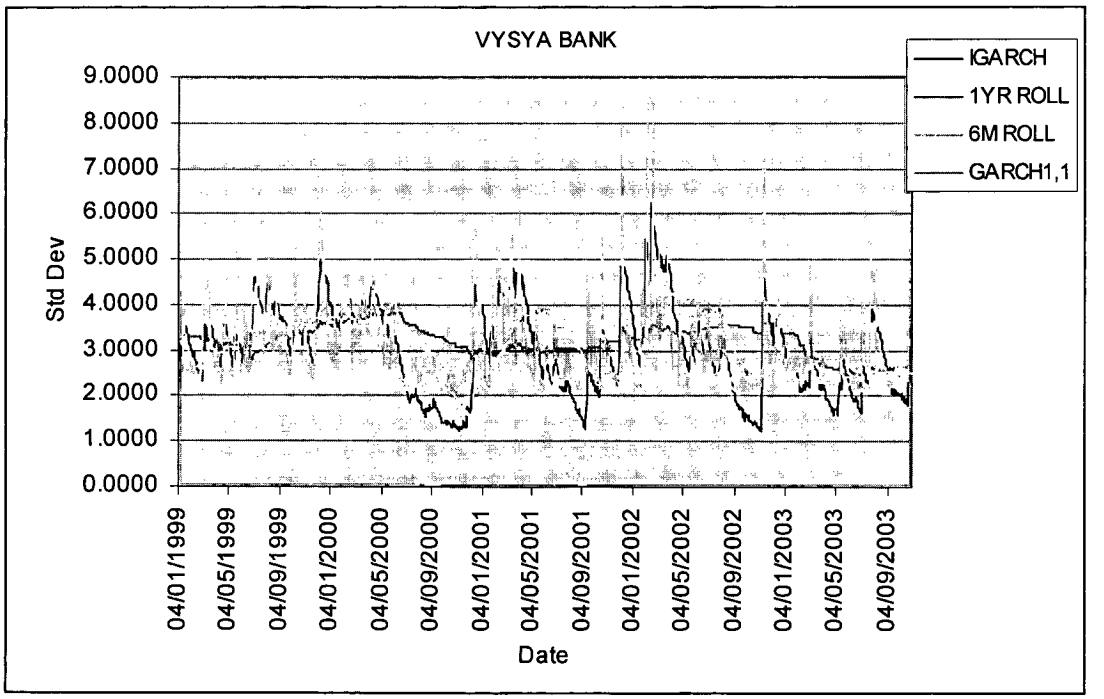
04/01/2003
04/05/2003
04/09/2003
Date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04/09/1999
04/01/2000
04/05/2000
04/09/2000
04/01/2001
04/05/2001
04/09/2001
04/01/2002
04/05/2002
04/09/2002
04/01/2003
04/05/2003
04/09/2003
Date

VI.1.3 Stationarity Condition Testing

To use the data for analysis, the time series should be subjected to stationarity condition. To claim that information on the past behavior of an asset's price or returns may be of some value in predicting its future, the implicit assumption is that that there is some *regularity* in the way the random nature of the time series is generated. This also implies that any models that claim to explain this behavior must also possess this fundamental regularity. One way to narrow down what "regularity" means for a random variable over time is the concept of *stationarity*. A time series, X_t, is said to be *weakly stationary* (or *wide-sense stationary* or *covariance stationary*) if it fulfills three properties:

- Mean is constant over time: $E[X_t] = \mu$ for all t. (36)
- Variance is constant over time: $Var[X_t] = E[(X_t - \mu)^2] = \sigma_X^2$ for all t. (37)
- Covariance between any two values of the series depends only on their distance apart in time (k) <u>not</u> on their absolute location in time (t).

$$Cov[X_t, X_{t-k}] = E[(X_t - \mu)(X_{t-k} - \mu)] = \gamma(k) \tag{38}$$

It is possible to relax these requirements further and still do some analysis but it becomes harder. If property 1 does not hold for example, then given n different observations on X, one would have to estimate n different means - one for each period. This means that there are immediately as many unknown parameters as data points, and we have not even worried about variances and covariances yet. By assuming weak

stationarity it becomes far simpler to estimate the single mean and variance, and the covariances of interest. Levels of economic and financial time series are generally non-stationary because they exhibit trends over time. Standard procedure is to transform the data, in an intelligent way, so that the result is stationary. This normally involves graphing the levels of the variables of interest against time. If the data appear to lie on a straight line, then first differences of the data (X_t-X_{t-1}) will are generally stationary. If the data lie on an exponential curve, then taking logs of the data and first differencing the logs {i.e. use $z_t=x_t-x_{t-1}$, where $x_t=ln(X_t)$} generally results in a stationary series.

Time series whose levels or log-levels are stationary are said to be integrated of order 0, termed I(0). Time series whose first-differences are stationary are said to be integrated of order 1, termed I(1). Time series whose k^{th}-differences are stationary are said to be integrated of order k, termed I(k). Most financial time series are either I(0) or I(1). Returns are generally I(0) and asset prices, which under market efficiency follow a Random Walk, are I(1). The D-F equation only tests for first order autocorrelation. If the order is higher, the test is invalid and the D-F equation suffers from residual correlation. It is important to know the order of integration of non-stationary variables, so they may be differenced before being included in a regression equation. The ADF test does this, but it should be noted that it tends to have low power (i.e. it fails to reject H_0 of non-stationarity even when false) against the alternative of a stationary series with ρ near to 1.

To test the data series for stationarity condition, the paper has used ADF Test, Phillips – Perron test as well as KPSS test. The test have been performed for stock index close values, their log values and returns series.

Stationarity is of particular importance to the empirical researcher because, in general, the results of classical econometric theory are derived under the assumption that variables of concern are stationary. An implication of this is that if we are interested in estimating parameters or testing hypotheses in cases where the set of variables is not entirely composed of ones which are stationary, standard techniques are largely invalid and, therefore, inappropriate. The results of regression analysis and subsequent testing in these cases may well be entirely "spurious", as Granger and Newbold (1974)[1] have pointed out. Throughout this paper, we draw the attention of the reader to those circumstances in which the results of classical regression analysis are inapplicable.

A quandary suggests itself at this point. If standard techniques of econometric analysis are applicable only where variables are stationary, how is one to proceed in the case where the variables in which we are interested are non-stationary? This is where the concept of stationary disequilibrium errors comes to the fore.

VI.1.3.1 Stationarity and unit roots

We begin by defining stationarity. A time series is stationary if its mean, variance and autocovariances are independent of time. Thus, suppose y_t is a time series (or stochastic

[1] C.W.J. Granger and P. Newbold. *Spurious regressions in econometrics*. Journal of Econometrics, 2:111--120, 1974.

process) that is defined for t = 1,2,... and for t = 0,-1,-2,... . Formally, y_t is covariance (weakly) stationary if the following conditions are satisfied (see Harvey (1981, page 22)):

$$E(y_t) = \mu \tag{39}$$

$$E\left[(y_t - \mu)^2\right] = Var(y_t) = \chi(0) \tag{40}$$

$$E\left[(y_t - \mu)(y_{t-\tau} - \mu)\right] = Cov(y_t, y_{t-\tau}) = \chi(\tau), \text{ for } \tau=1,2,... \tag{41}$$

Equations (39) and (40) require the process to have a constant mean and variance, while (41) requires that the covariance between any two values from the series (an autocovariance) depends only on the time interval between those two values (τ) and not on the point in time (t). The mean, variance and autocovariances are thus required to be independent of time.

For many purposes the autocorrelation function is more useful than the autocovariance function in (41) and is defined by

$$corr(y_t, y_{t-\tau}) = \frac{cov(y_t, y_{t-\tau})}{\sqrt{var(y_t)var(y_{t-\tau})}} = \frac{\chi(\tau)}{\chi(0)}, \quad \tau = 1,2,...$$

VI.1.3.2: Testing for Unit Roots

The Augmented Dickey Fuller regression

We have so far assumed that the disturbance term, e_t, is an iid process. If this assumption is incorrect then the limiting distributions and critical values obtained by Dickey and Fuller cannot be assumed to hold. The tests of Phillips and Perron are based on a relaxation of the assumptions concerning the disturbance term that Dickey and Fuller work with. However Dickey and Fuller (1981)[1] themselves demonstrate that the limiting distributions and critical values that they obtain under the assumption that e_t is an iid process are in fact also valid when e_t is autoregressive if the augmented Dickey-Fuller (ADF) regression is run. Thus, assume the data are generated with $\rho=1$ and that e_t is a stationary autoregression of order p

$$e_t = \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_p e_{t-p} + \varepsilon_t \qquad (42)$$

where ε_t now defines an iid process, and consider the reparameterised version of below,

$$\Delta y_t = \phi y_{t-1} + \alpha + \beta t + e_t \qquad (43)$$

where $H_0 : \phi=0$ is to be tested against $H_A : \phi < 0$. Given the equation for e_t in (42) we can write (43) as

$$\Delta y_t = \phi y_{t-1} + \alpha + \beta t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_p e_{t-p} + \varepsilon_t$$

which can be written, since with $\rho=1$ gives $e_t = y_t - y_{t-1}$, as

$$\Delta y_t = \phi y_{t-1} + \alpha + \beta t + \theta_1 (y_{t-1} - y_{t-2}) + \theta_2 (y_{t-2} - y_{t-3}) + \ldots + \theta_p (y_{t-p} - y_{t-p-1}) + \varepsilon_t$$

[1] Dickey, D. A. and Fuller, W.A. (1981). "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root ," Econometrica , 49, 1057-1072.

implying a regression of Δy_t on y_{t-1}, Δy_{t-1}, Δy_{t-2}, ..., Δy_{t-p} , as well as an intercept and time trend, is required. Dickey and Fuller demonstrate that the t-statistic for $\phi=0$ ($\rho=1$ if y_t is used as dependent variable) from this regression, the ADF(p) statistic, has the same non-standard limiting distribution if $\rho=1$ as the statistic t_3 which was defined in the last section. This implies that the critical values for a test based on the ADF(p) statistic are identical to those associated with the t_3 statistic of the previous section..

We are unlikely to know the correct value of p to use in the ADF regression and so will be required to decide this on the basis of the data available. In practice it is usual to include as many terms in the lagged dependent variable as is necessary to achieve white noise residuals.

Phillips and Perron tests

The statistics proposed by Phillips and Perron (1988)[1], termed Z statistics below, arise from their consideration of the limiting distributions of the various Dickey-Fuller statistics when the assumption that e_t is an iid process is relaxed. Phillips and Perron show that, given the quite general assumptions that they make concerning e_t, the t statistic for $\rho = 1$ in (20.3), t_3, has a limiting distribution that involves

$$\sigma_e^2 = \lim_{T \to \infty} \left[\frac{\sum_{t=1}^{t=T} E(e_t^2)}{T} \right] \qquad (44)$$

[1] Phillips, PCB and Perron P (1988): Testing for a unit in time series regression, Biometrica 75, 335-46

and

$$\sigma^2 = \lim_{T \to \infty} \frac{E\left[\sum_{t=1}^{t=T} e_t\right]^2}{T} \qquad (45)$$

If e_t is an iid process then σ^2 and σ_e^2 will be the same and the results of Phillips and Perron will give those previously obtained by Dickey and Fuller. However, in general, σ^2 and σ_e^2 will not be the same and the results of Dickey and Fuller, and the implied critical values for a unit root test based on t_3, will not be valid.

Phillips and Perron proposed transformations of the various statistics considered by Dickey and Fuller, for example a transformation of t_3 which we denote as $Z(t_3)$, involving the two parameters in (44) and (45) such that the Dickey-Fuller limit distributions, and critical values, are restored. This means we can use the critical values Dickey and Fuller give for the t_3 statistic if e_t is iid if we use $Z(t_3)$ when e_t is not iid. To use $Z(t_3)$, and the other Z statistics of Phillips and Perron, consistent estimates of the parameters in (44) and (45) are required. Phillips and Perron propose a number of ways in which such estimates can be obtained.

Both the Phillips and Perron and the ADF approaches are based on asymptotic theory. Thus in both cases it is important to consider how well the limiting distributions approximate the finite sample distribution of the relevant statistic. In addition it is

interesting to consider whether there is evidence concerning the relative power properties of the Phillips and Perron statistics as compared to the ADF statistics.

An indication as to whether the Z statistics should be used in addition to (or in place of) the ADF tests might be obtained in the diagnostic statistics from the ADF regression. If normality, autocorrelation or heterogeneity statistics are significant, one might adopt the Phillips and Perron approach. Further, power may be adversely affected by misspecifying the lag length in the augmented Dickey-Fuller regression, although it is unclear how far this problem is mitigated by choosing the number of lags using data-based criteria and the Z tests have the advantage that this choice does not have to be made. Against this, one should avoid the use of the Z tests if the presence of negative moving average components is somehow suspected in the disturbances. The statistics are defined, explained and applied in Phillips and Perron (1988)[1], and Perron (1988)[2]. Perron (1988) concludes that the results of Nelson and Plosser (1982)[3], where the unit root hypothesis is accepted using augmented Dickey-Fuller tests for the majority of the series under consideration, remain valid when the Phillips and Perron statistics are used.

KPSS Test

One potential problem with all the unit root tests so far described is that they take a unit root as the null hypothesis. Kwiatkowski et al. (1992)[4] provide an alternative test (which has come to be known as the *KPSS* test) for testing the null of stationarity

[1] Phillips, PCB and Perron P (1988): Testing for a unit in time series regression, Biometrica 75, 335-46
[2] Perron P (1988): Trends and Random Walks in Macroeconomic Time Series: Further Evudence from a New Approach, Journal of Economic Dynamics and Control, 12, 297-332
[3] Nelson, C R and Plosser , C I (1982): Trends in Random Walks in Macroeconomic Time Series, Journal of Monetary Economics, 10, 139-62
[4] Kwiatkowski, D., P. Phillips, P. Schmidt, and Y. Shin (1992) Testing the Null of Stationarity Against the Alternative of a Unit Root Journal of Econometrics 54, 159-178.

against the alternative of a unit root. This method considers models with constant terms, and either with (their v_τ statistic) or without (v_{mu}) a deterministic trend term. Thus, the KPSS test tests the null of a level- or trend-stationary process against the alternative of a unit root.

$$LM = \sum_{t=1}^{T} S_t^2 \Big/ T^2 f_0$$

where $S_t = \sum_{i=1}^{t} \hat{\varepsilon}_t$ is the cumulative residual function and $_0f$ is an estimator of the residual spectrum at frequency zero based on the residuals from the regression:

$$y_t = \alpha + \varepsilon_t$$

or:

$$y_t = \alpha + \beta t + \varepsilon_t$$

for the model with a trend.

The kernel -based estimator of the frequency zero spectrum f_0 is based on a weighted sum of the autocovariances, with the weights are defined by a kernel function. The estimator takes the form

$$\hat{f}_0 = \sum_{j=-(T-1)}^{T-1} \hat{\gamma}(j) K(j/l)$$

where l is the bandwidth parameter and K is Parzen kernel function defined as

$$K(x) = \begin{cases} 1-6x^2+6|x|^3 & if\, 0 \le |x| \le 1/2 \\ 2(1-|x|)^3 & if\, 1/2 < |x| \le 1 \\ 0 & otherwise \end{cases}$$

and where $\hat{\gamma}(j)$, the j-th sample autocovariances of the residual $\hat{\varepsilon}_t$, is defined as

$$\hat{\gamma}(j) = \sum_{t=j+1}^{T} (\hat{\varepsilon}_t * \hat{\varepsilon}_{t-j}) / T$$

The following table contains t he critical values for the LM test statistic:

Critical Values of KPSS Tests				
	1%	2.5%	5%	10%
Vmu(level stationary model)	0.739	0.574	0.463	0.347
Vτ(trend Stationary model)	0.216	0.176	0.146	0.119

The practical advantages to the KPSS test are twofold. First, they provide an alternative to the *ADF/PP* tests in which the null hypothesis is stationary. They are thus good complements for the tests we ve focused on so far. A common strategy is to present results of both *ADF/PP* and *KPSS* tests, and show that the results are consistent (e.g., that the former reject the null while the latter fails to do so, or vice -versa). In cases where the two tests diverge (e.g., both fail to reject the null), the possibility of fractional integration should be considered.

VI.1.3.3 Augmented Dickey-Fuller Test Results

In the usual DF tests, it is assumed that the error term *u(t)* was uncorrelated but in the case *u(t)* are correlated, Augmented Dickey-Fuller tests can be used to test the stationary condition. The test is conducted by augmenting the equations by adding the lagged values of the dependent variable. The number of lagged difference terms to include is determined empirically, the idea being to include enough terms so that the error term in the equation as given in equation 4 is serially uncorrelated. Presently we have used the ADF test of the unit root with drift hypothesis against the linear trend stationarity hypothesis.

Auxiliary model: $z(t)-z(t-1) = a.z(t-1) + b(1).(z(t-1)-z(t-2)) + \ldots + b(p).(z(t-p)-z(t-p-1)) + b(p+1) + b(p+2).t + u(t)$, ...(46)

$t = p+2,\ldots,n$, where $u(t)$ is white noise. We have used the ADF test of the unit root with drift hypothesis against linear trend stationarity hypothesis for which we have included the term $b(p+2)*t$ in the equation. (Fuller, W.A. (1996): Introduction to Statistical Time Series (2nd Ed.). New York: John Wiley and Said, S.E. and D.A.Dickey (1984): Testing for Unit Roots in Autoregresive Moving Average of Unknown Order. Biometrika 71, 599-607 Said, S.E. (1991): Unit Root Test for Time Series Data with a Linear Time Trend. Journal of Econometrics 47, 285-303). The variables to be tested is z(t) = Close values of S&P CNX NIFTY, Log Values of S&P CNX NIFTY and return of S&P CNX NIFTY series (first difference). Null hypothesis H(0): z(t) is a unit root with drift process: $a = 0$ and the alternative hypothesis H1: z(t) is a trend stationary process: $a < 0$. The test statistic is the t-value of a. and the default lag width is $p = [cn^r]$, where: $c = 5$ and $r = 0.25$ ($p = 36$) and $n= 2881$ (no. of observations). Selection of optimal p under the null hypothesis has been done by minimum Schwarz (SC) information criteria. ADF Test outcomes are given in Table-VI-6.

Table-VI-6 ADF Test Results

Series	Test statistic*	p-value	Optimal Lag
NIFTY Close	-2.9707	0.14000	1
Log_NIFTY	-2.8451	0.18000	1
Return_NIFTY	-12.8785	0.00000	13

* Critical values of ADF test statistic for 1%, 5% and 10% level of significance are -3.9676, -3.4144 and -3.1290

The ADF test results have revealed that the return series (first difference) is stationary while the original time series as well as their log values are non-stationary. Hence the study has used the log returns for the analysis.

VI.1.3.4 Phillips-Perron Test Results

We have used the Phillips-Perron test of the unit root hypothesis with drift hypothesis against the linear trend stationarity hypothesis. The equation used for maintained hypothesis:

$$z(t) = a.z(t-1) + b + c.t + u(t), \qquad \ldots(47)$$

where u(t) is a zero-mean stationary process.

And the null hypothesis H0: z(t) is a unit root with drift process (a = 1) and the alternative hypothesis H1: z(t) is a linear trend stationary process: a < 1. The test involved is based on n(Alpha - 1), where Alpha is the OLS estimate of the AR parameter 'a'. The test employs a Newey-West type variance estimator of the long-run variance of u(t), with truncation lag m = [c.n^r], where c > 0 and 0 < r < 1/2. Table VI-7 gives the results of Phillips – Perron test.

Table-VI-7: Phillips-Perron test Results

Series	Alpha	Test statistic*	*p*-value	Optimal Lag
NIFTY Close	0.9953	-14.68	0.2	3
Log_NIFTY	0.9952	-14.77	0.2	3
Return_NIFTY	0.0811	-2736.3	0	13
5% Critical region: < -21.78 and 10% Critical region: < -18.42				

VI.1.3.5 KPSS test Results

We have used the KPSS (Kwiatkowski, D., P. Phillips, P. Schmidt, and Y. Shin (1992) Testing the Null of Stationarity Against the Alternative of a Unit Root Journal of Econometrics 54, 159-178.) test of the unit root of the trend stationarity hypothesis against the unit root with drift hypothesis.

Null hypothesis H0: z(t) = c + d.t + u(t), ...(48)

where u(t) is a zero-mean stationary process and c and d are constants. Alternative hypothesis H1: z(t) is a unit root process with drift: z(t) = z(t-1) + c + u(t) The KPSS test employs a Newey-West type variance estimator of the long-run variance of u(t), with truncation lag m = [c.n^r], where c>0 and 0<r<1/2. The default values of c and r are c = 5, r = .25. The table VI-8 gives the results of KPSS test.

Table – VI -8: KPSS Test Results

Series	Test statistic*	Lag	5% Critical	10% Critical	Hypothesis
NIFTY Close	5.6953	3	> 0.146	> 0.119	Reject H0
Log_NIFTY	7.3048	3	> 0.146	> 0.119	Reject H0
Return_NIFTY	0.0773	13	> 0.146	> 0.119	Accept H0

VI.1.4 Autocorrelation Test Results

Two common tools exist to identify the autocorrelation structure in a time series: The autocorrelation function (ACF) & the partial autocorrelation function (PACF). The ACF indicates the strength of the correlation in a time series between x_t *and* x_{t-k} The PACF describes the correlation between x_t *and* x_{t-k} that isn't explained by lower values of k. For example, is there any left-over correlation at a lag of 2 that isn't explained by the lag 1 relationship? The Table-VI-9 gives the ACF and PACF along with the Box-Pierce Q statistics of the return series and as the p-values suggests, we reject the hypothesis of

non-serial correlation while Chart – VI-12 and Chart – VI-13 give the plot of ACF and PACF of log returns of S&P CNX NIFTY and squared returns of S&P CNX NIFTY respectively.

Table – VI-9: ACF and PACF (period 1990 to 2003)

Lag	ACFof Y(t) = DLNIFTY	[PAC(m)] of Y(t) = DLNIFTY	Standard error	Box-Pierce Q statistics for DLNIFTY	p-value	Significance levels: 10%	5%	Asymptotic Variance of Autocorrelation estimate (0.018712)	Asymptotic Variance of PAC estimate (0.018712)	Standard Normal at 5% (Two sides)
	r(m) = Corr(Y(t),Y(t-m))									1.96
1	0.082	0.082	0.0187	Q(1)=19.06	0.00001	2.71	3.84	4.3822	4.3822	Y
2	-0.008	-0.015	0.0187	Q(2)=19.24	0.00007	4.61	5.99	-0.4275	-0.8016	N
3	0.054	0.056	0.0187	Q(3)=27.58	0	6.25	7.81	2.8858	2.9927	Y
4	0.012	0.002	0.0187	Q(4)=27.96	0.00001	7.78	9.49	0.6413	0.1069	N
5	0	0	0.0187	Q(5)=27.96	0.00004	9.24	11.07	0	0.0000	N
6	0.012	0.01	0.0187	Q(6)=28.40	0.00008	10.64	12.59	0.6413	0.5344	N
7	-0.037	-0.04	0.0187	Q(7)=32.41	0.00003	12.02	14.07	-1.9773	-2.1377	Y
8	0.012	0.019	0.0188	Q(8)=32.80	0.00007	13.36	15.51	0.6413	1.0154	N
9	0.05	0.045	0.0187	Q(9)=39.82	0.00001	14.68	16.92	2.6721	2.4049	Y
10	-0.02	-0.024	0.0188	Q(10)=40.94	0.00001	15.99	18.31	-1.0688	-1.2826	N
11	0.007	0.011	0.0188	Q(11)=41.07	0.00002	17.27	19.67	0.3741	0.5879	N
12	0.048	0.041	0.0188	Q(12)=47.69	0	18.55	21.03	2.5652	2.1911	Y
13	-0.013	-0.018	0.0188	Q(13)=48.15	0.00001	19.81	22.36	-0.6947	-0.9619	N
14	0.05	0.052	0.0187	Q(14)=55.17	0	21.06	23.68	2.6721	2.7790	Y
15	0.019	0.005	0.0188	Q(15)=56.22	0	22.31	25.0	1.0154	0.2672	N
16	-0.019	-0.015	0.0188	Q(16)=57.23	0	23.54	26.3	-1.0154	-0.8016	N
17	-0.002	-0.006	0.0187	Q(17)=57.24	0	24.77	27.59	-0.1069	-0.3206	N
18	0.002	-0.002	0.0187	Q(18)=57.25	0.00001	25.99	28.87	0.1069	-0.1069	N
19	-0.011	-0.004	0.0187	Q(19)=57.60	0.00001	27.2	30.14	-0.5879	-0.2138	N
20	0.027	0.025	0.0187	Q(20)=59.63	0.00001	28.41	31.41	1.4429	1.3360	N
21	-0.001	-0.006	0.0187	Q(21)=59.64	0.00001	29.62	32.67	-0.0534	-0.3206	N
22	-0.034	-0.029	0.0187	Q(22)=62.92	0.00001	30.81	33.92	-1.817	-1.5498	N
23	0.008	0.003	0.0187	Q(23)=63.09	0.00001	32.01	35.17	0.4275	0.1603	N
24	-0.01	-0.013	0.0187	Q(24)=63.36	0.00002	33.2	36.41	-0.5344	-0.6947	N
25	-0.053	-0.045	0.0187	Q(25)=71.29	0	34.38	37.65	-2.8324	-2.4049	Y
26	0.024	0.027	0.0187	Q(26)=73.00	0	35.56	38.88	1.2826	1.4429	N
27	-0.031	-0.034	0.0187	Q(27)=75.73	0	36.74	40.11	-1.6567	-1.8170	N
28	-0.048	-0.037	0.0187	Q(28)=82.18	0	37.92	41.34	-2.5652	-1.9773	Y
29	0.066	0.066	0.0187	Q(29)=94.55	0	39.09	42.56	3.5271	3.5271	Y
30	0.022	0.016	0.0187	Q(30)=95.87	0	40.26	43.77	1.1757	0.8551	N

Chart-VI-12: ACF and PACF of S&P CNX NIFTY Log RETURNS

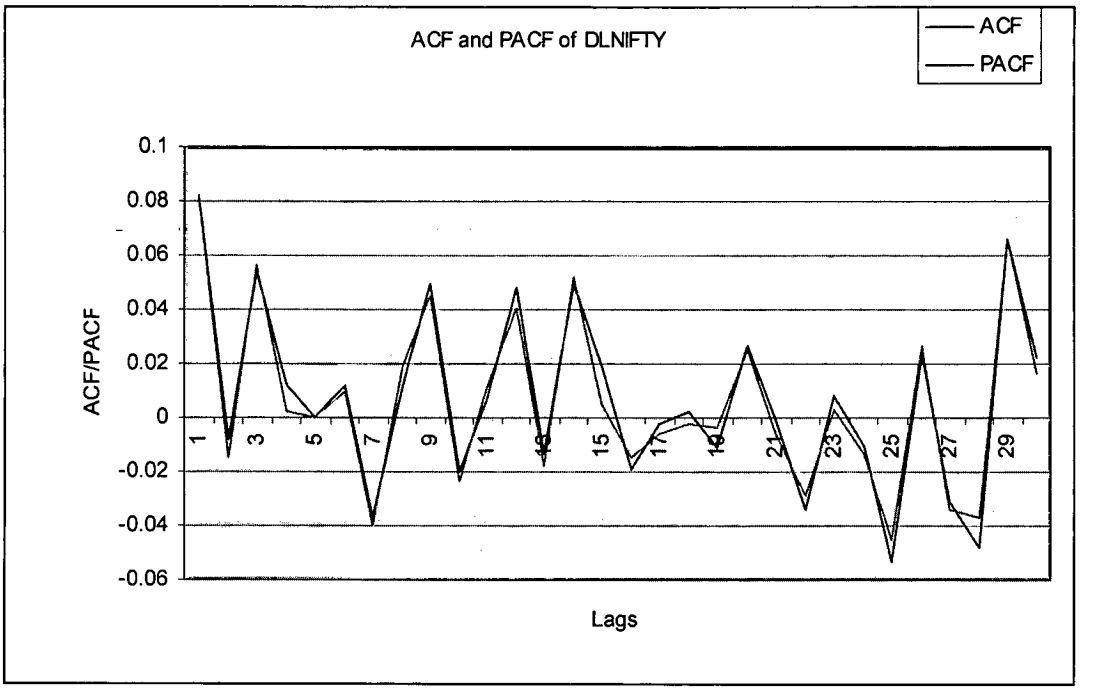
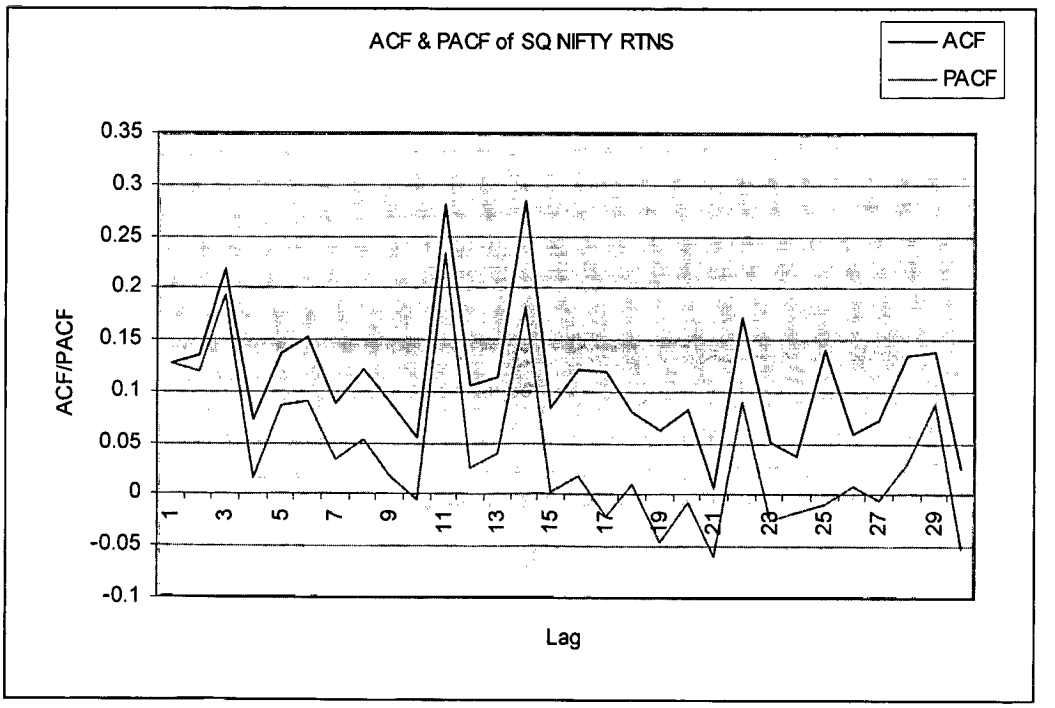


Chart-VI-13: ACF and PACF of S&P CNX NIFTY Squared Log RETURNS



We see that at various lags, we have serial autocorrelation in return series.

Chart-VI-14 ACF Plot of NIFTY

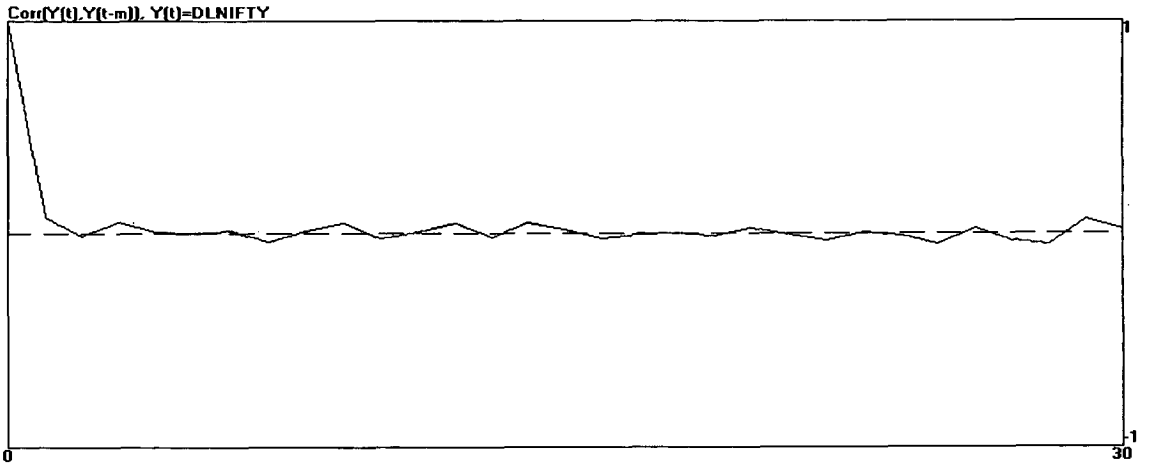
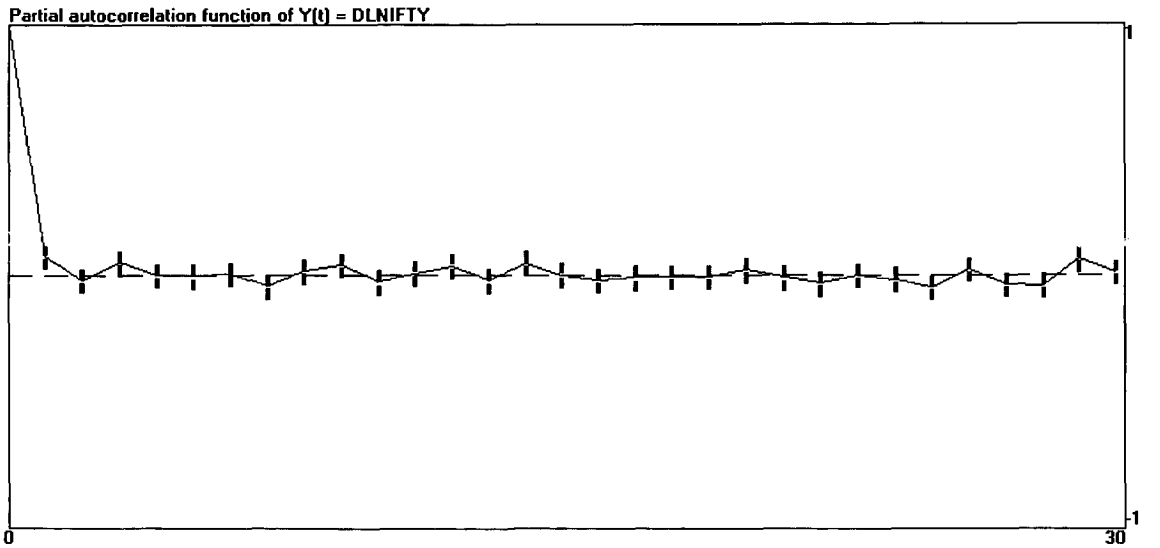


Chart-VI-15 PACF Plot of NIFTY



The lags of 7, 9, 12 and 14 are significant at 5% while lag 1,3 and 14 are significant at 1% level.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.042469	0.036213	1.172783	0.241
DLNIFTY(-1)	0.082403	0.018587	4.433229	0
DLNIFTY(-3)	0.051892	0.018613	2.787966	0.0053
DLNIFTY(-7)	-0.037463	0.018604	-2.01376	0.0441
DLNIFTY(-9)	0.045613	0.018623	2.449246	0.0144
DLNIFTY(-12)	0.04225	0.018659	2.264317	0.0236
DLNIFTY(-14)	0.049557	0.018622	2.661218	0.0078

VI.1.5 ARCH Test

Heteroskedasticity refers to unequal variance in the regression errors. Heteroskedasticity can arise in a variety of ways and a number of tests have been proposed. Typically a test is designed to test the null hypothesis of homoskedasticity (equal error variance) against some specific alternative heteroskedasticity specification. Many economic time series are nonstationary in mean and variance. Other features that some economic time series exhibit are episodes of unusually high variance that may persist for awhile. One way of modeling these features is to model the variance as well as the series. In forecasting an economic time series, we have seen the importance of using conditional forecasts, for example, one period ahead forecasts conditional on all current and past knowledge. In the same way, if the variance is not constant, conditional forecasts of the variance can be important to the forecaster, especially in situations where risk is important. An example is portfolio analysis where forecasts of the mean return for the holding period as well as the variance for the holding period are critical to the decision maker.

Suppose, for example, that the time series is an AR(1):

$$Y(t) = a_0 + a_1(t-1) + e(t) \qquad \text{.... (49)}$$

where the error has mean zero and,

$$\hat{e}^2(t) = \alpha_0 + \alpha_1 \hat{e}^2(t-1) + \alpha_2 \hat{e}^2(t-2) + \ldots + WN(t). \qquad (50)$$

If the parameters α_1, α_2, etc. etc. are zero then the expected estimated variance is constant or homoskedastic:

$$E_{t-1}[\hat{e}^2(t)] = \alpha_0. \qquad (51)$$

The above model postulates that volatility in the current period is related to the previous period plus a white noise error term. If a_2 is positive, it suggests that if volatility was

high in the previous period, it will continue to be high in the current period, indicating volatility clustering. If a_1 is zero, then there is no volatility clustering. (Engel, 1982)[1]

Engle Multiplicative ARCH model takes it one step further. Suppose the error process, e(t) has a multiplicative structure:

$$e(t) = WN(t) * \sqrt{[a_0 + a_1 + e^2(t-1)]} \qquad (52)$$

where the mean of the white noise series is zero and its variance is one, the white noise and lagged error, e(t-1), are independent, and α_0 is greater than zero and α_0 lies between zero and one. The mean of the error process, e(t), conditional or unconditional will be zero. The error process will not be serially correlated, and its unconditional variance will be constant. However, the conditional variance of the error process will be autoregressive of order one, i.e. ARCH(1).

After conducting the regression on the lagged squared residuals coming of the regression done with lagged values of the returns series data, we find $R^2 = 0.017178$ & T (number of observations) = 2854.

And to test if we actually have ARCH in the data we need to do White's ARCH test. And to do the same we need to compute R^2*T where T is the number of observations and R^2 is the R^2 from the regression done on squared errors. The value becomes 0.017178*2854 = 49.02654 that is higher than 3.841, (x^2 – *table)* the 5% critical values

[1] Engle, Robert F.: (1982) Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of the United Kingdom Inflation, *Econometrica*, Volume 50, p. 987-1007

with 1 degree of freedom. Hence we need to accept that the return series used for the analysis has evidence of ARCH. To take care of the same, we need to normalize the return series with their unconditional mean and variance.

VI.2. FOREIGN EXCHANGE DATA

We have considered the foreign exchange data for the period from July 1990 to September 2003. The daily foreign Indian Rupee – US Dollar exchange rate data has been taken from the RBI publications. The foreign exchange market has gone through many structural changes during last few years. From a fixed exchange rate system, we moved to liberalized exchange rate system and from there we moved to unified exchange rate system from March 01, 1993. India moved to convertibility in current account from August 1994 and slowly we have introduced many new policy changes to move the Indian currency to a full convertibility level. RBI appointed S S Tarapore committee to prepare a road map for full convertibility of Indian Rupee. In the light of the above we would like to see the characteristics of the foreign exchange data.

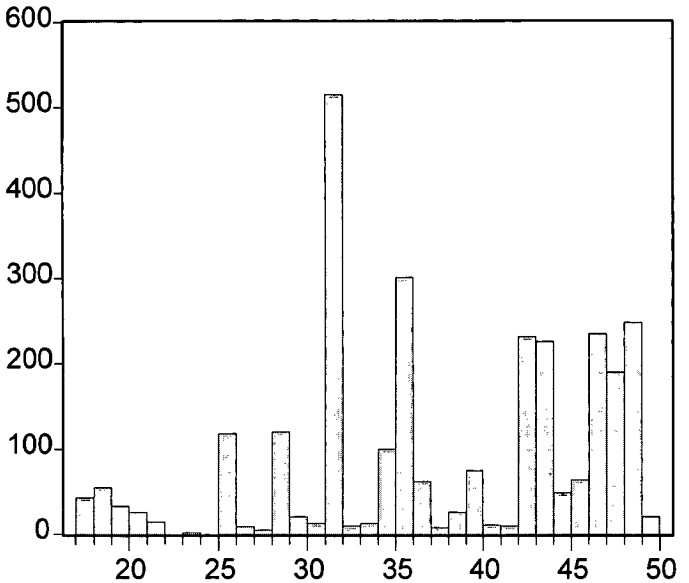
VI.2.1 Descriptive Statistics

The Table-VI-10 summarises the findings for the dataset that was divided into various time buckets according to their relevance in order to understand the structural changes happening in India due to economic reforms since 1991: The daily returns were calculated using the equation 1. We have more than 2800 data points that is quite large for any analysis of time series behaviour.

$$R_t = LN(P_t / P_{t-1}) * 100$$

where R_t is the return of day *t*, P_t is the price of the asset in day t and P_{t-1} is the price of the asset in day *t-1*. The daily exchange rate close values are plotted in Chart–VI-16, log values in Chart-VI-17 and log returns have been plotted in Chart–VI-18 that looks very close to a normal distribution but surely not a normal distribution.

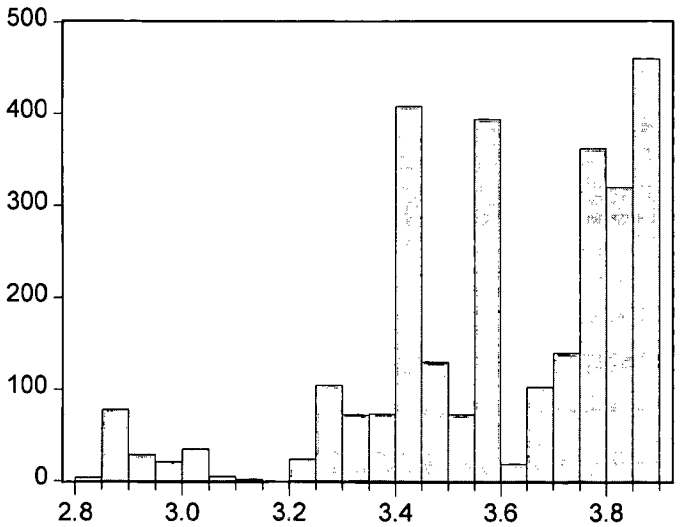
Chart – VI-16: Plot of EXCHANGE RATE CLOSE VALUES



Series: EXRATE
Sample 1 2856
Observations 2856

Mean	37.65367
Median	36.30750
Maximum	49.06000
Minimum	17.26000
Std. Dev.	8.453963
Skewness	-0.461739
Kurtosis	2.360308
Jarque-Bera	150.1802
Probability	0.000000

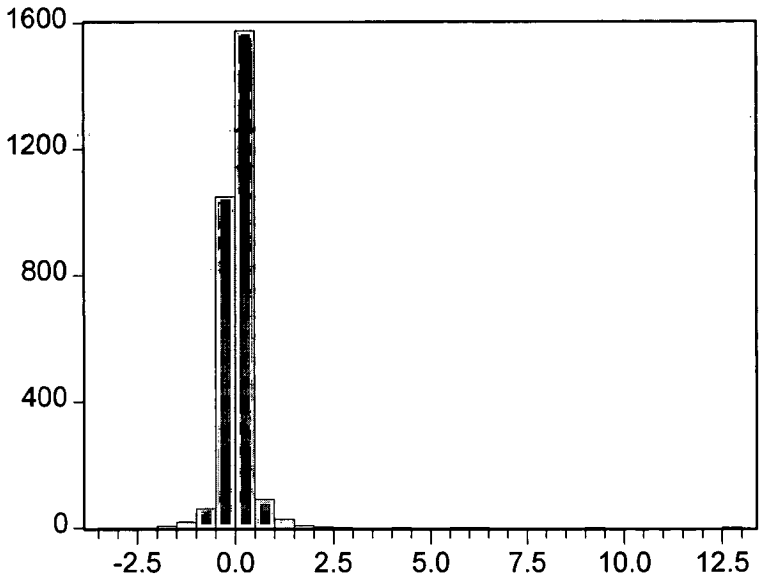
Chart – VI-17: Plot of Log Values of EXCHANGE RATE CLOSE VALUES



Series: LEX
Sample 1 2856
Observations 2856

Mean	3.599309
Median	3.592000
Maximum	3.893000
Minimum	2.848400
Std. Dev.	0.251689
Skewness	-1.004821
Kurtosis	3.704627
Jarque-Bera	539.6837
Probability	0.000000

Chart – VI-18: Plot of Log returns of EXCHANGE RATE CLOSE VALUES



Series: DLEX	
Sample 1 2856	
Observations 2856	
Mean	0.033929
Median	0.000000
Maximum	12.81101
Minimum	-3.297790
Std. Dev.	0.467899
Skewness	11.35160
Kurtosis	269.8606
Jarque-Bera	8535870.
Probability	0.000000

The Kurtosis is higher than 3 indicating excess kurtosis and the returns are positively skewed. The Jarque-Bera statistics surely rejects normality condition. We have plotted the Exchange Rate close values (Chart-VI-19) as well as their return series (Chart-VI-20) against the backdrop of the normal distribution.

Chart-VI-19: Plot of Exchange Rate close Values (Normal distribution)

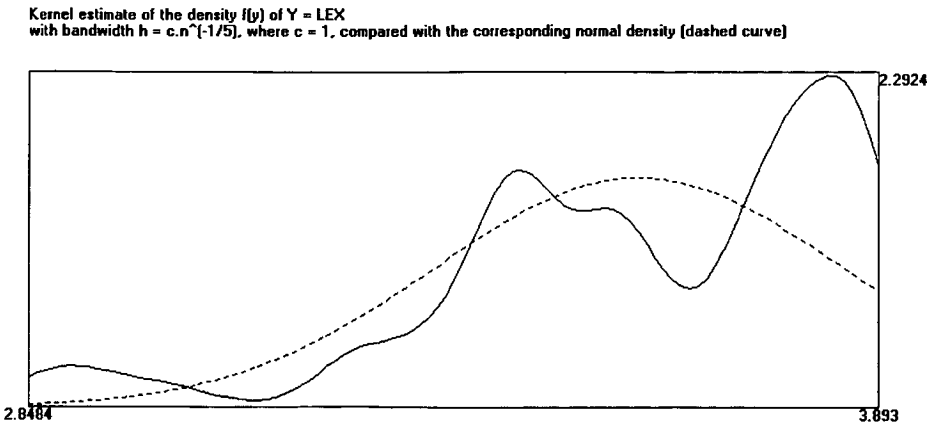
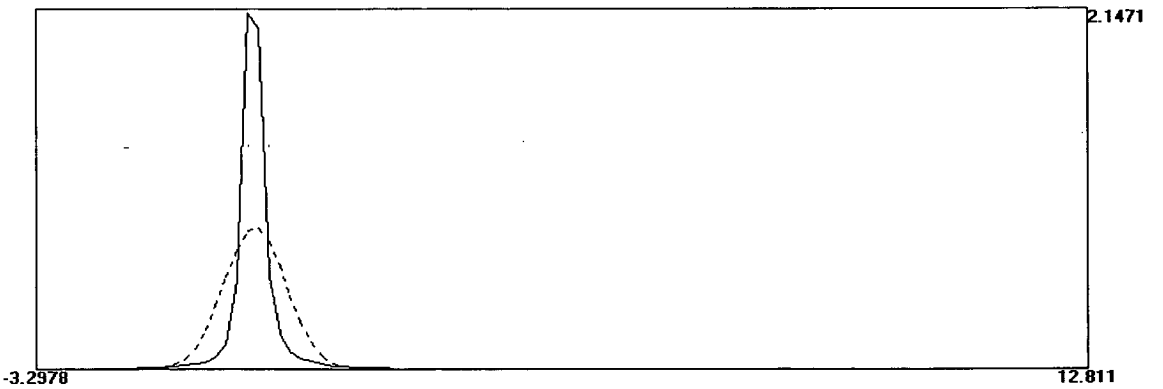


Chart-VI-20: Plot of Log Returns of Exchange Rate close Values (Normal distribution)

Kernel estimate of the density f(y) of Y = DLEX
with bandwidth h = c.n^[-1/5], where c = 1, compared with the corresponding normal density (dashed curve)



The Chart-VI-21 plots the movement of exchange rate while Chart-VI-22 plot their log values and Chart-VI-23 plots the log returns.

Chart-VI-21: Movement of Exchange Rate

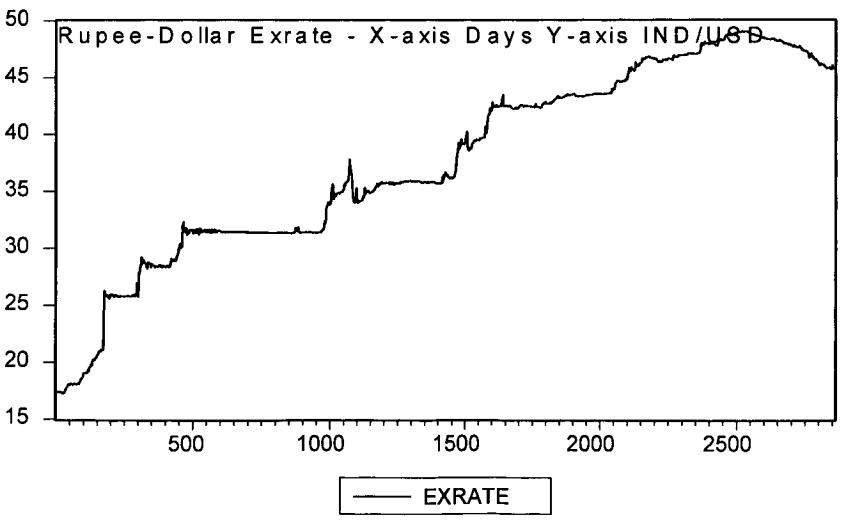


Chart-VI-22: Movement of Log Values of Exchange Rate

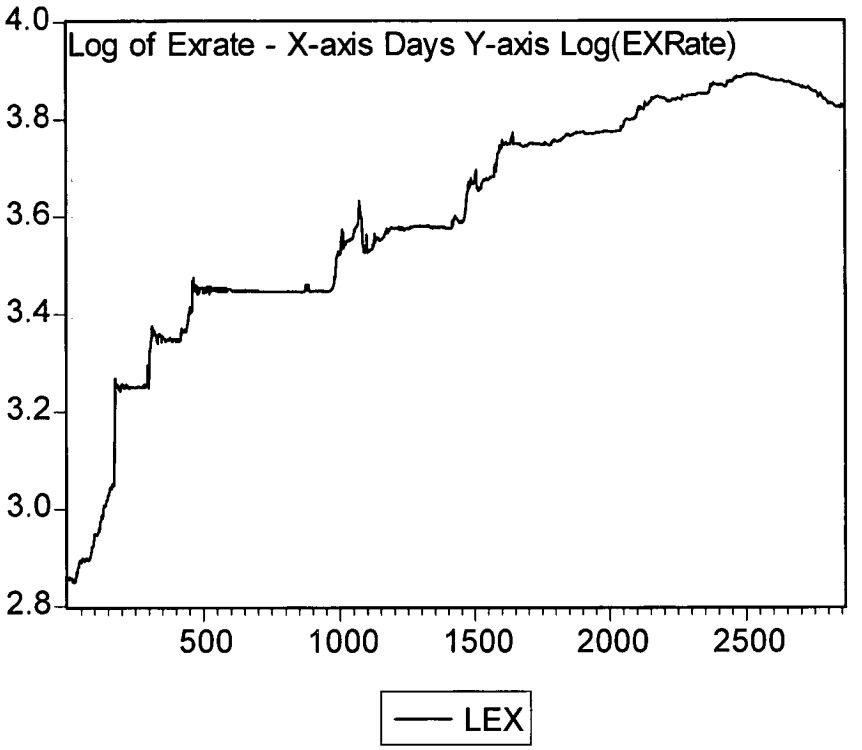


Chart-VI-23: Movement of Log Returns of Exchange Rate

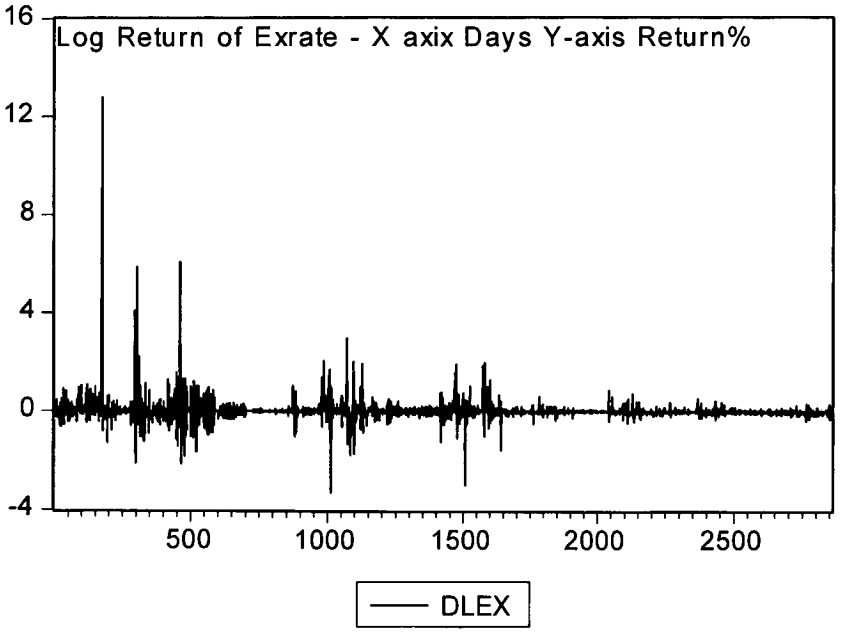


Table: VI-10 Descriptive Statistics of Daily Returns									
Period	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations
1990-03	0.0339	0.000	12.811	-3.2978	0.4679	11.3516	269.8606	853587	2856
1990-94	0.0702	0.000	12.811	-2.1267	0.7516	9.1910	134.7141	618290	839
1995-03	0.0188	0.000	2.9765	-3.2978	0.2729	0.1563	40.8254	120251	2017
1996-03	0.0147	0.000	2.9765	-2.9906	0.2521	0.8120	40.4809	105969	1807
1997-03	0.0155	0.000	1.9851	-2.9906	0.2055	-0.0661	53.6189	169217	1585
1998-03	0.0117	0.000	1.9851	-2.9906	0.1880	-1.2271	73.5914	282719	1360
1999-03	0.0069	0.000	0.8731	-0.5048	0.1138	1.3315	11.7789	3962.5	1130
2000-03	0.0061	0.000	0.8731	-0.4597	0.1176	1.4842	11.5455	3051.8	895
2001-03	-0.002	0.000	0.5242	-0.3842	0.1010	0.8466	7.2858	582.19	658
2002-03	-0.011	-0.02	0.3920	-0.3842	0.0948	0.3034	5.5527	121.04	422
2003-03	-0.025	-0.02	0.3203	-0.3842	0.1116	0.0926	4.2819	12.650	181

VI.2.2 Stationarity Condition Testing

VI.2.2.1 Augmented Dickey-Fuller Test

Presently we have used the ADF test of the unit root with drift hypothesis against the linear trend stationarity hypothesis.

Auxiliary model: z(t)-z(t-1) = a.z(t-1) + b(1).(z(t-1)-z(t-2)) + ... + b(p).(z(t-p)-z(t-p-1)) + b(p+1) +b(p+2).t + *u(t)*, (53)

t = p+2,...,n, where *u(t)* is white noise. We have used the ADF test of the unit root with drift hypothesis against linear trend stationarity hypothesis for which we have included the term b(p+2)*t in the equation. (Fuller, W.A. (1996): Introduction to Statistical Time Series (2nd Ed.). New York: John Wiley Said, S.E. and D.A.Dickey (1984): Testing for Unit Roots in Autoregresive Moving Average of Unknown Order. Biometrika 71, 599-607 Said, S.E. (1991): Unit Root Test for Time Series Data with a Linear Time Trend. Journal of Econometrics 47, 285-303). The variables to be tested is z(t) = Close

values of EXRATE, Log Values of EXRATE and return of EXRATE series (first difference). Null hypothesis H(0): z(t) is a unit root with drift process: a = 0 and the alternative hypothesis H1: z(t) is a trend stationary process: a < 0. The test statistic is the t-value of a. and the default lag width is p = [cn^r], where: c = 5 and r = 0.25 (p = 36) and n= 2856 (no. of observations). Selection of optimal p under the null hypothesis has been done by minimum Schwarz (SC) information criteria. ADF Test outcomes are given in Table-VI-11.

Table-VI-11 ADF Test Results

Series	Test statistic*	p-value	Optimal Lag
EXRateClose	-1.9110	0.65000	2
Log_EXRATE	-3.1533	0.10000	2
Return_EXRATE	-15.0390	0.00000	10

* Critical values of ADF test statistic for 1%, 5% and 10% level of significance are -3.9676, -3.4144 and -3.1290

The ADF test results have revealed that the return series (first difference) is stationary while the original time series as well as their log values are non-stationary. Hence the study has used the log returns for the analysis.

VI.2.2.2 Phillips-Perron Test

TableVI-12: Phillips-Perron Test Results

Series	Alpha	Test statistic*	*p*-value	Optimal Lag
EXRateClose	0.9979	-6.13	0.73000	2
Log_EXRATE	0.9970	-8.74	0.54000	2
Return_EXRATE	-0.0555	-3439.96	0.00000	12
5% Critical region: < -21.78 and 10% Critical region: < -18.42				

The Phillips-Perron test results have revealed that the return series (first difference) is stationary while the original time series as well as their log values are non-stationary. Hence the study has used the log returns for the analysis.

VI.2.2.3 KPSS test

Table:VI-13: KPSS Test Results

Series	Test statistic*	Lag	5% Critical	10% Critical	Hypothesis
EXRateClose	6.7746	2	> 0.146	> 0.119	Reject
Log_EXRATE	9.5578	2	> 0.146	> 0.119	Reject
Return_EXRATE	0.1215	10	> 0.146	> 0.119	Accept

The KPSS test results have revealed that the return series (first difference) is stationary while the original time series as well as their log values are non-stationary. Hence the study has used the log returns for the analysis.

VI.2.2.4 Autocorrelation Test Results

Two common tools exist to identify the autocorrelation structure in a time series: The autocorrelation function (ACF) & the partial autocorrelation function (PACF). The ACF indicates the strength of the correlation in a time series between x_t *and* x_{t-k} The PACF describes the correlation between x_t *and* x_{t-k} that isn't explained by lower values of k. For example, is there any left-over correlation at a lag of 2 that isn't explained by the lag 1 relationship? The Table-VI-14 gives the ACF and PACF along with the Box-Pierce Q statistics of the return series and as the p-values suggests, we reject the hypothesis of non-serial correlation while Chart –VI- 24 and Chart – VI – 25 gives the ACF and PACF charts of log returns of INR-USD Exchange rate and squared return of the INR-USD Exchange rate.

TableVI-14: ACF and PACF Statistics and Box Pierce Q Statistics for Serial Autocorrelation

Lag	ACFof Y(t) = DLEXRATE	[PAC(m)] of Y(t) = DLEXRATE	Standard error	Box-Pierce Q statistics for DLEXRATE	p-value	Significance levels: 10%	5%	Asymptotic Variance of Autocorrelation estimate (0.018712)	Asymptotic Variance of PAC estimate (0.018712)	Standard Normal at 5% (Two sides)
	r(m) = Corr(Y(t),Y(t-m))									1.96
1	-0.051	-0.051	0.0187	Q(1)=7.36	0.00666	2.71	3.84	-2.7255	-2.7255	Y
2	0.193	0.191	0.0184	Q(2)=113.44	0	4.61	5.99	10.3142	10.2074	Y
3	-0.01	0.008	0.0187	Q(3)=113.73	0	6.25	7.81	-0.5344	0.4275	N
4	-0.019	-0.059	0.0187	Q(4)=114.81	0	7.78	9.49	-1.0154	-3.1531	N
5	-0.018	-0.022	0.0187	Q(5)=115.74	0	9.24	11.07	-0.9619	-1.1757	N
6	0.022	0.038	0.0187	Q(6)=117.17	0	10.64	12.59	1.1757	2.0308	N
7	-0.019	-0.009	0.0187	Q(7)=118.14	0	12.02	14.07	-1.0154	-0.4810	N
8	0.08	0.068	0.0187	Q(8)=136.25	0	13.36	15.51	4.2753	3.6340	Y
9	-0.012	-0.002	0.0187	Q(9)=136.64	0	14.68	16.92	-0.6413	-0.1069	N
10	0.035	0.007	0.0187	Q(10)=140.10	0	15.99	18.31	1.8705	0.3741	N
11	0.007	0.011	0.0187	Q(11)=140.25	0	17.27	19.67	0.3741	0.5879	N
12	-0.056	-0.061	0.0187	Q(12)=149.24	0	18.55	21.03	-2.9927	-3.2599	Y
13	0.029	0.024	0.0187	Q(13)=151.66	0	19.81	22.36	1.5498	1.2826	N
14	-0.033	-0.01	0.0187	Q(14)=154.86	0	21.06	23.68	-1.7636	-0.5344	N
15	0.01	0.001	0.0188	Q(15)=155.13	0	22.31	25.	0.5344	0.0534	N
16	0.021	0.02	0.0188	Q(16)=156.36	0	23.54	26.3	1.1223	1.0688	N
17	0.026	0.029	0.0188	Q(17)=158.35	0	24.77	27.59	1.3895	1.5498	N
18	0.01	0.002	0.0188	Q(18)=158.63	0	25.99	28.87	0.5344	0.1069	N
19	0.049	0.038	0.0188	Q(19)=165.61	0	27.2	30.14	2.6186	2.0308	Y
20	-0.048	-0.038	0.0188	Q(20)=172.13	0	28.41	31.41	-2.5652	-2.0308	Y
21	0.027	0.004	0.0188	Q(21)=174.20	0	29.62	32.67	1.4429	0.2138	N
22	-0.022	0.003	0.0188	Q(22)=175.63	0	30.81	33.92	-1.1757	0.1603	N
23	0.04	0.036	0.0188	Q(23)=180.10	0	32.01	35.17	2.1377	1.9239	Y
24	0.015	0.015	0.0188	Q(24)=180.71	0	33.2	36.41	0.8016	0.8016	N
25	0.051	0.038	0.0188	Q(25)=188.23	0	34.38	37.65	2.7255	2.0308	Y
26	-0.011	-0.018	0.0188	Q(26)=188.58	0	35.56	38.88	-0.5879	-0.9619	N
27	-0.001	-0.026	0.0188	Q(27)=188.58	0	36.74	40.11	-0.0534	-1.3895	N
28	-0.012	0.003	0.0188	Q(28)=188.97	0	37.92	41.34	-0.6413	0.1603	N
29	0.016	0.022	0.0188	Q(29)=189.73	0	39.09	42.56	0.8551	1.1757	N
30	-0.031	-0.024	0.0188	Q(30)=192.47	0	40.26	43.77	-1.6567	-1.2826	N

The lags of 2, 8 and 12 are significant at 1% and lag 1 and 9 at 5% level.

Chart-VI- 24: ACF and PACF of Log returns of Exchange Rate

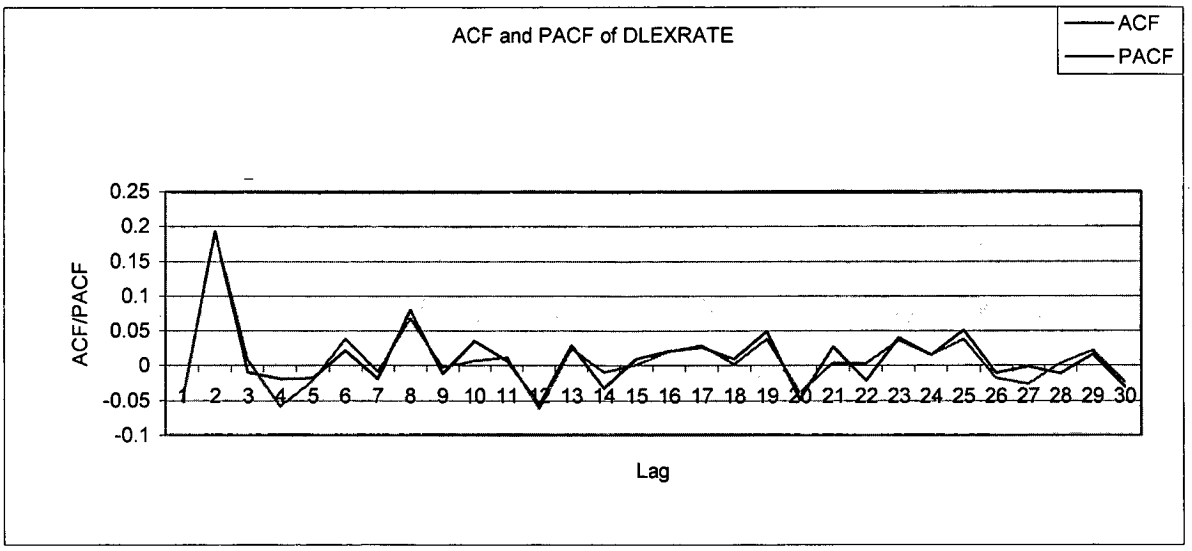
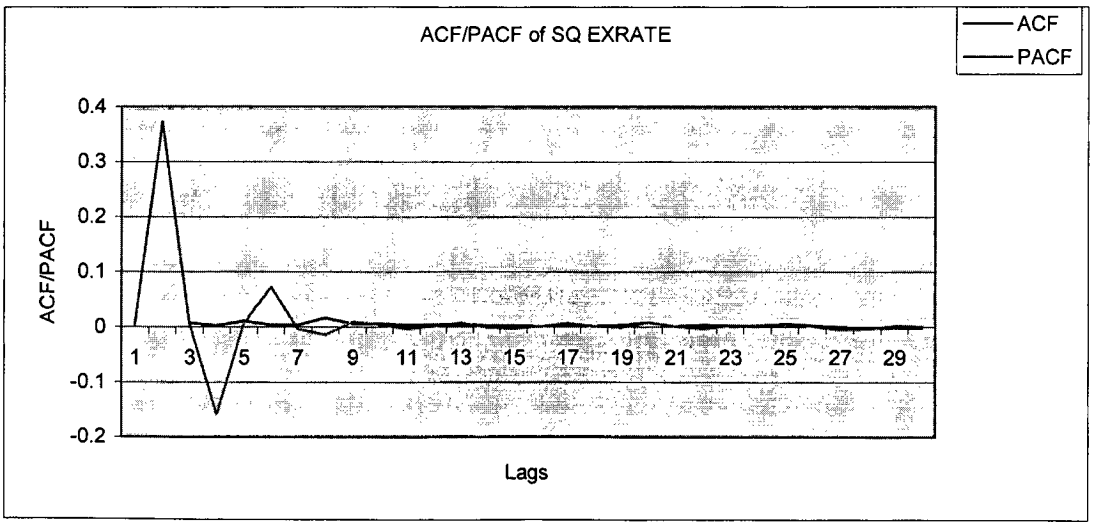


Chart-VI- 25: ACF and PACF of Squared Log returns of Exchange Rate



The following table gives the significant lags for autocorrelation function. It can be seen that lag 2, 8 and 12 are significant at 1% level while lag 1 and 19 are significant at 5% level.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.027392	0.008705	3.146811	0.0017
DLEX(-1)	-0.03984	0.018341	-2.17197	0.0299
DLEX(-2)	0.190166	0.018359	10.35838	0
DLEX(-8)	0.073136	0.018327	3.990729	0.0001
DLEX(-12)	-0.06026	0.018331	-3.28734	0.001
DLEX(-19)	0.043227	0.018323	2.359171	0.0184

Box-Pierce Q statistics shows serial correlation in data. The ACF and PACF graphs of Exchange rate returns are shown in Chart-VI-26and Chart-VI-27.

Chart-VI-26: ACF plot of Exchange Rate Returns

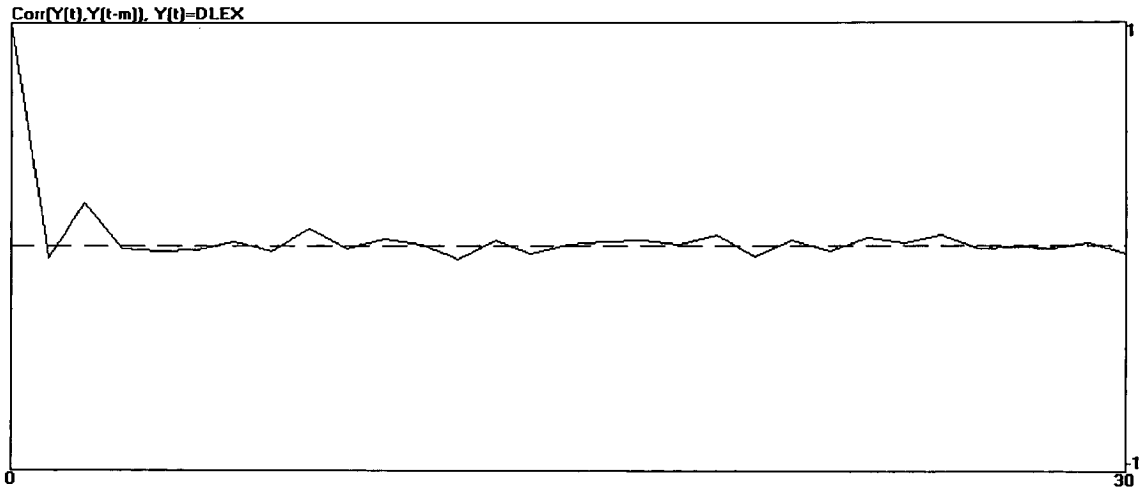
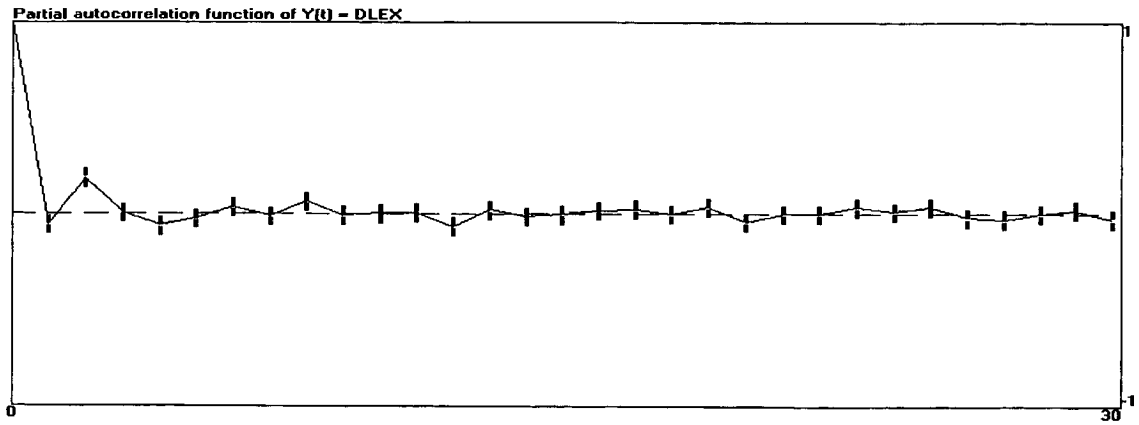


Chart-VI-27: PACF plot of Exchange Rate Returns



We find that the exchange rate series is non stationary in level but stationary. We will normalize the series for doing the long memory test.

CHAPTER VII

VII.0 RESULTS

VII.1. LONG MEMORY

VII.1.1 Evidence of Long Memory in Stock Market Data

We have used the stock market data for the long memory test. We have calculated the log returns of index S&P CNX NIFTY and used the same for calculating the variance ratio. We have used various period blocks like 2 weeks, 1 month, 3 months, 6, 9, 12, 24 and 60 months to calculate the variance ratio. We have assumed 250 working trading days in a year and about 21 days a month. We have more than 2800 data points for our analysis. We have conducted the test for the full data set from July 1990 to September 2003 as well as for a sub-sample period from July 1995 to September 2003. The sub-sample period has been chosen from July 1995 as major market reforms were introduced in India from this period. Performing the variance ratio test on the about 13 years stock index data following results were obtained:

Table: VII – 1: Variance Ratio Test Results of S&P CNX NIFTY

Period	1990-2003		1995-2003	
Lag	Variance	Variance Ratio	Variance	Variance Ratio
14 Days	36.1087	0.9544	25.9480	0.9067
1month	83.0713	1.0456	56.5589	0.9411
3 months	222.2875	0.9326	136.9037	0.7593
6 months	353.3267	0.7471	227.9719	0.6373
9 months	536.7700	0.7507	287.4320	0.5314
1-year	782.1575	0.8270	386.3638	0.5400
2- years	1003.4501	0.5305	642.4144	0.4490
5-years	1284.8113	0.2717	430.5415	0.1204

For the period 1990-2003, the above results show that in all the lags except 1 month, the variance ratio has been between 0 to 1 indicating mean reversion tendency. For the lag of 1 month shows a very close case to 1 indicating the possibility of Random Walk. But none of the lags show any sign of long memory that is no indication of the persistence or a trend-reinforcing tendency in stock market returns. The sub-sample period shoed that for all time lags, the variance ratio is between 0 and 1 indicating mean reversion. It clearly showed no sign of long memory process in stock market data.

The same data has been used to estimate for Rescaled Range analysis to calculate Hurst Exponent for all relevant periods of time using the full (July 1990 to September 2003) period data as well as for the sub-sample period (July 1995 to September 2003). The results of the test are listed below in Table-VII-2:

Table: VII – 2: R S Analysis (H) Results

Time Bucket	Hurst Exponent			
	1990-2003	C	1995-2003	C
14 Days	0.688	0.2977	0.7042	0.3272
1month	0.6551	0.2399	0.6628	0.2532
3 months	0.6428	0.2189	0.6544	0.2387
6 months	0.6359	0.2073	0.639	0.2125
9 months	0.616	0.1745	0.6115	0.1672
1 year	0.6101	0.1649	0.6086	0.1625
2 years	0.6063	0.1588	0.6088	0.1628
5 years	0.5777	0.1137	0.5653	0.0947

None of the values for the time lags is equal to 0.50 indicating that Indian stock market can not be said to follow random walk in so far as the daily returns are concerned when we use S&P CNX NIFTY as the market proxy. This shows that there is a definite possibility for persistence in the S&P CNX NIFTY returns for all time lags. Here we

have a persistent or trend-reinforcing series and it indicates that long memory structure possibly exists.

VII.2. Evidence of Long Memory in Exchange Rate Data

We have used the exchange rate reference rates released by RBI for the long memory test. We have calculated the log returns of exchange rate and used the same for calculating the variance ratio. We have used various period blocks like 2 weeks, 1 month, 3 months, 6, 9, 12, 24 and 60 months to calculate the variance ratio. We have assumed 250 working trading days in a year and about 21 days a month. We have more than 2800 data points for our analysis. We have conducted the test for the full data set from July 1990 to September 2003 as well as for a sub-sample period from July 1995 to September 2003. The sub-sample period has been chosen from July 1995 as major market reforms were introduced in India from this period. Performing the variance ratio test on the about 13 years exchange rate data following results (Table – VII – 3) were obtained:

Table – VII-3: Variance Ratio Results of Exchange Rate

Time Bucket	1990-2003		1995-2003	
Lag	Variance	Variance Ratio	Variance	Variance Ratio
14 Days	2.0507	0.9313	0.8202	1.0730
1month	4.744	1.0259	1.9210	1.1967
3 months	15.0699	1.0863	5.7067	1.1851
6 months	30.464	1.1068	9.7410	1.0195
9 months	48.6499	1.169	13.1634	0.9112
1 year	78.9232	1.4336	18.3067	0.9580
2 years	129.2941	1.1743	33.3692	0.8731
5 years	160.5458	0.5833	56.8889	0.5954

For the full period (1990-2003), the above tests show some interesting results. It shows that in the 1, 3, 6, 9, 12, 24 months, the variance ratio has been greater than 1 that indicates the persistence or a trend-reinforcing tendency in exchange rate returns. However, the 1-month period shows a very close case of Random Walk. In the lag periods of 2 weeks and 5 years the same is between 0 to 1 indicating mean reversion tendency. However, when we did the analysis for sub-sample 1995-2003, it showed that periods of upto 6 months have variance ratio greater than 1 indicating persistence or trend-reinforcing while other periods showed trends of mean reversion.

The same data has been used for Rescaled Range Analysis to estimate the Hurst Exponent "H" for all relevant periods of time. The results of the test are listed below in Table-VII – 4.

TableVII-4: Rescaled Range (H) Results of Exchange Rate Data

Time Bucket	Hurst Exponent			
	1990-2003		1995-2003	
14 Days	0.624	0.1876	0.6572	0.2435
1month	0.564	0.0928	0.6037	0.1546
3 months	0.5775	0.1134	0.6204	0.1816
6 months	0.574	0.1080	0.6057	0.1578
9 months	0.5761	0.1113	0.6031	0.1536
1 year	0.5758	0.1108	0.5976	0.1449
2 years	0.5998	0.1484	0.6117	0.1675
5 years	0.6246	0.1885	0.6331	0.2026

None of the values for the time lags is equal to 0.50 indicating that Indian foreign exchange market cannot be said to follow random walk in so far as the daily returns are concerned when we use RBI reference rates as the market proxy. However all the lags

show H values greater than 0.5 indicating persistence or trend-reinforcing process. This shows that there is a definite possibility for persistence in the exchange rate returns for all time lags. If we take the full data, the values are close to 0.5 indicating noise in the data but for the later period, the results support long memory process.

VII.3. MARKET INTERLINKAGES

VII.3.1. Macroeconomic Variables and Stock Prices

It is widely believed that stock market is related to macroeconomic fundamentals of an economy, as companies that are listed for trading in stock exchanges are the ones who contribute significantly to the economy's growth. The notion that macroeconomic factors can drive the movement of stock prices is now widely accepted. However, it was only in the past decade or so that attempts have been made to capture the effect of economic forces in a theoretical framework and calibrate these effects empirically. According to standard stock valuation model, the determinants of stock price are the expected cash flows from the stock and the required rate of return. Chen, Roll and Ross (1986) showed that economic variables have a systematic influence on stock return as a result of their effect on future dividends and discount rate and they provided the foundation for the belief in the existence of a long-term equilibrium relationship between stock price and related macroeconomic variables. A central issue in macroeconomics is the question of how financial markets are connected to the real side of the economy. The issue has gained momentum due to increasing cross border movement of funds as fund managers try to move to markets where possibility of higher returns vis-à-vis risk is high. The ongoing integration of international capital markets and the repeated occurrence of large financial crises have raised the concern about the topic beyond academic circles.

The cointegration of macroeconomic variables and stock market has been an extensive area of research in financial econometrics. In financial economics, there has been number of studies concerning developed markets like USA, Japan, UK and European markets (see Lee (1992)[1], Mukherjee and Naka (1995)[2], Poon and Taylor (1991)[3], and Leigh (1997)[4]). Some of the studies have also centered on emerging markets (Naka, Mukherjee and Tufte (1999)[5]). The stock market, being an important part of the financial system should have a systemic linkage with fundamentals of the economy. The economic reason behind the logic is the price of a stock necessarily reflect all the future cash flows discounted by the appropriate discount rate. The future cash flows depend on many economic factors like GDP growth, price index (WPI), interest rate, exchange rate fluctuations, global and domestic oil prices, etc. The current study has focused on Indian market with about seven and half years data set. This study also investigates the short run causal relationship between the stock market and other macroeconomic variables in India for the period April1996-July 2003. We have taken this period as stock market reforms in India gained momentum after 1995 and many regulatory changes were introduced in this period. In this study we have used major macroeconomic indicators like Money supply, foreign exchange reserves, foreign

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[1] Lee, B.S., (1992), "Causal relation among stock returns, interest rates, real activity, and inflation", Journal of Finance, 47, 1591-1603.

[2] Mukherjee, D. and A. Naka, (1995), "Dynamic relations between macroeconomic variables and the Japanese stock market: an application of a vector error correction model", Journal of Financial Research, 18, 223-237.

[3] Poon, S. and S.J. Taylor, (1991), *"Macroeconomic factors and the U.K. stock markets"*, Journal of Business Finance and Accounting, 18, 619-636.

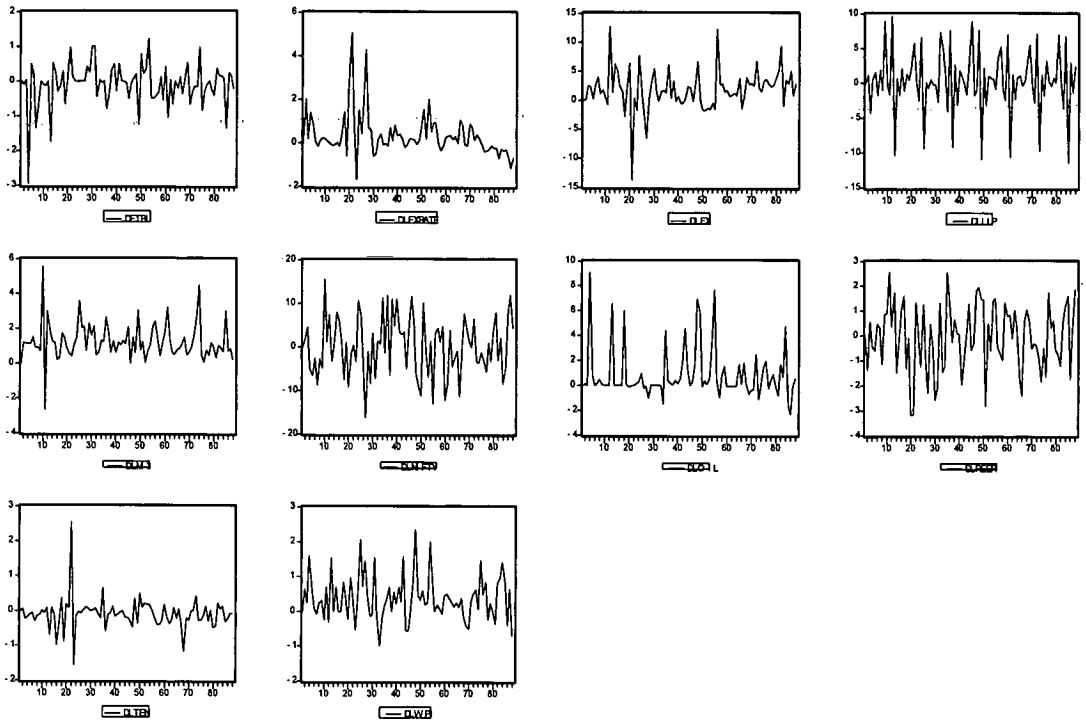
[4] Leigh, L., 1997), *"Stock market equilibrium and macroeconomic fundamentals"*, IMF Working Paper WP/97/15, International Monetary Fund.

[5] Naka, A, T. Mukherjee, and D. Tufte, "Macroeconomic Variables and the Performance of the Indian Stock Markets," Financial Management Association meeting, Orlando, October 1999. (http://www.business.uno.edu/econ/staff/naka.html)

exchange rate, real effective exchange rate, interest rate of short term as well as long term (91-day T-Bills yield and 10 year spot rate), oil prices, index of industrial production, wholesale price index and stock index (NIFTY). The WPI, IIP, oil price index and REER have a base of 1993-94. Money supply, 91-days T-bills cut-off yields, exchange rate time series and REER data have been collected from RBI website and various publications.

From the existing literature, the linkage between macroeconomic variables and stock prices have been established for major markets like USA, Japan while for other markets the same can not be said for certainty. The present study deals with more than 7 years (April 1996-July 2003). We have used monthly-published data of macroeconomic variables like oil prices (oil index), money supply (M3), index of industrial production (IIP), foreign exchange reserves, foreign exchange rate (Rupee-US$ rate), wholesale price index, short term interest rate (91day T-Bills yield), ten year spot interest rate, REER, and the stock index (S&P CNX NIFTY). The Chart – VII-1 shows the first difference series of 10 variables used in the study.

Chart – VII – 1 : Plot of First difference of Macroeconomic variables



The summary statistic of the stationarity condition test of all the variables is given in Table –VII-5.

TABLE –VII-5: Augmented Dickey Fuller Test Results of Macroeconomic Variables

Variables	Test statistic# (p-values)	Optimal Lag	Variables	Test statistic# (p-values)	Optimal Lag
LOIL	-1.8409 (0.68000)	1	LEXRATE	-0.2312(0.9900)	1
DLOIL	-3.6832**(0.02000)	4	DLEXRATE	0*	2
LM3	-2.6472 (0.26000)	1	YLD91D	-1.5075(0.82000)	3
DLM3	0*	1	DFYLD	-4.7637 (0.0000)	3
LFX	0.6811(1.000)	1	LNIFTY	-2.2284(0.47000)	1
DLFX	0(	1	DLNIFTY	0*	1
LWPI	-2.9454(0.1500)	1	TENYRYLD	-1.7462(0.7200)	1
DLWPI	0*	1	DFTENYR	0*	3
LIIP	-1.8688(0.67000)	12	LREER	-2.1686(0.5000)	1
DLIIP	-2.9072(0.16000)	12	DLREER	0*	2

*(**) indicates significant at 1% and 5% respectively – Critical values: -3.9676, -3.4144,-3.1290 at 1, 5, 10% level significance

*(**) indicates significant at 1% and 5% respectively.

We have also conducted the Phillips Peron Test for the unit root and the same is given Table VII-6.

Table VII-6: Phillips-Peron Test Results of Macroeconomic Variables

Variables	Alpha	Test Statistic*	p-values
LOIL	0.9342	-5.88	0.75
DLOIL	0.1034	-69.68#	0
LM3	0.7705	-19.66##	0.08
DLM3	-0.1642	-95.25#	0
LFX	0.9767	-2.15	0.97
DLFX	-0.0065	-86.64#	0
LWPI	0.8411	-15.83	0.16
DLWPI	0.0678	-76.31#	0
LIIP	0.3594	-60.96##	0
DLIIP	0.4661	-127.16##	0
LEXRATE	1.0112	-0.27	1
DLEXRATE	0.2735	-62.9#	0
YLD91D	0.8876	-9.08	0.51
DFYLD	-0.136	-97.25#	0
LNIFTY	0.9089	-9.64	0.47
DLNIFTY	0.0899	-78.34#	0
TENYRYLD	0.8741	-8.86	0.52
DFTENYR	-0.2383	-102.36#	0
LREER	0.9151	-8.56	0.55
DLREER	0.1206	-71.72#	0

(##) indicates significant at 1% (10%) level

Having satisfied with the results of unit root tests, we proceed to conduct the Johansen's cointegration test for the variables. We have tried with various lags 1, 2, 3 and 4 but we have only 88 observations and 10 variables, we though it prudent to test the results with 2 lags. The Johansen's cointegration test results are given in Table that shows existence of more than 2 cointegrating vectors at 1% significance level. Hence we have to use the vector error correction model (VECM) so that it would restrict the long run behaviour of the endogenous variables to converge to their cointegrating relationship while allowing for short run adjustments dynamics.

* 5% Critical region: < -21.78 and 10% Critical region: < -18.42

Table-VII-7: Cointegration Test Results (with lag of 2)					
Period	Eigenvalues (Descending Order)	Null Hypothesis#	Trace Statistics*	Critical Value 5%	1%
1996 - 2002	0.69	r=0**	335.15	233.13	247.18
	0.51	r=<1**	235.40	192.89	204.95
	0.41	r=<2**	174.15	156.00	168.36
	0.38	r=<3*	129.76	124.24	133.57
	0.28	r=<4	89.47	94.15	103.18
	0.27	r=<5	61.16	68.52	76.07
	0.21	r=<6	34.25	47.21	54.46
	0.10	r=<7	14.38	29.68	35.65
	0.04	r=<8	5.14	15.41	20.04
	0.02	r=<9	1.36	3.76	6.65

- 'r' indicates number of cointegrating relationship. *(**) denotes rejection of the hypothesis at the 5%(1%) level.

For Null hypothesis regarding *r*, Trace Statistics is derived as $\lambda_{trace} = -T \sum_{i=r+1}^{N} \ln(1-\lambda_{r+1})$ where T is number of observations and λ_r is the *r*-th Eigenvalue in ascending order.

Linear Granger Causality Test Results

The test results of Granger Causality between various markets are presented in Table–VII-8. We have tested the results with a lag of 2 as we have done in the cointegration test and report the lag 2 results.

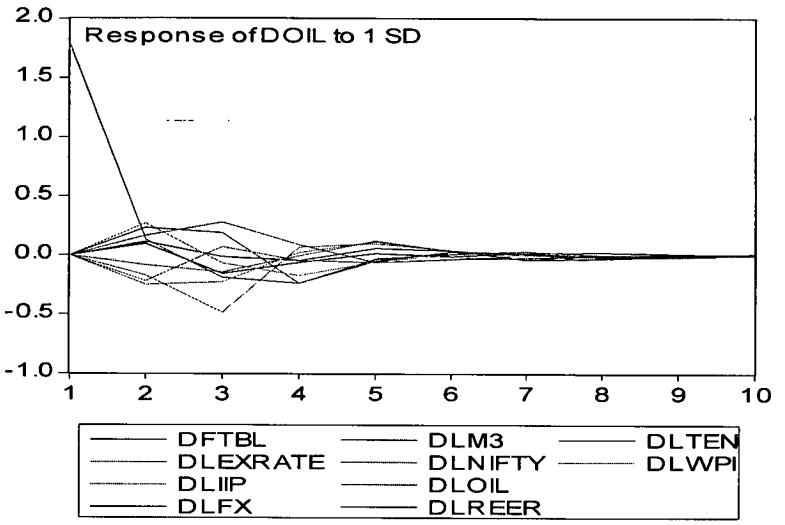
Table VII-10 : Pairwise Granger Causality Tests (From Row to Column NOT =>) (Bracketed values are p-values) (1996-2003)

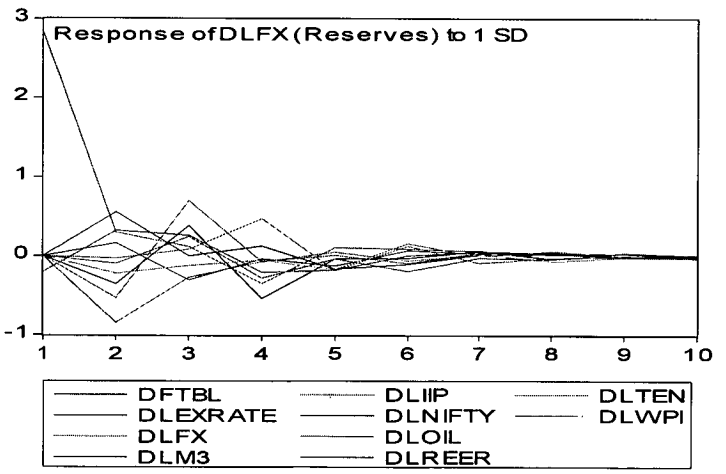
	DFTEN	DFYLD	DLEXRT	DLFX	DLIIP	DLM3	DLNIFTY	DLOIL	DLREER	DLWPI
DFTEN		0.0057 (.9942)	3.9989** (0.0220)	4.2931*** (0.017)	1.4853 (0.2325)	1.001 (0.3717)	0.0918 (0.9123)	0.1906 (0.8268)	0.4111 (0.6642)	0.4217 (0.6573)
DFYLD	1.4846 (0.2326)		0.2317 (0.7937)	0.6641 (0.5175)	0.0176 (0.9826)	0.4054 (0.668)	2.3219* (0.1045)	1.3708 (0.2597)	1.2923 (0.2802)	1.8284 (0.1672)
DLEXRT	9.8663*** (0.0002)	1.0707 (0.3476)		7.5833*** (0.0009)	0.0627 (0.9392)	0.0001 (0.999)	2.0771 (0.1319)	0.5954 (0.553)	1.3178 (0.2733)	2.2866 (0.1081)
DLFX	11.971*** (0.0000)	1.9169 (0.1537)	0.0026 (0.9973)		1.3249 (0.2715)	1.6953 (0.1899)	0.0534 (0.9480)	0.5703 (0.5675)	0.1882 (0.8287)	1.1551 (0.3201)
DLIIP	0.0376 (0.963)	2.1446 (0.1237)	1.6139 (0.2054)	0.3890 (0.6789)		0.8311 (0.4392)	0.2370 (0.7895)	0.0923 (0.9118)	1.4113 (0.2497)	3.5885** (0.0321)
DLM3	0.3610 (0.698)	0.8438 (0.4337)	0.8145 (0.4464)	1.3167 (0.2736)	4.3738** (0.0157)		0.3962 (0.6741)	3.0667** (0.0520)	3.9583** (0.022)	1.6955 (0.1899)
DLNIFTY	0.2316 (0.7937)	0.1696 (0.8443)	1.0237 (0.3638)	0.15 (0.8609)	0.0098 (0.990)	3.0878** (0.0510)		1.8290 (0.1671)	2.0551 (0.1346)	0.6493 (0.5250)
DLOIL	0.1059 (0.8996)	1.3670 (0.2607)	0.9891 (0.3763)	0.5348 (0.5877)	0.3333 (0.7174)	2.1298 (0.1254)	2.1152 (0.1272)		0.3550 (0.1760)	0.4939 (0.6120)
DLREER	3.7820** (0.0269)	3.5923** (0.032)	0.1860 (0.8305)	4.2153** (0.0181)	1.8257 (0.1676)	1.8078 (0.1705)	0.6554 (0.5219)	1.0487 (0.3550)		3.0888** (0.0509)
DLWPI	0.7820 (0.4609)	0.1568 (0.8551)	1.7657 (0.1775)	0.1419 (0.8678)	2.9149* (0.0599)	1.5631 (0.2157)	7.3255*** (0.0011)	0.6846 (0.5071)	1.8140 (0.1695)	

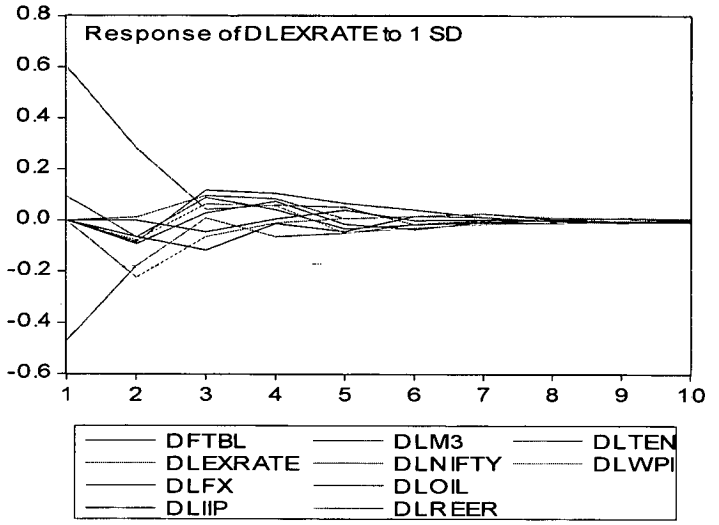
*, ** and *** denote rejection of null hypothesis at 10%, 5% and 1% significance level, respectively and NOT => implies does not Granger Cause.

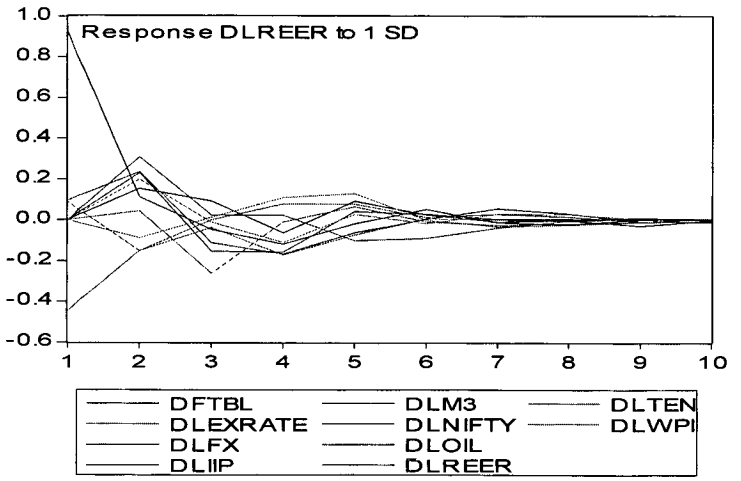
The impulse response graphs are also presented in the Chart-VII-2 bellow:

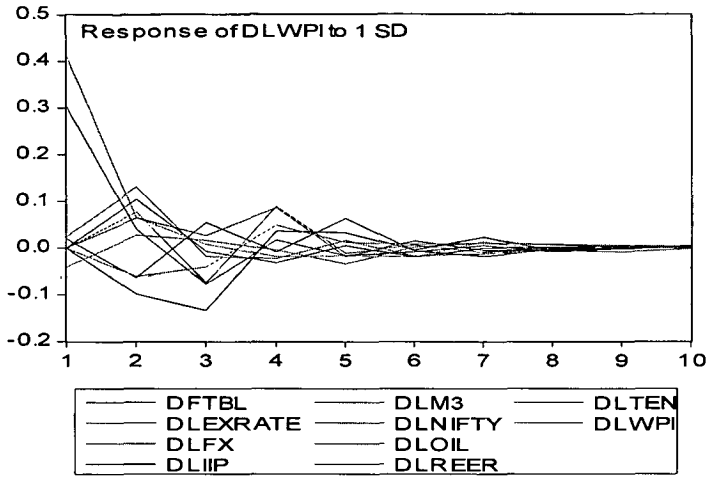
Chart – VII – 2: Impulse Response of Variables

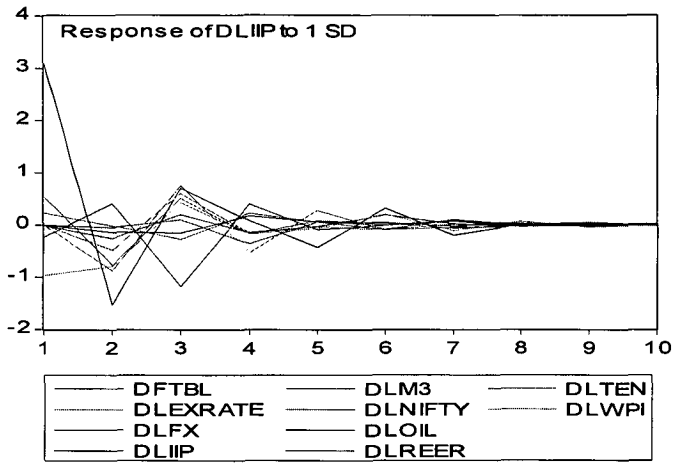


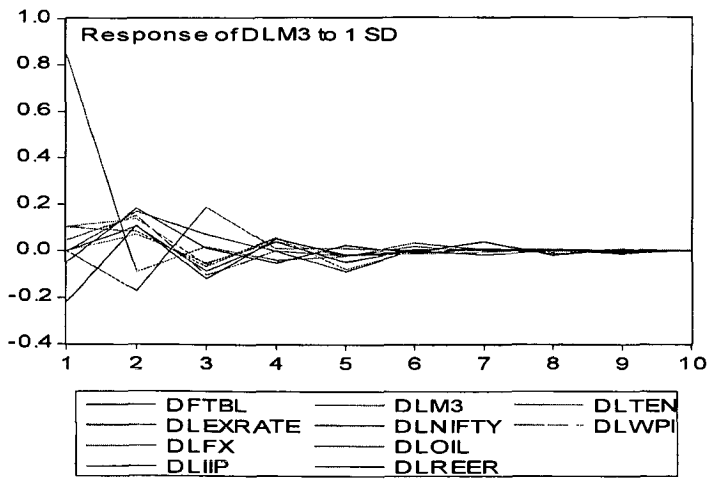


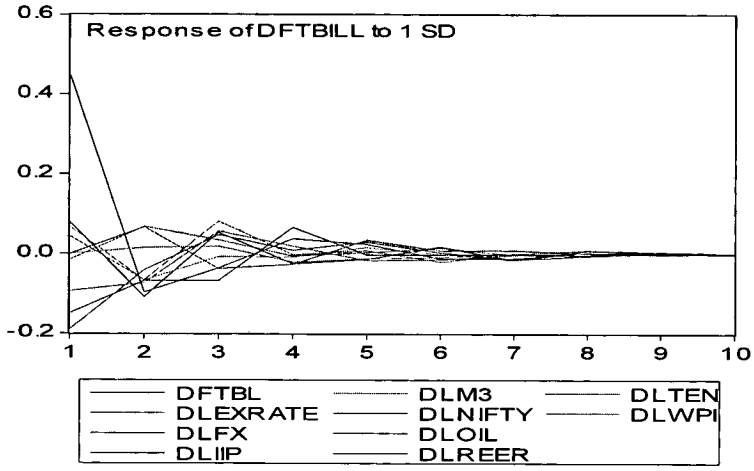

Response of DLEXRATE to 1 SD
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
1
2
3
4
5
6
7
8
9
10
DFTBL
DLM3
DLTEN
DLEXRATE
DLNIFTY
DLWPI
DLFX
DLOIL
DLIIP
DLREER


Response DLREER to 1 SD
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
1
2
3
4
5
6
7
8
9
10
DFTBL
DLM3
DLTEN
DLEXRATE
DLNIFTY
DLWPI
DLFX
DLOIL
DLIIP
DLREER


Response of DLWPI to 1 SD
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
1 2 3 4 5 6 7 8 9 10
DFTBL
DLM3
DLTEN
DLEXRATE
DLNIFTY
DLWPI
DLFX
DLOIL
DLIIP
DLREER


Response of DLIIP to 1 SD
4
3
2
1
0
-1
-2
1 2 3 4 5 6 7 8 9 10
DFTBL
DLM3
DLTEN
DLEXRATE
DLNIFTY
DLWPI
DLFX
DLOIL
DLIIP
DLREER


Response of DLM3 to 1 SD
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
1 2 3 4 5 6 7 8 9 10
DFTBL
DLM3
DLTEN
DLEXRATE
DLNIFTY
DLWPI
DLFX
DLOIL
DLIIP
DLREER


Response of DFTBILL to 1 SD
0.6
0.4
0.2
0.0
-0.2
1
2
3
4
5
6
7
8
9
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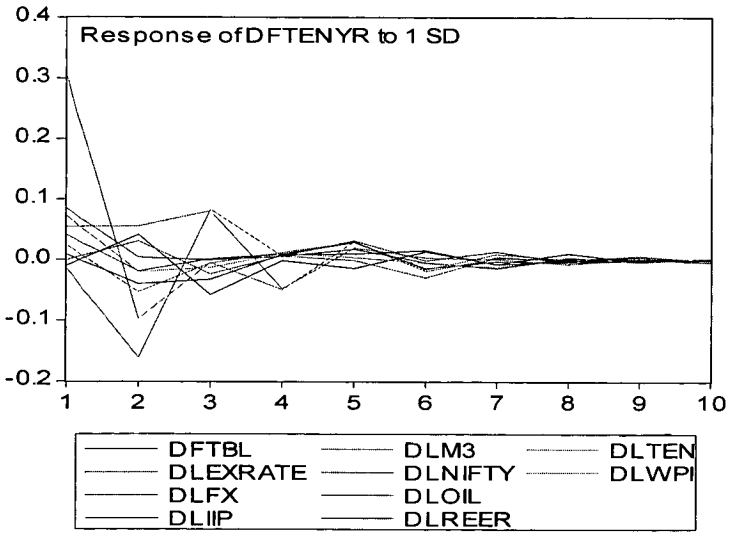
DFTBL
DLM3
DLTEN
DLEXRATE
DLNIFTY
DLWPI
DLFX
DLOIL
DLIIP
DLREER


Response of DFTENYR to 1 SD
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
1
2
3
4
5
6
7
8
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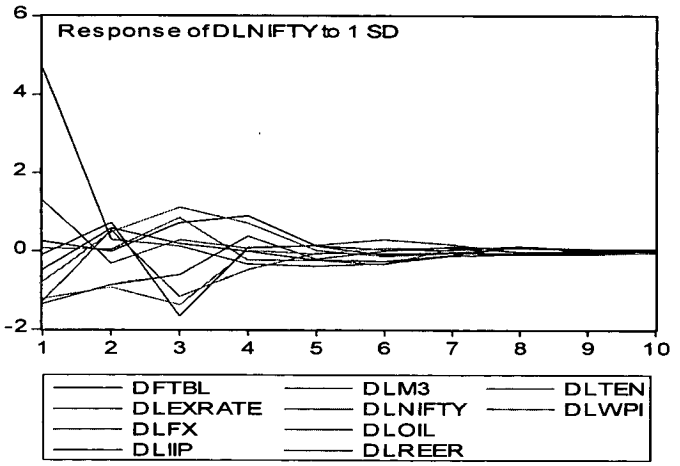
DFTBL
DLM3
DLTEN
DLEXRATE
DLNIFTY
DLWPI
DLFX
DLOIL
DLIIP
DLREER



Robustness of Relationship

To study robustness of the results we further explore the relations in 10 dimension systems, i.e. the stock returns and the ten possible combinations of nine variables from the original of eight. The (OLS) regression has been carried out on the first difference series. Table VII-9 presents the results.

Table VII-9: Coefficient test

	EXRATE	FX RESV	IIP	WPI	M3	OIL	REER	TENYR	YLD91D
NIFTY	-	+	+	-	+	-**	+	-	+
Without									
EXRATE		+***	+	-	-	-***	+	-	+
FX RESV	-**		+	+	+	-**	+	-	-
IIP	-	+		-	-	-***	+	-	+
WPI	-	+	+		+	-**	+	-	+
M3	-	+	+	+		-**	+	-	+
OIL	-	+	+	-	+		+	-	+
REER	-	+	+	+	+	-**		-	+
TENYR	-***	+	+	-	+	-**	+		-
YLD91D	-	+	+	+	+	-**	+	-	
Overall	-	+	+	?	+	-	+	-	+

*,** and *** indicating significant at 1%, 5% and 10% level

From the above, we find that oil prices have significant influence in explaining the stock prices whereas the other variables have not been significant. The situation did not change when we dropped one variable at a time except in case of exchange rate (in two situations it became significant). Surprisingly we found that other economic factors did not have significant influence on stock returns. However their economic relationship have been confirmed through signs except for 91 day T-bills yield which showed a positive relationship with stock prices. This may be due to the fact that 91-day T-Bills rates are more rigid compared to 10 year yields as there is little liquidity in T-Bills in the secondary market and there is limitation on the quantum of available T-Bills in the secondary market. The same analysis was also carried out including the lagged values of stock index and situation did not change except in case of T-Bills yield which showed the positive relationship. It has to be remembered that except in case of oil prices and to a small extent in case of exchange rate, other variables at not statistically significant to explain the stock prices. The results remained the same. The Table –VII-10 gives the results of the same.

Table VII-10: Coefficients Test Result (with lagged Value)

	EXRATE	FX RESV	OIL	IIP	M3	REER	WPI	TENYR	YLD91D	NIFTY(1)
NIFTY	-	+	-**	+	+	+	-	-	-	+
Without										
EXRATE		+***	-**	+	+	+	-	-	+	+
FX RESV	-***		-**	+***	+	+	-	-	-	+
OIL	-	+		+	+	+	-	-	+	+
IIP	-	+	-***		+	+	-	-	+	+
M3	-	+	-**	+		+	+	-	-	+
REER	-	+	-**	+	+		+	-	-	+
WPI	-	+	-**	+		+	+	-	-	+
TENYR	-***	+	-**	+	+	-	-		-	+
YLD91D	-	+	-**	+	+	+	-	-		+
NIFTY(-1)	-	+	-**	+	+	+	-	-	+	
Overall	-	+	-	+	+	+	-	-	-	+

*,** and *** indicating significant at 1%, 5% and 10% level

VII.3.3. Global Market Interlinkages

The integration of global equity markets have been a well studied topic since October 1987 though most of the studies have been conducted taking into account the developed markets like the USA, European countries and Japan. Recent literature has focused on emerging markets mainly due to 1997-98 Asian crises. In this study we have examined the interdependence of the major stock markets in Asia and linkages of these Asian stock markets with the developed stock markets of the USA, UK and France. For the USA, we have taken NASDAQ, S&P 500 and DJIA, for UK we have considered FTSE and for France we have considered CAC. We considered these indices as they are representative of the markets there. The NASDAQ has been a stock exchange that has been widely and closely followed by market participants of other countries. NASDAQ being an Exchange that has primarily focused on technology stocks and invited companies from other countries, specifically from emerging countries, to list their stocks in the Exchange. In many cases, common stocks are being traded in local markets as well as in NASDAQ and hence theoretically it gives justification for some linkage. Further, the global investors have been flocking to various markets for diversification of risk but since similar participants operate in all these markets, losses in one market forces a global investor to liquidate his investment in other countries, thereby creating some amount of linkages among markets.

In this study we have chosen some of the emerging markets as well as developed markets like US and Japan to study interlinkage using using cointegration (or VAR)

techniques. According to this approach if stock prices indices of two or more countries are found to be cointegrated then this implies that stock markets of these countries are interdependent. Taylor and Tonks (1989)[1] studies the market integration concerning markets of U.S., Germany, Netherlands and Japan using monthly data on stock price indices for the sub-periods, April1973 – September 1979 and October 1979 – June 1986 and employed is a bivariate cointegration technique (Engle and Granger, 1987)[2]. They found stock price index of the U.K. was cointegrated with the stock price index of the U.S., Germany, Netherlands and that of Japan for the later period but not for the former period. Based on these results they suggested that there is no long-term gain from diversification for the U.K investors after the abolition of exchange control. Kasa (1992)[3] also explored common stochastic trends in the stock markets of the U.S., the U.K., Japan, Germany and Canada using monthly and quarterly data from 1974 to 1990 and found that a single common stochastic trend driving these countries stock markets. Byers and Peel (1993)[4] examined the interdependence between stock price indices of the U.S., the U.K., Japan, Germany and the Netherlands using bivariate and multivariate cointegration techniques for the period October 1979 – October 1989 but unlike Taylor and Tonks they did not find any cointegration either for the group as a whole or for the pairs of markets.

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[1] Taylor, M.P. and I. Tonks (1989). \The internationalisation of stock markets and the abolition of U.K. exchange control", *Review of Economics and Statistics*, Vol. 71, pp.332{336.

[2] Engle, R. F. and C. W. J. Granger (1987), "Co-integration and Error Correction: Representation, Estimation, and Testing," *Econometrica* 55, 251-276.

[3] Kasa, K. (1992). \Common stochastic trends in international stock markets", *Journal of Monetary Economics*, Vol. 29, pp. 95{124

[4] Byers, J.D. and Peel, D.A. (1993), "Some Evidence on the Interdependence of National Stock Markets and the Gains from International Portfolio Diversification", Applied Financial Economics, **3**, 3, 239-42.

Kanas (1998)[1] explored the linkages between the U.S. and European stock markets using the daily data and found that the U.S. stock market was not pairwise cointegrated with any of the six European stock markets. Roca (1999)[2] investigated the price linkages between the equity markets of Australia and that of the U.S., U.K., Japan, Hong Kong, Singapore, Taiwan and Korea using weekly stock market and found that no cointegration between Australia and other markets. But he found that the Granger causality tests revealed that Australia is significantly linked with the U.S. and the U.K. Eun and Shim (1989)[3] also find that price changes in one market are transmitted to the other markets within a maximum of 48 hours.

There is conflicting evidence on the issue of international stock market linkages and hence the issue needs further investigation. In this paper we examine the linkages among the three emerging Asian markets which have introduced substantial reforms during last one decade and these markets have some common trading time zone which can help investors to move from one market to another if the need arises unlike a market like US which has a no common time zone when these markets are open. We have used the close values of stock indices NSE NIFTY, NASDAQ Composite, NIKKEI 225, HANGSENG, Singapore STI, Taiwan TAIEX, S&P 500, DJIA, CAC of France and FTSE of London for the period from July 1990 to May 2003 to test the inter-linkage. These indices have been chosen as they are the representatives of the national markets.

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[1] Kanas, A., 1998, Linkages between the US and European equity markets: further evidence from cointegration tests, *Applied Financial Economics,* 8, 607-614.

[2] Roca, Eduardo D. (1999) .Short-term and Long-term Price Linkages Between the Equity Markets of Australia and its Major Trading Partners., *Applied Financial Economics*, **9**, 501-511.

[3] Eun, C. S. and Shim, S. (1989) . International Transmission of Stock Market Movements., *Journal of Financial and Quantitative Analysis*, **24**, 241-56.

In the entire data set, we have some common time zones while the markets like US, UK and France have different time zones and not overlapping with Indian market timings. Hence we have taken the previous days closing indices for these markets for our analysis. First we have tested the stationarity condition of the data series used for the study. We have found that all the series are non-stationary at I(0) but stationary at I(1).

The simple correlation of these markets as well as the descriptive statistics of the markets are given in Table-VII-11 and Table – VI - 12 and Table –VI- 13 and market movement, returns and the market volatility are plotted in Chart-VII-3, Chart-VII-4 and Chart-VII-5. The volatility has been calculated using the formula $(\sigma_t)^2 = \lambda(\sigma_{t-1})^2 + (1-\lambda)(r_t)^2$ where σ_t is the standard deviation, λ is assigned 0.94 and $\mathbf{r_t}$ is the daily logarithmic return, the standard IGARCH formula used by RiskMetrics[1].

Table - VII-11: Correlation of Global Markets (1990-2003)

	NIFTY	SING	TAI	NASD	HANG	NIKK	FTSW	SP500	CAC	DJI
NIFTY	1									
SING	0.1177	1								
TAI	0.0774	0.2919	1							
NASD	-0.0140	0.0044	-0.0165	1						
HANG	0.1270	0.6306	0.2516	0.0012	1					
NIKK	0.1003	0.3614	0.2378	-0.0311	0.3570	1				
FTSW	-0.0109	-0.0219	-0.0080	0.3642	-0.0202	-0.0599	1			
SP500	-0.0101	-0.0185	-0.0210	0.7789	-0.0128	-0.0430	0.4694	1		
CAC	-0.0324	-0.0248	-0.0125	0.3780	-0.0205	-0.0558	0.7730	0.4816	1	
DJI	0.0009	-0.0082	-0.0068	0.6444	-0.0062	-0.0309	0.4645	0.9400	0.4727	1

[1] Riskmetrics@™

Table VII-12: Descriptive Statistics(1990-2003)

	DLCAC	DLDJI	DLFTSE	DLHANG	DLNAS	DLNFTY	DLNIKK	DLSING	DLSP	DLTAI
Mean	0.0156	0.0433	0.0213	0.0328	0.0361	0.0505	-0.0593	0.0069	0.0385	0.0087
Median	0.0059	0.0470	0.0135	0.0000	0.0809	0.0262	-0.0051	-0.0315	0.0403	-0.0509
Maximum	10.2949	7.3793	7.2286	17.4615	13.2546	18.9006	9.4030	13.9638	7.0528	18.7381
Minimum	-11.9768	-9.2243	-6.3986	-14.7346	-11.4299	-12.5219	-9.4443	-11.3888	-7.2533	-14.1143
Std. Dev.	1.6151	1.1870	1.2312	1.9265	1.7824	1.9623	1.6425	1.5263	1.1934	2.1400
Skewness	0.0476	-0.0752	0.1505	0.3336	0.0078	0.4678	0.2463	0.3023	0.0897	0.2504
Kurtosis	7.1143	7.5101	6.4256	12.6081	7.9521	12.0202	6.0226	11.7881	6.2873	8.9704
Jarque-Bera	1814.99	2182.27	1267.25	9940.91	2628.16	8813.28	1005.07	8315.77	1161.56	3846.96
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table –VII -13: Descriptive Statistics of Volatility(1990-2003)

	VCAC	VDJI	VFTSE	VNAS	VHANG	VNIFTY	VNIKK	VSP	VSTI	VTAIX
Mean	1.5047	1.1120	1.1385	1.5827	1.7647	1.7992	1.5678	1.1122	1.4016	1.9700
Median	1.3194	1.0227	1.0451	1.3985	1.5782	1.6357	1.4771	1.0327	1.2713	1.7197
Maximum	3.6632	2.7915	3.0422	5.2986	6.8132	7.0662	3.6815	2.6120	5.0805	6.7271
Minimum	0.6247	0.4504	0.4921	0.5277	0.7058	0.6924	0.5937	0.4140	0.5074	0.7419
Std. Dev.	0.5838	0.4246	0.4631	0.8237	0.7819	0.8183	0.5316	0.4402	0.6253	0.9393
Skewness	1.4785	1.0118	1.3191	1.1384	2.1513	2.2647	1.0254	0.7474	1.5860	2.5493
Kurtosis	4.8496	3.8394	4.9078	4.1083	10.4585	11.2336	4.2644	3.1091	6.7988	10.6238
Jarque-Bera	1303.7	514.3	1135.9	687.2	7945.6	9463.7	622.1	240.7	2624.7	9014.6
Probability	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Sum	3870.2	2860.2	2928.1	4070.6	4538.7	4627.5	4032.3	2860.6	3604.9	5066.8
Sum Sq. Dev.	876.2	463.5	551.5	1744.5	1571.9	1721.8	726.4	498.3	1005.4	2268.2
Observations	2572	2572	2572	2572	2572	2572	2572	2572	2572	2572

Chart – VII-3 Market Movements (Level Series – 1990-03)

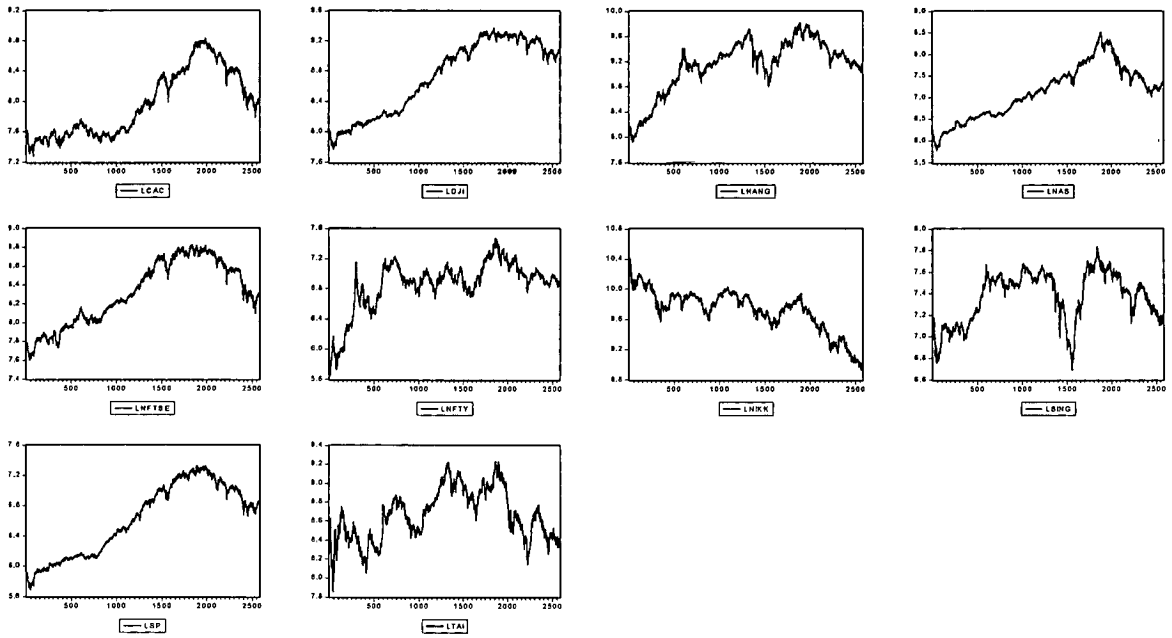

Chart –VII-4 Returns of Markets (1990-2003)

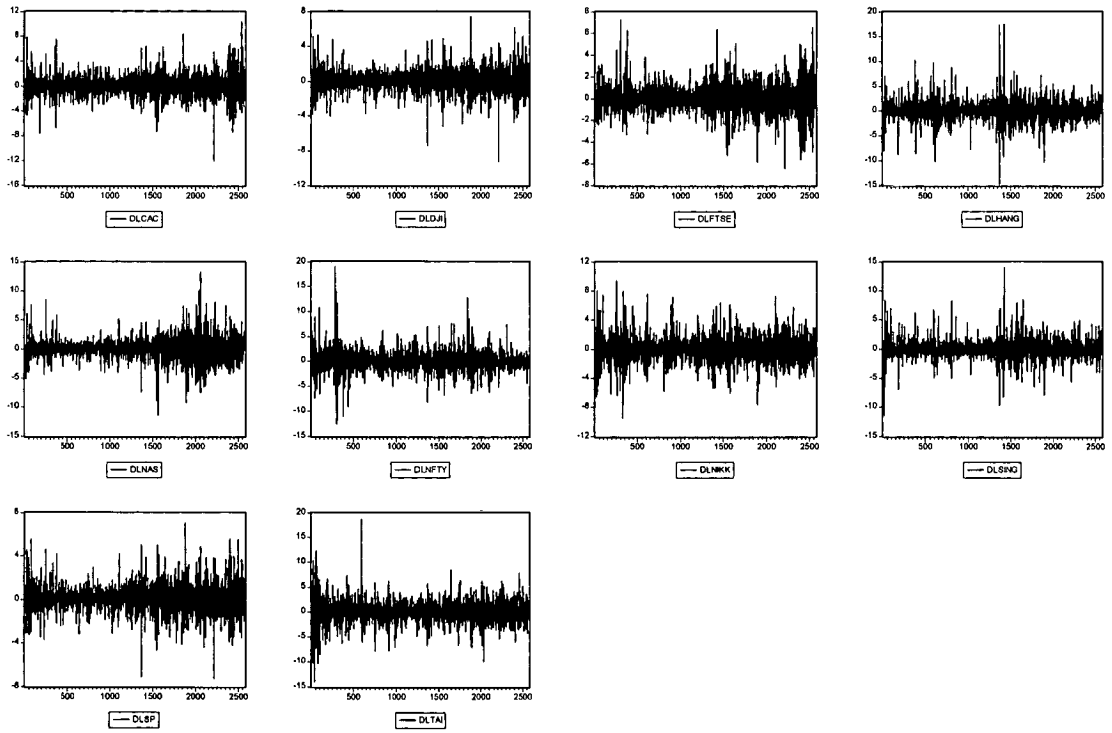

Chart VII-5 Volatility of Markets (1990-2003) using IGARCH with decay factor 0.94

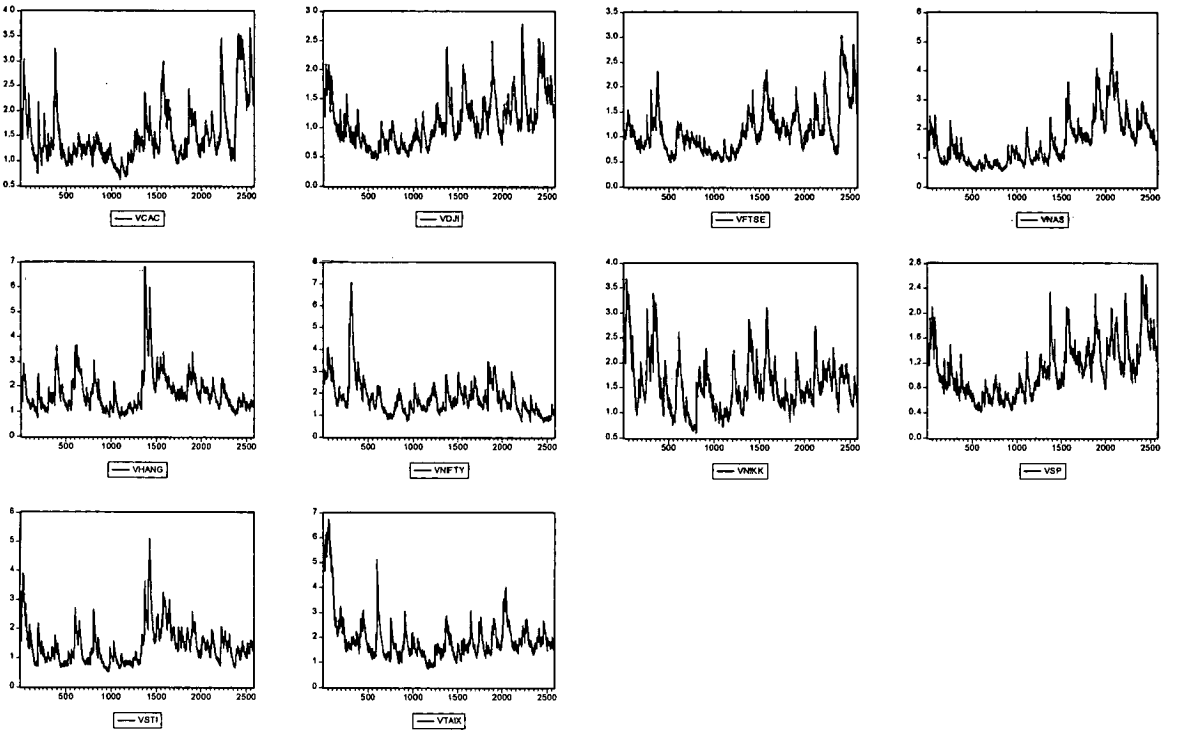

Table VII-14: Stationarity Condition in Global markets Data Series						
Variables	Level (log)			First Difference		
	Test statistsic	*p*-values	Optimal Lag$	Test statistsic	*p*-values	Optimal Lag$
NIFTY	-3.1509***	0.1	1	-13.1572*	0	12
NASDAQ	-0.8024	0.96	1	-14.1084*	0	10
S&P500	-0.5376	0.98	1	-15.2121*	0	10
DJIA	-0.9118	0.95	1	-15.1851*	0	10
FTSE	-0.6969	0.97	1	-15.3853*	0	10
CAC	-0.9995	0.94	1	-13.3154*	0	13
STI	-1.85	0.68	1	-11.0298*	0	17
NIKKEI	-2.5251	0.31	1	-14.1399*	0	11
HIS	-1.6682	0.76	1	-14.4097*	0	10
TAIEX	-2.0887	0.55	1	-11.5799*	0	21

*Note: The critical values of ADF statistic are –3.9676, -3.4144 and -3.129 at 1%, 5% and 10% significant levels. *{***} indicates significant at 1% and 10% respectively. $ - opt imal lag on the basis of SC.*

As we can see from the above table, the test statistic for all variables except NIFTY shows that the series (variables used) are non-stationary at level but stationary in their

first differences. NIFTY is stationary in its level but with 10% significant level and stationary in first difference. The significant test shows that all variables in their first difference are significant at 1% level. Hence the series can be used for our analysis of cointegration as well as testing of causality.

The relationship between Indian market with other global markets was estimated using an OLS on return series for full period as well as in a sub recent period. It was found that regional markets like Hong Kong, Japan and Singapore have more influence on Indian market.

Table VII-15: Coefficients Test

	1990-2003		1995-2003	
Variable	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
C	0.049475	0.1973	0.002092	0.9572
DLNAS	-0.00287	0.9392	0.018392	0.6006
DLFTSE	0.466069	0.2623	-0.221243	0.6148
DLSING	0.054951	0.0993***	0.080102	0.0155**
DLSP	-0.103545	0.4123	-0.115192	0.3509
DLHANG	0.074628	0.0043*	0.122134	0*
DLDJI	0.124823	0.2312	0.142131	0.1593
DLCAC	-0.070632	0.065***	-0.025822	0.5241
DLNIKK	0.058657	0.0225	0.063737	0.0214**
DLTAI	0.030714	0.1056	0.031366	0.1701

, ** and * indicates significant at 1%, 5% and 10% level*

The Johansen's cointegration test has been done using both the criteria and trace test has shown that the period 1995-2003 had a mild cointegration showing existence of 1 cointegrating vector and possibility of long run equilibrium but the Max-eigenvalue test has shown no existence of the cointegrating vector(s) during any time buckets. Other time buckets have not shown any long run equilibrium. The results are shown in Table –VII-16 and Table –VII-17.

Table VII -16: Cointegration Test results (Trace Test)

Period	Eigenvalues (Descending Order)	Null Hypothesis#	Trace Statistics*	Critical Value	
	Lag 2			5%	1%
1990 - 2003	0.01977	r=0	225.97340	233.13000	247.18000
	0.01742	r=<1	174.68750	192.89000	204.95000
	0.01394	r=<2	129.54220	156.00000	168.36000
	0.01208	r=<3	93.47999	124.24000	133.57000
	0.00788	r=<4	62.26729	94.15000	103.18000
	0.00677	r=<5	41.94984	68.52000	76.07000
	0.00430	r=<6	24.49981	47.21000	54.46000
	0.00344	r=<7	13.43109	29.68000	35.65000
	0.00142	r=<8	4.57126	15.41000	20.04000
	0.00036	r=<9	0.91455	3.76000	6.65000
1995-2003	0.03375	r=0	248.0068@	233.13000	247.18000
	0.02851	r=<1	186.8882	192.89000	204.95000
	0.02108	r=<2	135.3984	156.00000	168.36000
	0.0199	r=<3	97.46362	124.24000	133.57000
	0.01088	r=<4	61.66662	94.15000	103.18000
	0.00932	r=<5	42.17866	68.52000	76.07000
	0.00739	r=<6	25.50846	47.21000	54.46000
	0.0038	r=<7	12.29507	29.68000	35.65000
	0.00193	r=<8	5.465255	15.41000	20.04000
	0.00113	r=<9	2.017461	3.76000	6.65000
1999-2003	0.05518	r=0	227.90240	233.13000	247.18000
	0.04022	r=<1	174.03410	192.89000	204.95000
	0.03859	r=<2	135.08110	156.00000	168.36000
	0.02516	r=<3	97.73799	124.24000	133.57000
	0.02313	r=<4	73.55741	94.15000	103.18000
	0.01677	r=<5	51.34666	68.52000	76.07000
	0.01444	r=<6	35.30001	47.21000	54.46000
	0.01133	r=<7	21.49469	29.68000	35.65000
	0.00766	r=<8	10.67775	15.41000	20.04000
	0.00355	r=<9	3.37652	3.76000	6.65000

'#' 'r' indicates number of cointegrating relationship.'@' - indicates significant at 1% level. * - For a null hypothesis regarding r, Trace Statistics is derived as $Trace = -T\sum_{i=r+1}^{5}\log(1-\lambda_i)$ where T is number of observations and λ_r is the r-th Eigen-value in ascending order.

Table VII - 17: Cointegration Test results (Max-Eigen Value)

Period	Eigenvalues (Descending Order)	Null Hypothesis#	Max-Eigen Statistics*	Critical Value	
	Lag 2			5%	1%
1990 - 2003	0.01977	r=0	51.28595	62.81000	69.09000
	0.01742	r=<1	45.14522	57.12000	62.80000
	0.01394	r=<2	36.06226	51.42000	57.69000
	0.01208	r=<3	31.21270	45.28000	51.57000
	0.00788	r=<4	20.31745	39.37000	45.10000
	0.00677	r=<5	17.45003	33.46000	38.77000
	0.00430	r=<6	11.06872	27.07000	32.24000
	0.00344	r=<7	8.85983	20.97000	25.52000
	0.00142	r=<8	3.65671	14.07000	18.63000
	0.00036	r=<9	0.91455	3.76000	6.65000
1995-2003	0.03375	r=0	61.11854	62.81000	69.09000
	0.02851	r=<1	51.48984	57.12000	62.80000
	0.02109	r=<2	37.93479	51.42000	57.69000
	0.01991	r=<3	35.79700	45.28000	51.57000
	0.01089	r=<4	19.48796	39.37000	45.10000
	0.00932	r=<5	16.67019	33.46000	38.77000
	0.00740	r=<6	13.21339	27.07000	32.24000
	0.00383	r=<7	6.82982	20.97000	25.52000
	0.00194	r=<8	3.44779	14.07000	18.63000
	0.00113	r=<9	2.01746	3.76000	6.65000
1999-2003	0.05518	r=0	53.86836	62.81000	69.09000
	0.04022	r=<1	38.95295	57.12000	62.80000
	0.03859	r=<2	37.34312	51.42000	57.69000
	0.02516	r=<3	24.18058	45.28000	51.57000
	0.02313	r=<4	22.21075	39.37000	45.10000
	0.01677	r=<5	16.04665	33.46000	38.77000
	0.01444	r=<6	13.80532	27.07000	32.24000
	0.01133	r=<7	10.81695	20.97000	25.52000
	0.00766	r=<8	7.30123	14.07000	18.63000
	0.00355	r=<9	3.37652	3.76000	6.65000

'#' 'r' indicates number of cointegrating relationship. '*' - For a null hypothesis regarding r, Trace Statistics is derived as $\lambda_{max} = - T \ln (1 - \hat{\lambda}_{p+1})$ where T is number of observations.

Linear Granger Causality Test Results

The test results of Granger Causality between various markets are presented in Table–VII-18. We experimented with a lag of 2 as we have done in the cointegration test and report the lag 2 results.

Table-VII-18: Pairwise Granger Causality Tests (From Row to Column NOT =>) (Bracketed values are p-values) (1990-2003)

	DLHANG	DLNAS	DLNFTY	DLNIKK	DLSING	DLTAI	DLFTSE	DLSP	DLDJ	DLCAC
DLHANG		0.82 (0.44)	0.02 (0.98)	1.79 (0.17)	1.74 (0.18)	5.90* (0.00)	0.21 (0.81)	0.22 (0.81)	0.46 (0.63)	1.62 (0.20)
DLNAS	137.95* (0.00)		13.98* (0.00)	111.06 * (0.00)	104.74* (0.00)	38.57* (0.00)	68.66* (0.00)	1.48 (0.23)	0.36 (0.70)	57.28* (0.00)
DLNFTY	0.01 (0.99)	1.07 (0.34)		0.54 (0.58)	0.12 (0.89)	0.38 (0.68)	0.39 (0.68)	1.09 (0.39)	1.05 (0.35)	0.14 (0.87)
DLNIKK	4.06** (0.02)	0.95 (0.39)	0.50 (0.61)		1.52 (0.22)	3.49** (0.03)	2.89** (0.06)	0.31 (0.73)	0.22 (0.80)	3.30** (0.04)
DLSING	2.41*** (0.09)	0.12 (0.89)	1.14 (0.32)	4.19** (0.02)		14.88* (0.00)	0.01 (0.99)	1.00 (0.37)	0.38 (0.68)	1.30 (0.27)
DLTAI	1.39 (0.25)	0.33 (0.72)	1.28 (0.28)	0.04 (0.96)	0.61 (0.54)		1.28 (0.28)	0.88 (0.42)	0.69 (0.50)	0.66 (0.52)
DLFTSE	234.31* (0.00)	0.56 (0.57)	14.03* (0.00)	145.31* (0.00)	188.24* (0.00)	27.36 (0.00)		0.01 (0.99)	0.23 (0.80)	1.36 (0.26)
DLSP	184.89* (0.00)	1.81 (0.16)	17.34* (0.00)	144.82* (0.00)	156.52* (0.00)	45.77* (0.00)	125.65* (0.00)		0.64 (0.53)	91.89* (0.00)
DLDJI	165.21* (0.00)	0.50 (0.61)	17.43* (0.00)	123.23* (0.00)	167.74* (0.00)	45.20* (0.00)	100.62* (0.00)	0.20 (0.82)		72.90* (0.00)
DLCAC	206.94* (0.00)	1.99 (0.14)	16.18* (0.00)	148.26* (0.00)	176.22* (0.00)	43.55* (0.00)	1.03 (0.36)	1.49 (0.23)	2.1 (0.12)	

*, ** and *** denote rejection of null hypothesis at 1%, 5% and 10% significance level, respectively and NOT => implies does not Granger Cause.

Table –VII-19: Pairwise Granger Causality Tests (From Row to Column NOT =>) (Bracketed values are p-values) (1995-2003)

	DLHANG	DLNAS	DLNFTY	DLNIKK	DLSING	DLTAI	DLFTSE	DLSP	DLDJ	DLCAC
DLHANG		1.06 (0.35)	0.61 (0.54)	2.65*** (0.07)	1.41 (0.14)	7.41* (0.00)	0.03 (0.97)	0.35 (0.71)	0.99 (0.37)	0.50 (0.61)
DLNAS	111.41* (0.000		22.21* (0.00)	93.55* (0.00)	68.80* (0.00)	40.15* (0.00)	58.00* (0.00)	1.14 (0.32)	1.04 (0.35)	49.51* (0.00)
DLNFTY	0.25 (0.78)	0.06 (0.94)		0.06 (0.94)	1.84 (0.16)	11.53* (0.00)	0.47 (0.62)	0.13 (0.88)	0.51 (0.60)	0.53 (0.59)
DLNIKK	2.95** (0.05)	0.79 (0.46)	0.64 (0.53)		1.76 (0.17)	6.43* (0.00)	1.37 (0.25)	0.18 (0.83)	0.21 (0.81)	1.54 (0.21)
DLSING	2.92** (0.05)	0.28 (0.75)	0.88 (0.42)	2.59*** (0.08)		11.13* (0.00)	0.32 (0.73)	0.78 (0.46)	0.34 (0.71)	0.40 (0.67)
DLTAI	0.82 (0.44)	0.30 (0.74)	0.77 (0.46)	0.09 (0.92)	2.02 (0.13)		1.72 (0.180	1.23 (0.29)	0.91 (0.40)	1.88 (0.15)
DLFTSE	199.42* (0.00)	0.50 (0.61)	22.02* (0.00)	111.98* (0.00)	137.67* (0.00)	111.41* (0.00)		0.36 (0.70)	1.04 (0.35)	1.18 (0.31)
DLSP	154.58* (0.00)	1.90 (0.15)	26.37* (0.00)	120.15* (0.000	111.16* (0.000	41.64* (0.000	118.98* (0.00)		0.79 (0.45)	92.83* (0.00)
DLDJI	133.72* (0.00)	0.48 (0.62)	25.63* (0.00)	96.83* (0.00)	111.99* (0.00)	38.01* (0.00)	96.37* (0.00)	0.02 (0.98)		70.29* (0.00)
DLCAC	163.21* (0.00)	1.77 (0.170	26.25* (0.00)	118.17* (0.00)	122.13* (0.00)	29.87* (0.00)	1.56 (0.21)	1.28 (0.28)	1.68 (0.19)	

*, ** and *** denote rejection of null hypothesis at 1%, 5% and 10% significance level, respectively and NOT => implies does not Granger Cause.

Table –VII - 20: Pairwise Granger Causality Tests (From Row to Column NOT =>) (Bracketed values are p-values) (1999-2003)

	DLHANG	DLNAS	DLNFTY	DLNIKK	DLSING	DLTAI	DLFTSE	DLSP	DLDJ	DLCAC
DLHANG		1.57 (0.21)	4.47** (0.01)	2.38*** (0.09)	0.60 (0.54)	6.02* (0.00)	1.62 (0.19)	0.68 (0.50)	0.72 (0.48)	1.61 (0.19)
DLNAS	91.46* (0.00)		17.37* (0.00)	71.58* (0.00)	43.47* (0.000	27.16* (0.00)	32.32* (0.00)	1.55 (0.21)	1.21 (0.29)	29.34* (0.00)
DLNFTY	0.00 (0.99)	0.74 (0.47)		1.36 (0.26)	2.21 (0.11)	8.00* (0.00)	0.70 (0.49)	0.13 (0.87)	0.11 (0.89)	0.27 (0.75)
DLNIKK	1.83 (0.15)	0.65 (0.52)	1.43 (0.23)		1.52 (0.21)	3.62** (0.03)	1.53 (0.21)	0.41 (0.66)	0.62 (0/53)	1.36 (0.25)
DLSING	1.94 (0.14)	0.10 (0.90)	3.87** (0.02)	5.78* (0.00)		6.64* (0.00)	0.80 (0.44)	0.34 (0.70)	0.27 (0.76)	1.59 (0.20)
DLTAI	1.08 (0.33)	0.71 (0.49)	0.78 (0.45)	0.66 (0.51)	2.09 (0.12)		1.79 (0.160	2.23 (0.11)	1.88 (0.15)	1.88 (0.15)
DLFTSE	107.07* (0.00)	0.03 (0.96)	15.35* (0.00)	66.98* (0.000	71.44* (0.00)	11.33* (0.00)		0.50 (0.95)	0.29 (0.74)	0.26 (0.77)
DLSP	102.55* (0.00)	1.46 (0.23)	19.05* (0.000	76.87* (0.00)	63.14* (0.00)	26.84* (0.00)	75.65* (0.00)		0.49 (0.60)	59.72* (0.00)
DLDJI	76.92* (0.00)	0.33 (0.72)	19.01* (0.00)	55.92* (0.00)	61.24* (0.00)	23.02* (0.00)	61.29* (0.00)	0.05 (0.94)		44.69* (0.00)
DLCAC	98.78* (0.00)	0.59 (0.55)	19.80* (0.00)	74.58* (0.00)	69.93* (0.00)	18.14* (0.00)	98.78* (0.00)	0.20 (0.81)	0.56 (0.56)	

*, ** and *** denote rejection of null hypothesis at 1%, 5% and 10% significance level, respectively and NOT => implies does not Granger Cause.

The results how that developed markets like US, UK and France have a significant impact on most of the other markets including India while Indian market does not have much of impact on other markets though some of other markets have some amount of causality among themselves.

VII.3.4 Exchange Rate and Stock Market Interlinkages in India

The possible inter-linkage between stock prices and exchange rates are suggested by several arguments/hypotheses, particularly important are those identified in 'goods

market approaches' (Dornbusch and Fischer, 1980)[1] explaining likely impact of exchange rate on stock prices and the 'portfolio balance approaches' for justifying impact in reverse direction. The arguments provided in 'goods market approaches' flow from that as many companies borrow in foreign currencies to fund their operations, a change in exchange rate affects the cost of funds and value of earnings of many firms, which in turn affect the competitiveness of a firm and its stock prices – a depreciation (appreciation) of local currency makes exporting goods more (less) attractive to foreigners, resultant increase (decrease) of foreign demand of goods raises the revenue of firms, value of firms appreciates and thus stock prices increase. The sensitivity of an importing firm to a change in exchange rate is just opposite to that of an exporting firm. Therefore, on a macro basis, the impact of exchange rate fluctuations on stock market seems to depend on both the importance of a country's international trades in its economy and the degree of the trade imbalance. To complete the linkage, influence in reverse direction can be justified by 'portfolio balance approaches' under the exchange rate regime that allows exchange rate to be determined by market mechanism (i.e., the demand and supply condition). A blooming stock market would attract capital flows from foreign investors, which may cause an increase in the demand for a country's currency. Thus, local currency appreciates. The reverse would happen in case of falling stock prices where the investors would try to sell their stocks to avoid further losses and would convert their money into foreign currency to move out of the country. There would be demand for foreign currency in exchange of local currency. As a result, rising (declining) stock prices would lead to an appreciation (depreciation) in local currency.

[1] Dornbusch, R. and S. Fischer (1980), "Exchange Rates and Current Account," *American Economic Review* 70, 960-971.

Moreover, foreign investment in domestic equities could increase over time due to benefits of international diversification that foreign investors would gain. Furthermore, movements in stock prices may influence exchange rates (and money demand) because investors' wealth (and liquidity demand) could depend on the performance of the stock market.

Although theories suggest causal relations between stock prices and exchange rates, existing empirical evidence on the issue provides mixed results. Consider first some studies based on micro level data. For example, Jorion (1990, 1991)[1], Bodnar and Gentry (1993)[2], and Bartov and Bodnar (1994)[3] all fail to find a significant relation between simultaneous dollar movements and stock returns for U.S. firms. He and Ng (1998)[4] find that only about 25 percent of their sample of 171 Japanese multinationals has significant exchange rate exposure on stock returns. Griffin and Stulz's (2001)[5] empirical results show that weekly exchange rate shocks have a negligible impact on the value of industry indexes across the world. However, Chamberlain, Howe, and Popper (1997)[6] find that the U.S. banking stock returns are very sensitive to exchange rate movements, but not for Japanese banking firms. While such findings are different

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[1] Jorion, P. (1990), "The Exchange Rate Exposure of U.S. Multinationals," *Journal of Business* 63, 331-345. and Jorion, P. (1991), "The Pricing of Exchange Rate Risk in the Stock Market," *Journal of Financial and Quantitative Analysis* 26, 363-376.

[2] Bodnar, G., and W. Gentry, 1993, Exchange rate exposure and industry characteristics: Evidence from Canada, Japan, and the USA, *Journal of International Money and Finance* 12, 29-45.

[3] Bartov, E., and G. Bodnar, 1994, Firm valuation, earnings expectations, and the exchange-rate exposure effect, *Journal of Finance* 49, 11755-1785.

[4] He, J. and L. K. Ng, (1998), "The Foreign Exchange Exposure of Japanese Multinational Corporations," *Journal of Finance* 53, 733-753.

[5] Griffin, J. M. and R. M. Stulz (2001), "International Competition and Exchange Rate Shocks: A Cross-Country Industry analysis of Stock Returns," *Review of Financial Studies* 14, 215-241.

[6] Chamberlain, S.; J. S. Howe, and H. Popper (1997), "The Exchange Rate Exposure of U. S. and Japanese Banking Institutions," *Journal of Banking and Finance* 21, 871-892.

from those reported in prior research, Chamberlain *et al.* attributed the contrast to the use of daily data in their study instead of monthly data as used in most prior studies.

On a macro level, several studies document relatively stronger relationship between stock price and exchange rate. Ma and Kao (1990)[1], for instance, find that a currency appreciation negatively affects the domestic stock market for an export-dominant country and positively affects the domestic stock market for an import-dominant country, which seems to be consistent with the goods market theory. Ajayi and Mougoue (1996)[2], using daily data for eight countries, show significant interactions between foreign exchange and stock markets, while Abdalla and Murinde (1997)[3] document that a country's monthly exchange rates tends to lead its stock prices but not the other way around. Pan, Fok & Lui (1999)[4] used daily market data to study the causal relationship between stock prices and exchange rates and found that the exchange rates Granger-cause stock prices with less significant causal relations from stock prices to exchange rate. They also find that the causal relationship have been stronger after the Asian crisis.

In the context of Indian economy, a few recent studies have examined integration of forex and stock markets empirically using macro-level data for liberalisation era. For

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[1] Ma, C. K. and G. W. Kao (1990), "On Exchange Rate Changes and Stock Price Reactions," *Journal of Business Finance & Accounting* 17, 441-449.

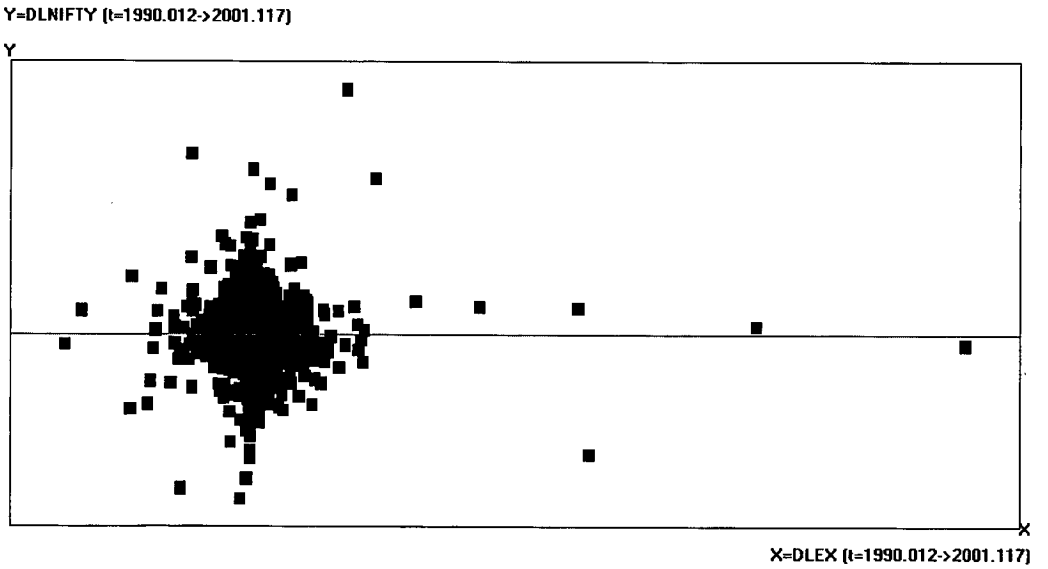
[2] Ajayi, R. A. and M. Mougoue (1996), "On the Dynamic Relation between Stock Prices and Exchange Rates," *Journal of Financial Research* 19, 193-207.

[3] Abdalla, I. S. A. and V. Murinde (1997), "Exchange Rate and Stock Price Interactions in Emerging Financial Markets: Evidence on India, Korea, Pakistan, and Philippines," *Applied Financial Economics* 7, 25-35.

[4] Pan, Fok & Lui (1999), Dynamic Linkages Between Exchange Rates and Stock Prices: Evidence from Pacific Rim Countries, Shippensburg University Working Papers.

example, Nag and Mitra (1999-2000)[1] investigate the integration of three financial markets, viz., money market, forex market and stock market. Based on empirical results using daily data on call money rate, exchange rate (Indian Rupee/US Dollar) and stock price index (BSE Sensex) for the period October 1996 to July 1999, they arrive at two important conclusions. First, short-run money market and forex market are gradually getting integrated and prices in these markets are sensitive to price movements in other financial markets. Second, the capital market continues to be somewhat insular to the changes in the rate variables in other financial markets.

Chart – VII -6: Scatter Plot of Exchange Rate and NIFTY Returns



The scatter diagram of stock index and exchange rate returns does not show any clear relationship or trend between themselves. The data used in this empirical study are daily stock market index and exchange rate (expressed in Indian Rupee per U.S. dollar) for India. From March 1993, India introduced unified exchange rate system and started the

[1] Nag, A. K. and Amit Mitra (1999-2000), "Integration of Financial Markets in India: An Empirical Investigation", *Prajnan*, Vol. XXVIII, No. 3, pp. 219-41.

process of exchange rate determination by market forces, though there has been some sort of intervention by the central bank depending upon situations. However, as well known, exchange rate decontrol has been a time consuming process and in 1994 India adopted the current account convertibility. Keeping pace with the liberalization process in financial sector, exchange rate liberalization has also been done in phases and hence it would be interesting to break the period into various time buckets to see how the causal relationship has behaved over various time buckets. Again, there has also been substantial regulatory changes taking place in capital market and over a period of time, many international best practices have been implemented in a phased manner. However, there have been concerns about the regulations on foreign investors' ownership of stocks issued by domestic firms. Though it is a major issue that guides the flow of funds into various markets, for India it has been a time consuming affair and even today we have sectoral limits for foreign ownership.

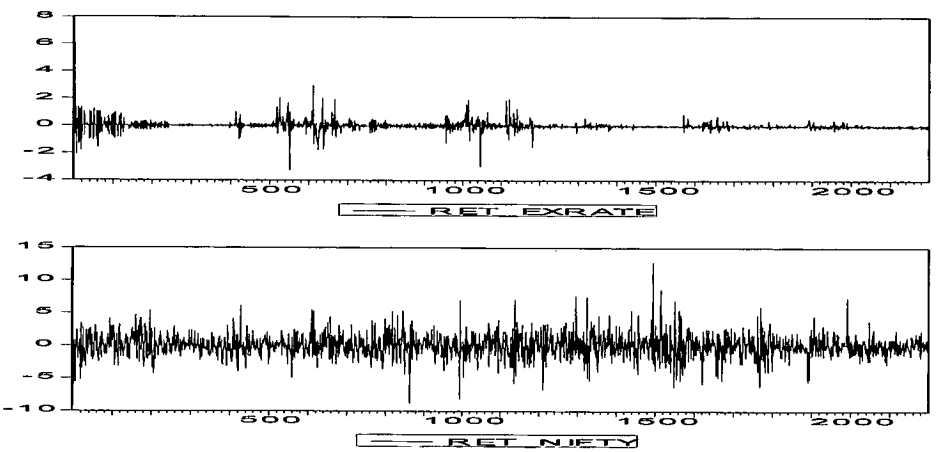
The Granger causality test requires that all data series involved are stationary; otherwise the inference from the F-statistic might be spurious because the test statistics will have nonstandard distributions. The ADF test results indicate that there is a unit root in all the logarithmic series (i.e. log(ER) and log(NF) series) and thus these log-level series can be described as $I(1)$ processes, indicating that their first-order differences (denoted by ΔLog(ER) and ΔLog(NF), respectively) are stationary. Plot of ΔLog(ER) and ΔLog(NF) also appear to be oscillating around a constant value (Figure 1). Further, application of ADF tests on ΔLog(ER) and ΔLog(NF) also confirms the stationarity of underlying series (Table –VII-21).

Table VII-21: Results of ADF Tests for Unit Root

Variable	Optimal p[#]	Test Statistics[$]
Log(ER)	5	-2.151
Log(NF)	1	-2.726
ΔLog(ER)	5	-17.895*
ΔLog(NF)	0	-45.545*

'#' Optimal p is selected based on minimum Schwarz Information Criterion.
'$' Critical Values of ADF test statistics for 1%, 5% and 10% level of significance are –3.9676, -3.4144 and –3.1290, respectively.
'*' Significant at 1% level.

Chart – VII -7 : Returns in Exchange Rate and Nifty Index



We now employ Johansen's (1991) maximum likelihood method to examine whether or not the logarithms of exchange rate and stock price index for the country are cointegrated. The Table-VII-22 reports the relevant results. As can be seen in the table, there is no cointegration vector between the underlying series. Consequently, an error correction term need not be included in the Granger causality test equations.

Table VII -22: Multivariate Cointegration Test Between log(RE) and log(NF)

Period	Eigen Values (Descending Order)	Hull Hypothesis#	Trace Statistic*	Critical Values (Trace)	
				at 5%	at 1 %
	0.004463	r=0	10.26026	15.41	20.04
March 93 - 2002	0.000208	r=<1	0.455485	3.76	6.65

'#' 'r' indicates number of cointegrating relationship.

'*" For a null hypothesis regarding r, Trace Statistics is derived as $Trace = -T\sum_{i=r+1}^{2}\log(1-\lambda_t)$ where T is number of observations and λ_r is the r-th Eigen-value in ascending order.

Linear Granger Causality Test Results

The test results of Granger-causality between exchange rates and stock prices are given in Table-VII-23 A lag orders of one, two, three, four and five (i.e., n =1,2,3,4 and 5) are used in equations 4 and 5 without any error-correction term. We experimented with a maximum lag of 5-days from the consideration that there are 5 trading days in a week and we hope that 5 days period would be adequate to get effects of one market to another under the assumption of substantial informational efficiency.

Table VII -23: Pairwise Granger Causality Tests Between ΔLog(ER) and ΔLog(NF)

Period	Null Hypothesis#	F-Values$	P-Values
March 1993 - 2002	ΔLog(NF) ≠> ΔLog(ER)	1.70417	0.13027
	ΔLog(ER) ≠> ΔLog(NF)	0.51041	0.7686
1993	ΔLog(NF) ≠> ΔLog(ER)	2.50716	0.03256*
	ΔLog(ER) ≠> ΔLog(NF)	1.61944	0.15802
1994	ΔLog(NF) ≠> ΔLog(ER)	1.16323	0.32878
	ΔLog(ER) ≠> ΔLog(NF)	1.27622	0.27574
1995	ΔLog(NF) ≠> ΔLog(ER)	0.97559	0.43387
	ΔLog(ER) ≠> ΔLog(NF)	1.32136	0.25659
1996	ΔLog(NF) ≠> ΔLog(ER)	0.50659	0.7711
	ΔLog(ER) ≠> ΔLog(NF)	1.21477	0.30337
1997	ΔLog(NF) ≠> ΔLog(ER)	1.98707	0.08185
	ΔLog(ER) ≠> ΔLog(NF)	0.99769	0.42016
1998	ΔLog(NF) ≠> ΔLog(ER)	1.19896	0.31076
	ΔLog(ER) ≠> ΔLog(NF)	0.53617	0.74875
1999	ΔLog(NF) ≠> ΔLog(ER)	1.21313	0.30403
	ΔLog(ER) ≠> ΔLog(NF)	0.33378	0.89215
2000	ΔLog(NF) ≠> ΔLog(ER)	0.5305	0.7532
	ΔLog(ER) ≠> ΔLog(NF)	0.75373	0.58416
2001	ΔLog(NF) ≠> ΔLog(ER)	2.59108	0.02671*
	ΔLog(ER) ≠> ΔLog(NF)	1.85445	0.10358
2002	ΔLog(NF) ≠> ΔLog(ER)	3.07255	0.01054*
	ΔLog(ER) ≠> ΔLog(NF)	2.04028	0.07403

'#' The symbol ≠> implies 'does not Granger Cause'. Thus X ≠> Y means variable X does not Granger cause Y.
'$" F-Values are derived using lag p = 5 in related regression equations (in our exercise equations 4 and 5 without error-correction terms).
'*" Significant at 5% level.

For the full sample period, the reported *F*-values as well as p-values suggest that these two markets did not have any causal relationship. If we go into individual years to see if the liberalization in both the markets have brought them together or not, then also we do not see any significant causal relationship between exchange rate and stock price movements except for the years 1993, 2001 and 2002, during when unidirectional causal influence from stock index return to return in forex market is detected (as corresponding F-statistics are significant at 5 % level of

significance). Very mild causal influence in reverse direction is also found in some years (1997, 2002). We examine the dynamic linkages between the foreign exchange and stock markets for India. While the literature suggests the existence of significant interactions between the two markets, our empirical results show that generally returns in these two markets are not inter-related, though in recent years, the return in stock market had causal influence on return in exchange rate with possibility of mild influence in reverse direction. These results have opened up some interesting issues regarding the exchange rate and stock price causal relationship. In India, though stock market investment does not constitute a very significant portion of total household savings compared to other form of financial assets, it may have a significant impact on exchange rate movement as FII investment has played a dominant role.

Gweke Feedback Robust Test

For estimating above feedback measures, choice of p and q is very crucial. As argues by Geweke (1978)[1], a larger value of p in each equation helps to ensure that errors are not autocorrelated, while a smaller value of q increases the power of the tests. In their empirical analysis based on daily data, Bracker et al. (1999)[2] set p=10 and q=5.

The advantage of using Geweke (1982)[3] measures of feedback over traditional F-statistics is that asymptotic distribution of each Geweke feedback measure is also known under the alternative hypothesis that feedback is present. Thus Geweke feedback

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[1] Geweke, J. (1978), "Testing the Exogeneity Specification in the Complete Dynamic Simultaneous Equations Model", *Journal of Econometrics*, Vol. 6, pp. 163-85.

[2] Bracker, D.S. Docking, P.D. Koch (1999) .Economic Determinants of Evolution in International Stock Market Integration. *Journal of Empirical Finance*, **6**, 1-27.

[3] Geweke, J. (1982), "Measurement of Linear Dependence and Feedback Between Multiple Time Series", *Journal of American Statistical Association*, Vol. 77, pp. 304-13.

measures represent cardinal measures of the degree of dependence present in given sample. Observing this advantage, Bracker et al. (1999)[1] compare unidirectional feedback measures for different yearly samples to observe how a leader/follower relationship between pairs of international stock markets changes over time. In our study, we also use Geweke feedback measures to assess the extent of market integration in different years.

For calculating daily returns in foreign exchange and capital markets, we employed daily data on stock market index S & P CNX NIFTY of National Stock Exchange (NSE) and exchange rate (expressed in Indian Rupee per U.S. dollar) for India. We denote the chosen stock price index and exchange rate by NF and ER, respectively. Sample period covers ten financial years, from April 1993 to end-March 2003.

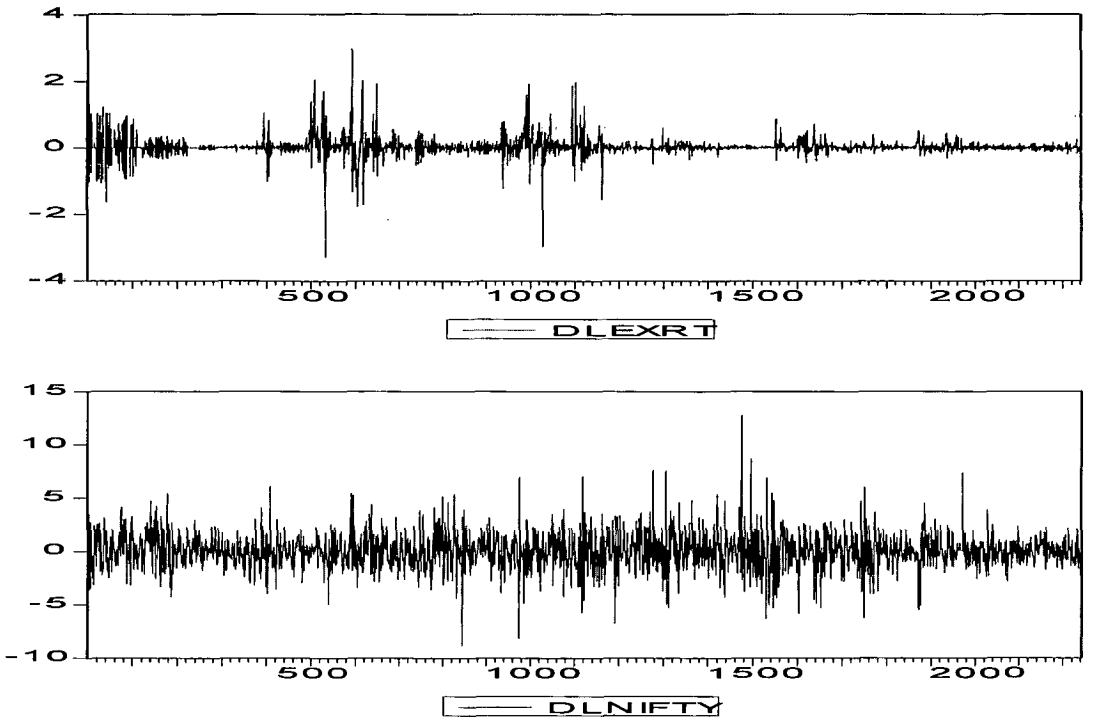
The selection of our study period (i.e. April 1993 to March 2003) is guided by several considerations, such as, (i) from March 1993, India introduced unified exchange rate system and started the process of exchange rate determination by market forces, though there has been some sort of intervention by the central bank depending upon situations. However, as well known, exchange rate decontrol has been a time consuming process and in 1994 India adopted the current account convertibility. Keeping pace with the liberalization process in financial sector, exchange rate liberalization has also been done in phases; (ii) Again, there has also been substantial regulatory changes have taken place during the period and over a period of time, many international best practices

[1] Bracker, Kevin; Diane Scott Docking and Paul D. Koch (1999), "Economic Determinants of Evolution in International Stock Market Integration", *Journal of Empirical Finance*, Vol. 6, No.1, pp. 1-27.

have been implemented in a phased manner. However, there have been concerns about the regulations on foreign investors' ownership of stocks issued by domestic firms. Though it is a major issue that guides the flow of funds into various markets, for India it has been a time consuming affair and even today we have sectoral limits for foreign ownership. In view of these developments, it is perceived that if at all financial markets are integrated, the extent of integration might be changing over time. In order to analyse this changing pattern, entire data period is broken into various sub-periods and causal relationship and Geweke feedback measures are investigated for each sub-periods separately. Our basis of partitioning data period is financial year and thus the sub-periods we consider are the financial years 1993-94, 1994-95, …., 2002-03.

The daily returns in foreign exchange and capital markets are calculated by ΔLog(ER) and ΔLog(NF), respectively, where Δ is the first order difference operator and Log(.) represents logarithmic function. These returns represent continuously compounded returns in respective markets. For performing causality/integration tests, we need to ensure stationarity of these return series.

Chart – VII -8: Returns in Exchange Rate and Nifty Index



Grangers' Causality Tests in VAR Framework – Application of Block F-Tests

The test results of Granger-causality between returns in foreign exchange and stock markets are given in Table-VII-24. We experimented with three alternative values of p (i.e. p=2, p=5 and p=10) in VAR model explained in the methodology section. However, results in all these cases give more or less similar conclusions regarding causal relationship. We, therefore, present results corresponding to p=10 for different financial years[1]. As can be seen from Table-VII-25, contemporaneous relationship

[1] Fixing p=10 indirectly we assume that a period of two-weeks (which normally has 10 trading days) would be adequate to get effects of one market to another.

between returns in two markets is very strong (statistically significant at 1% level) during four financial years, 1998-99, 1999-00, 2001-02 and 2002-03. In all other years, this relationship is statistically insignificant. The hypothesis of no causal influence of ΔLog(ER) on Y= ΔLog(NF) could not be accepted only in three years, viz., 1994-95 (10% level), 1995-96 (1% level) and 1998-99 (10% level). The causal impact in reverse direction is detected to be significant in the years 1994-95 (1% level), 1996-97 (5% level), 2001-02 (1% level) and 2002-03 (10% level). Thus, the tests based on block F-statistics in VAR framework do reveal the sign of mild-to-strong causal relationship (either contemporaneously and lagged) between returns in foreign exchange and capital markets during some years considered here. But, as stated above, we cannot assess the changing pattern of extent of causal influence over years.

Table VII-24: Pairwise Granger's Causality Tests in VAR Framework (X = ΔLog(ER) and Y= ΔLog(NF))

Year	Null Hypothesis H_{01}		Null Hypothesis H_{02}		Null Hypothesis H_{03}	
	$\chi_1^2=(nr_{uv}^2)$	Sig. Level	F-Statistics	Sig. Level	F-Statistics	Sig. Level
1993-94	0.0432	0.8353	0.6417	0.7767	1.5226	0.1343
1994-95	0.1108	0.7392	1.7429#	0.0742	3.8800**	0.0001
1995-96	0.0381	0.8453	3.8652**	0.0001	1.2621	0.2544
1996-97	0.4405	0.5068	0.4655	0.9107	1.9121*	0.0453
1997-98	0.2574	0.6119	1.1219	0.3472	1.2047	0.2896
1998-99	8.5477**	0.0035	1.8218#	0.0586	1.5189	0.1344
1999-00	15.1640**	0.0000	0.4074	0.9422	0.5061	0.8847
2000-01	1.9173	0.1662	0.8355	0.5949	0.7495	0.6772
2001-02	17.4660**	0.0000	1.3531	0.2044	3.3227**	0.0005
2002-03	14.3480**	0.0001	1.2085	0.2874	1.7348#	0.0753

Note: Results are obtained by fixing p = 10 in Eqs. (3). '**' Significant at 1% level. '*' Significant at 5 % level. '#' Significant at 10% level

Estimated Geweke Measures of the Extent of Market Integration

Our final tests on market integration are carried out based on Geweke (1982) feedback measures. In Table 3, we present estimates of these measures for different years. As can be seen from this Table, estimates of Geweke's feedback measures are strikingly strongly significant. In each year, all of $n\hat{F}_{X.Y}$, $n\hat{F}_{X\to Y}$ and $n\hat{F}_{Y\to X}$ measures are strongly significant (mostly at 1% level. Some at 5% level), indicating high degree of integration between foreign exchange and capital markets in each of the years. These results contrast with the results obtained using block F-tests under VAR framework.

Table VII-25: Geweke Feedback Measures and Tests for Market Integration (X = ΔLog(ER) and Y= ΔLog(NF))

Year	Null Hypothesis H_{01}		Null Hypothesis H_{02}		Null Hypothesis H_{03}	
	$n\hat{F}_{X.Y}$	Sig. Level	$n\hat{F}_{X->Y}$	Sig. Level	$n\hat{F}_{Y->X}$	Sig. Level
1993-94	37.09**	0.0000	14.98*	0.0104	22.07**	0.0005
1994-95	50.30**	0.0000	18.16**	0.0028	31.99**	0.0000
1995-96	36.81**	0.0000	20.98**	0.0008	15.76**	0.0076
1996-97	35.29**	0.0000	13.43*	0.0197	21.38**	0.0007
1997-98	37.93**	0.0000	16.16**	0.0064	21.49**	0.0007
1998-99	47.34**	0.0000	14.92*	0.0107	23.19**	0.0003
1999-00	42.99**	0.0000	13.12*	0.0222	13.81*	0.0168
2000-01	30.80**	0.0000	15.37**	0.0089	13.35*	0.0203
2001-02	62.63**	0.0000	15.65**	0.0079	27.39**	0.0001
2002-03	42.09**	0.0000	19.24**	0.0017	22.52**	0.0001

Note: Results are obtained by fixing (p,q) = (10,5) in Eqs. (4) – (7). '**' Significant at 1% level of significance. '*' Significant at 5% level.

We examined changing pattern in extent of integration between foreign exchange and capital markets in India across different financial years during the liberalisation era. Empirical results based on daily data for a period of ten financial years from April 1993 to March 2003 are not robust on the selection of testing methodology. When analysis is conducted in VAR-framework, empirical results do not point much impressive causal relationship between returns in two markets, though there was evidence of strong causal

relationship in some specific financial years. Strikingly, analysis based on Geweke's feedback measures detects strong bi-directional as well as contemporaneous causal relationship between returns in these markets. Empirical results, presented in this paper, therefore, have opened up a possible debate on the integration between exchange rate and capital markets in India during the liberalisation era. Future study may focus on settling the testing/estimation technique for assessing the extent of market integration and also explanations as to why the extent of integration across different years varies.

CHAPTER VIII

VIII.0 FINDINGS and CONCLUDING REMARKS

"In spite of all the changing, uncertain, and erroneous factors that must be considered in connection with records of stages of the Nile River, it is believed that they disclose some important information; and there is a fair prospect that they may yield more data with further study and the cumulation of ideas for various students." (.....Jarvis)

The words of Jarvis (1936) are very prophetic, for in fact data collected from the Nile River have spurred the development of a whole field of mathematics (i.e., fractional Brownian motion and fractional Gaussian noise) along with a field of statistics concerned with the behavior of long memory time series. Although long-range dependence was initially discovered in the Nile River series by Hurst (1951), statistical modeling of this time series was first done as a self-similar process in terms of a fractional Gaussian noise (FGN) model (Mandelbrot and van Ness 1968; Mandelbrot and Wallis 1969) in the doctoral works of Mohr (1981) and Graf (1983).

The objective of this study was to understand the long memory process in Indian capital and foreign exchange markets as well as to understand their level of interlinkages. The study has relevance in the current market structure as the Indian capital and foreign exchange markets are undergoing significant changes due to various policy initiatives undertaken by regulatory bodies in expediting financial sector reforms. The

informational efficiency has improved considerably as level of disclosures have improved in the market through various levels of corporate governance. Infrastructural setups and changes introduced during last twelve years have helped the markets to consolidate. Today Indian equity derivatives market is one of the leading markets in the world as per the study conducted by Derivatives Industry Association and the capital market compares with global markets in terms of systems and practices and benchmarks.

In the backdrop of financial sector reforms in India, very little empirical work has been done in Indian market using the market data pertaining to large part of the reforms period . The main reasons for the same are difficulty in getting quality data and low level of integration of Indian market with global markets before liberalization era as well as in early post-liberalisation period.. Due to opening up of the Indian economy, foreign investment has been steadily coming to the market and today FII investment stands at about USD23 billions. Large flow of foreign exchange is having an impact not only in the capital market but also in the domestic exchange rate as well as money supply that has far reaching implications for macroeconomic variables like interest rate. Further setting up National Stock Exchange of India (NSE) has been an important and milestone policy initiative by the Government that helped strengthening the capital market infrastructure in India.

The basic hypothesis in long memory process evolved from the simple fact that prices of a financial asset like stocks or foreign exchange are random process as informational

efficiency (weak form of efficient market hypothesis) relies on the fact that price of a stock would change with only new information. And since new information can not be predicted ahead of time of their actual arrival, the prices are also not predictable. Hence there would be no long memory process in these market returns. On the background of this hypothesis, we have proceeded to test if the Indian stock market and foreign exchange data can tell us something about the long memory process. In order to study long memory process, we have used the stock market data as well as foreign exchange rate for the period from July 1990 to September 2003. For the purpose of understanding cointegration and linkages, we used the data from April 1993 as India introduced unified exchange rate system only from March 1993. The benchmark stock market index S&P CNX NIFTY and RBI reference INR/USD rates were used for our study of long memory process. There are 2 benchmark indices that capture the market sentiment in India: S&P CNX NIFTY and BSE SENSEX. Both these indices are market capitalization based indices and have different base periods. The first index, S&P CNX NIFTY, is based on 50 liquid stocks traded in National stock Exchange of India (NSEIL) and the index is managed by IISL, a subsidiary company of NSEIL and CRISIL with technical collaboration from Standard & Poor, USA. The second index, BSE SENSEX, is based on 30 stocks traded in The Stock Exchange, Mumbai (BSE), being the oldest stock exchange in India. The choice of benchmark index was based on an analysis made by Nath (2002)[1] which showed that S&P CNX NIFTY is a better index in comparison to BSE Sensex in terms of risk and return profile using the indices data from 1995 to 2002. We have selected the benchmark index S&P CNX NIFTY for

[1] Nath G C (2002): " Integration of Global Equity Markets – A Case for India" – Indian Capital Market, Delhi University, ed: Dr. Shirin Rathode and Dr. Amitav Gupta

the study keeping the above in mind. For the exchange rate, we did not have much of choice as Rupee-US Dollar rate is the most effective rate used in Indian market. The trading data is not available in the public domain for which we used the RBI reference rates for the same which is published daily by RBI. The data used are daily data covering more than 2800 data points covering about 13 years. We considered the long period would take care of any cyclical trends in the data and would produce robust results.

With regard to literature survey, we noted that similar studied have been conducted for longer periods concerning developed markets and the results are mixed (Greene and Fielitz (1977)[1] report evidence of persistence in daily U.S. stock returns series, Barkoulas, Baum, and Travlos (2000)[2], report evidence in Greek stock market, Tolvi (2003)[3] reports the same in Finnish stock market). The results in these studies, however, are often quite conflicting across different tests, and also not robust to minor changes in the testing methods.

We find very little work has been done on emerging and less developed markets like India. The study by Barkoulas, Baum and Travlos(2000) showed the presence of long memory process in Greek stock market and opened up research issues concerning the possibility of long memory process in emerging market data as these markets are evolving in terms of systems and market practices. This clearly led our motivation for

[1] Green, M., Fielitz (1977), "Long Term Deopendence in Common Stock Returns" Journal of Financial Economics, 4, pp339-349

[2] Barkoulas, J. T., Baum, C. F., & Travlos, N. (2000). Long memory in the Greek stock market, Applied Financial Economics, 10, 177–184.

[3] Tolvi (2003): Long memory in the Finnish stock market, http://aws.tt.utu.fi/LongMem.pdf

the study of long memory process in India financial market. However, there is extensive literature on the subject though the debate is still open and provides motivation to researchers to come back to the subject from time to time. The literature on integration and causal relationship among markets are voluminous though not much work has been done on Indian context which was mainly due to lack of quality data. The literature gained momentum in Indian academic world in last 2 years and more attention to the subject is given today due to the announcement of this 2003 Nobel Prize to Engle and Granger for their seminal work on the subject. Our study has also used the famous Granger Causality test to study the short-term dynamics and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methodology of Engle to understand the conditional volatility in the financial markets in India.

For conducting the study on Long Memory Process, we have used two robust methods, Variance Ratio Test developed by Andrew Lo and Mackinley (1988)[1] and Classical Rescaled Range Analysis developed by hydrologist, Hurst (1951)[2]. There are volumes of literature on the quality of these tests in terms of robustness. Very little improvement has been done on these tests in recent years. Hence we have used these tests to empirically study the long period data set pertaining to Indian market.

Variance Ratio is a measure of the randomness of a return series. Variance ratio is computed by dividing the variance of returns estimated from longer intervals by the

[1] Lo, A. and C. MacKinlay,(1988), "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies* 1, 41-66.

[2] Hurst, H.E.(1951). "Long-Term Storage Capacity of Reservoirs," *Transactions of the American Society of Civil Engineers*, 116, 770-799.

variance of returns estimated from shorter intervals, (for the same measurement period), and then normalizing this value to one by dividing it by the ratio of the longer interval to the shorter interval. A variance ratio that is greater than one suggests that the returns series is positively serially correlated or that the shorter interval returns trend within the duration of the longer interval. A variance ratio that is less than one suggests that the return series is negatively serially correlated or that the shorter interval returns tend toward mean reversion within the duration of the longer interval.

Rescaled Range or commonly known as R/S Analysis was developed by Hurst. He was an English hydrologist, who worked in the early 20th century on the Nile River Dam project. When designing a dam, the yearly changes in water level are of particular concern in order to adapt the dam's storage capacity according to the natural environment. Studying an Egyptian 847-year record of the Nile River's overflows, Hurst observed that flood occurrences could be characterized as persistent, i.e. heavier floods were accompanied by above average flood occurrences, while below average occurrences were followed by minor floods. In the process of this findings he developed the Rescaled Range (R/S) Analysis which is used today in finance literature to study the market efficiency and persistence.

The Hurst exponent occurs in several areas of applied mathematics, including fractals and chaos theory, long memory processes and spectral analysis. Hurst exponent estimation has been applied in areas ranging from biophysics to computer networking. The modern techniques for estimating the Hurst exponent comes from fractal mathematics. Estimating the Hurst exponent for a data set provides a measure of

whether the data is a pure random walk or has underlying trends. Another way to state this is that a random process with an underlying trend has some degree of autocorrelation. When the autocorrelation has a very long (or mathematically infinite) decay this kind of Gaussian process is sometimes referred to as a *long memory process*. Processes that we might naively assume are purely random sometimes turn out to exhibit Hurst exponent statistics for long memory processes.

For studying long term equilibrium and dynamics of macroeconomic variables and market linkages, we have used Johansen's cointegration test which has been proved to be the most robust test. We have conducted both Trace Test and Max Eigenvalue Test though Trace test has been found to be more robust in financial literature (see Cheung and Lai). We have reported both the results as and when required. For short-term dynamics we have used Granger Causality test in vector auto-regression (VAR) framework. However, to test contemporaneous relationship between the capital and foreign exchange markets we have also used the robust Geweke Feedback test.

The data used for the study has been tested for stationarity condition (unit root test) using various robust tests like Augmented Dickey Fuller Test (with drift hypothesis against linear trend – the trend stationarity being the most appropriate alternative for unit root hypothesis), Phillip-Perron Test and KPSS Test with appropriate lags. The lags have been selected using the minimum Schwarz Information Criterion. We found that ADF test statistics for both exchange rate and stock index values as well as their log transformations (log values) (commonly known as level) are statistically insignificant at 5 % level of significance, which indicate that there is a unit root in all the logarithmic

series and process is non-stationary or I(1). Thus these log-transformed series can be described as I(1) processes, indicating that their first-order differences (which actually represent return series considered here) are stationary. The log return series or commonly know as first difference has been found to be stationary or I(0) using the above tests. The data series found to be non-normal as normality condition tested through measure of Kurtosis and Jarque-Bera test showed clear indications about non-normality. The exchange rate data showed higher peaks and both the data sets showed longer tails indicating presence of heteroskedasticity in data. The autocorrelation test through plot of ACF and PACF clearly showed serial correlation structure in both stock market and exchange rate data. We have also identified the lags which showed statistical significance for serial correlation in both exchange rate and stock market data. We have standardized/normalized the data in order to have uniformity and comparing the data across all periods. For our study we have divided the entire period into various time buckets to understand how the structure of information is changing. We have divided the time buckets into 2 weeks, 1 month, 3 months, 6 months, 9 months, 1 years, 2 years and 5 years. We have assumed 250 working days in a year and 21 trading days in a month for our analysis. For doping the long memory process study we have also taken a sub-period from 1995 to 2003 to understand the robustness of our results. The sub-sample period has been chosen from July 1995 as major market reforms were introduced in India from this period.

We have calculated the log returns of index S&P CNX NIFTY and used the same for calculating the variance ratio. Performing the variance ratio test on the about 13 years stock index data following results were obtained:

Table-VII-1: Variance Ratio Test Results of S&P CNX NIFTY

Time Bucket	1990-2003		1995-2003	
	Variance	Variance Ratio	Variance	Variance Ratio
14 Days	36.1087	0.9544	25.9480	0.9067
1month	83.0713	1.0456	56.5589	0.9411
3 months	222.2875	0.9326	136.9037	0.7593
6 months	353.3267	0.7471	227.9719	0.6373
9 months	536.7700	0.7507	287.4320	0.5314
1-year	782.1575	0.8270	386.3638	0.5400
2- years	1003.450	0.5305	642.4144	0.4490
5-years	1284.811	0.2717	430.5415	0.1204

For the period 1990-2003, the above results show that in all the lags except 1 month, the variance ratio has been between 0 to 1 indicating mean reversion tendency. For the lag of 1 month shows a very close case to 1 indicating the possibility of Random Walk. But none of the lags show any sign of long memory: there is no indication of the persistence or a trend-reinforcing tendency in stock market returns. The sub-sample period showed that for all time lags, the variance ratio is between 0 and 1 indicating mean reversion. It clearly showed no sign of long memory process in stock market data.

The same data has been used to estimate for Rescaled Range analysis to calculate Hurst Exponent for all relevant periods of time using the full (July 1990 to September 2003) period data as well as for the sub-sample period (July 1995 to September 2003). The results of the test are listed below.

Table-VIII-2: R S Analysis (H) Results				
Time Bucket	Hurst Exponent			
	1990-2003	C	1995-2003	C
14 Days	0.688	0.2977	0.7042	0.3272
1month	0.6551	0.2399	0.6628	0.2532
3 months	0.6428	0.2189	0.6544	0.2387
6 months	0.6359	0.2073	0.639	0.2125
9 months	0.616	0.1745	0.6115	0.1672
1 year	0.6101	0.1649	0.6086	0.1625
2 years	0.6063	0.1588	0.6088	0.1628
5 years	0.5777	0.1137	0.5653	0.0947

None of the values for the time lags is equal to 0.50 indicating that Indian stock market can not be said to follow random walk in so far as the daily returns are concerned when we use S&P CNX NIFTY as the market proxy. The results show that there is a definite possibility for persistence in the S&P CNX NIFTY returns for all time lags. Here we have a persistent or trend-reinforcing series and it indicates that long memory structure possibly exists.

Performing the variance ratio test on the about 13 years exchange rate data we get following results.

Table-VIII-3 : Variance Ratio Results of Exchange Rate				
Period	1990-2003		1995-2003	
	Variance	Variance Ratio	Variance	Variance Ratio
14 Days	2.0507	0.9313	0.8202	1.0730
1month	4.744	1.0259	1.9210	1.1967
3 months	15.0699	1.0863	5.7067	1.1851
6 months	30.464	1.1068	9.7410	1.0195
9 months	48.6499	1.169	13.1634	0.9112
1 year	78.9232	1.4336	18.3067	0.9580
2 years	129.2941	1.1743	33.3692	0.8731
5 years	160.5458	0.5833	56.8889	0.5954

For the full period (1990-2003), the above tests show some interesting results. It shows that in the 1, 3, 6, 9, 12, 24 months, the variance ratio has been greater than 1 that indicates the persistence or a trend-reinforcing tendency in exchange rate returns. However, the 1-month period shows a very close case of Random Walk. In the lag periods of 2 weeks and 5 years the same is between 0 to 1 indicating mean reversion tendency. However, when we did the analysis for sub-sample 1995-2003, it showed that periods upto 6 months have variance ratio greater than 1 indicating persistence or trend-reinforcing while other periods showed trends of mean reversion.

The same data has been used for Rescaled Range Analysis to estimate the Hurst Exponent "H" for all relevant periods of time. The results of the test are listed below.

Table-VIII-4: Rescaled Range (H) Results of Exchange Rate Data				
	Hurst Exponent			
Period	1990-2003		1995-2003	
14 Days	0.624	0.1876	0.6572	0.2435
1month	0.564	0.0928	0.6037	0.1546
3 months	0.5775	0.1134	0.6204	0.1816
6 months	0.574	0.1080	0.6057	0.1578
9 months	0.5761	0.1113	0.6031	0.1536
1 year	0.5758	0.1108	0.5976	0.1449
2 years	0.5998	0.1484	0.6117	0.1675
5 years	0.6246	0.1885	0.6331	0.2026

None of the values for the time lags is equal to 0.50 indicating that Indian foreign exchange market cannot be said to follow random walk in so far as the daily returns are concerned when we use RBI reference rates as the market proxy. However all the lags show H values greater than 0.5 indicating persistence or trend-reinforcing process. This shows that there is a definite possibility for persistence in the exchange rate returns for all time lags. If we take the full data period, the values are close to 0.5 indicating noise in the data but for the later period, the results support long memory process.

While studying the interlinkages of macroeconomic variables in Indian economy, we find that oil prices have significant influence in explaining the stock prices whereas the other variables have not been statistically significant. The situation did not change when we dropped one variable at a time except in case of exchange rate and short term interest rate. Here we find some amount of causal relationship. Surprisingly we found that other economic factors like M3, foreign exchange reserves, IIP, WPI, REER did not have significant influence on stock returns. As stated earlier, their economic

relationship has been confirmed through signs except for 91 day T-bills yield which showed a positive relationship with stock prices. This may be due to the fact that 91-day T-Bills rates are more rigid compared to 10 year yields as there is little liquidity in T-Bills in the secondary market and there is limitation on the quantum of available T-Bills in the secondary market. The same analysis was also carried out including the lagged values of stock index and situation did not change except in case of T-Bills yield which showed the positive relationship. It has to be remembered that except in case of oil prices and to a small extent in case of exchange rate, other variables at not statistically significant to explain the stock prices.

We also studied the interlinkages among global markets including India through stock leading benchmark indices of various countries like USA, UK, France, Singapore, Hong Kong, Taiwan, etc. The results how that developed markets like US, UK and France have a significant impact on most of the other markets including India while Indian market does not have much of impact on other markets though some of other markets have some amount of causality among themselves.

We moved on to study interlinkages of the stock and foreign exchange market in India and for doing so, we divided into sample sub-periods of financial years. We took the period from April 1993 as India introduced unified exchange rate system from March 1993. The study did not find a long term equilibrium relationship due to absence of cointegrating vectors while using Johansen's cointegration test. For the full sample period, the reported F-values as well as p-values suggest that these two markets did not have any causal relationship for short-term dynamics using the full data period. If we go

into individual years to see if the liberalization in both the markets have brought them together or not, then also we do not see any significant causal relationship between exchange rate and stock price movements except for the years 1993, 2001 and 2002, during when unidirectional causal influence from stock index return to return in forex market is detected (as corresponding F-statistics are significant at 5 % level of significance). The results for 1993 may not be considered significant (may be a spurious relationship) as at that point exchange rate liberalization was at infant stage and current account convertibility was only introduced in August 1994. Very mild causal influence in reverse direction is also found in some years (1997, 2002). While the literature suggests the existence of significant interactions between the two markets, our empirical results show that generally returns in these two markets are not inter-related, though in recent years, the return in stock market had causal influence on return in exchange rate with possibility of mild influence in reverse direction. These results have opened up some interesting issues regarding the exchange rate and stock price causal relationship. In India, though stock market investment does not constitute a very significant portion of total household savings compared to other form of financial assets, it may have a significant impact on exchange rate movement as FII investment has played a dominant role.

We moved to test the relationship using robust Geweke feedback methodology. We examined changing pattern in extent of integration between foreign exchange and capital markets in India across different financial years during the liberalisation era. Empirical results based on daily data for a period of ten financial years from April 1993

to March 2003 are not robust on the selection of testing methodology. When analysis is conducted in VAR-framework, empirical results do not point much impressive causal relationship between returns in two markets, though there was evidence of strong causal relationship in some specific financial years. Strikingly, analysis based on Geweke's feedback measures detects strong bi-directional as well as contemporaneous causal relationship between returns in these markets. Empirical results, presented in this paper, therefore, have opened up a possible debate on the integration between exchange rate and capital markets in India during the liberalisation era. Future study may focus on settling the testing/estimation technique for assessing the extent of market integration and also explanations as to why the extent of integration across different years varies.

VIII.1. FURTHER RESEARCH

The study has opened up many further research issues. From the policy framework side, we need to understand the movement of exchange rate in suggesting the risk management guidelines for stock market. Short term interlinkages have confirmed that one market affects other market in recent years as both the markets are getting increasingly integrated. The foreign investment coming to the market is getting invested in equity market driving prices upward and putting the pressure on foreign exchange rate. This has implications for sterilizing the inflows for the country as it would virtually detect the money supply in the economy and force the central bank to actively pursue market stabilization. This has been evident through RBI's proposal of introducing market stabilization bonds in the market to sterilize the high level of foreign inflows which has gone beyond USD100 billion in terms of reserves.

The results of the study indicates strong persistence or long memory process in foreign exchange market at least for periods upto 6 months for both full sample period as well as for sub-periods. But the stock market results are split. Variance Ratio Test indicates absence of long memory process in Indian stock market data but the Rescaled Range Analysis showed clear indication of long memory process. Hence further research is required to develop more robust methods to test the long memory process in Indian market data. These findings are new addition to the Indian financial market literature.

Understanding the linkage dynamics has become important as the markets are increasingly getting integrated. The foreign exchange inflows due to FII investment is causing stock price increase and also helping the domestic currency to appreciate against USD. Appreciation of INR against USD will cause loss to exporters and will possibly affect the bottom line of the companies who have exports as source of revenue and cause their prices to fall in the stock market. This may affect the sentiment of the stock market. Hence it has policy implications.

Market linkage dynamics also indicate that at times Indian markets get affected due to happenings in other markets. This is important in case of bad news as markets become volatile and require expert risk management mechanism to provide safety to investors. Hence a risk management system should not only take into account the happenings in domestic market in a stand alone mode, but also to take into account in other markets in the country as well as other global markets. Further research required to understand lead

lag relationship of such causal relationship and their extent of integration so that policy guidelines can use such research.

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Appendix – 1

Step by Step Approach to Calculate R/S statistics

1. Define the time series of asset price and put them in a time format with ascending order.
2. Calculate the logarithmic returns by taking $LN(P_t/P_{t-1})$
3. Divide the time period into T contiguous sub-periods of length n
4. For each sub-period calculate the mean value of the return
5. Find out the accumulated departure from mean for each sub-period
6. The Range is defined as the maximum minus minimum for each sub-period.
7. Calculate the sample standard deviation for each sub-period.
8. Each Range is normalized by dividing the same by the standard deviations corresponding to it. That becomes R/S value for each sample period.
9. Then Find the average R/S value for length n.
10. Continue the process for various values of n=2 weeks, 1 month, 3 months, 6 months, 9 months, 1 year, 2 years, 5 years. To find out R/S values pertaining to various time buckets.

Appendix – II

Augmented Dickey-Fuller (ADF) test For Unit Root

Auxiliary model:
z(t)-z(t-1) = a.z(t-1) + b(1).(z(t-1)-z(t-2)) + ...
+ b(p).(z(t-p)-z(t-p-1)) + b(p+1) + b(p+2).t + u(t),
t = p+2,...,n, where u(t) is white noise.
Null hypothesis H(0):
z(t) is a unit root with drift process: a = 0.
Alternative hypothesis H1:
z(t) is a trend stationary process: a < 0.
The test statistic is the t-value of a.
The default lag width is p = [cn^r], where
c = 5 and r = .25.
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p = 36 = [c.n^r], where c=5, r=.25, n=2856

Variable to be tested:
z(t) = EXRATE
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.0028	-2.1891 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.49000
z(t-1)-z(t-2)	-0.0427	-2.2519
z(t-2)-z(t-3)	0.1294	6.8258
z(t-3)-z(t-4)	0.0182	0.9533
z(t-4)-z(t-5)	-0.0289	-1.5124
z(t-5)-z(t-6)	-0.0069	-0.3628
z(t-6)-z(t-7)	0.0064	0.3343
z(t-7)-z(t-8)	-0.0121	-0.6321
z(t-8)-z(t-9)	0.0627	3.2810

z(t-9)-z(t-10)	-0.0126	-0.6575
z(t-10)-z(t-11)	0.0221	1.1543
z(t-11)-z(t-12)	0.0117	0.6132
z(t-12)-z(t-13)	-0.0602	-3.1502
z(t-13)-z(t-14)	0.0179	0.9370
z(t-14)-z(t-15)	-0.0211	-1.0996
z(t-15)-z(t-16)	0.0068	0.3544
z(t-16)-z(t-17)	0.0134	0.7016
z(t-17)-z(t-18)	0.0172	0.9006
z(t-18)-z(t-19)	0.0016	0.0861
z(t-19)-z(t-20)	0.0440	2.3007
z(t-20)-z(t-21)	-0.0199	-1.0377
z(t-21)-z(t-22)	-0.0092	-0.4802
z(t-22)-z(t-23)	-0.0061	-0.3186
z(t-23)-z(t-24)	0.0148	0.7744
z(t-24)-z(t-25)	0.0190	0.9937
z(t-25)-z(t-26)	0.0408	2.1365
z(t-26)-z(t-27)	-0.0144	-0.7502
z(t-27)-z(t-28)	-0.0254	-1.3264
z(t-28)-z(t-29)	0.0026	0.1375
z(t-29)-z(t-30)	0.0088	0.4583
z(t-30)-z(t-31)	-0.0273	-1.4282
z(t-31)-z(t-32)	0.0460	2.4103
z(t-32)-z(t-33)	0.0118	0.6162
z(t-33)-z(t-34)	-0.0148	-0.7762
z(t-34)-z(t-35)	-0.0328	-1.7140
z(t-35)-z(t-36)	-0.0111	-0.5870
z(t-36)-z(t-37)	-0.0155	-0.8178
1	0.0874	2.8386
t	0.0000	1.4859
Residual s.e.:	13.60678E-002	
R-square:	0.04564	
n:	2819	

Test result:
H0 is not rejected at the 10% significance level
Wald test that the lag width can be reduced from 36 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
35	0.669	1	3.841	2.705	0.41347
34	0.972	2	5.991	4.605	0.61518
33	4.245	3	7.815	6.251	0.23617
32	4.865	4	9.488	7.780	0.30145
31	5.060	5	11.071	9.237	0.40854
30	10.402	6	12.591	10.645	0.10870
29	12.499	7	14.067	12.017	0.08529 (*)

28	13.278	8	15.507	13.361	0.10262	
27	13.290	9	16.919	14.683	0.14994	
26	15.055	10	18.307	15.987	0.13008	
25	15.667	11	19.675	17.275	0.15397	
24	19.643	12	21.026	18.549	0.07414	(*)
23	20.288	13	22.362	19.812	0.08826	(*)
22	21.689	14	23.684	21.064	0.08523	(*)
21	21.737	15	24.995	22.307	0.11490	
20	21.787	16	26.296	23.541	0.15022	
19	23.072	17	27.588	24.769	0.14692	
18	27.606	18	28.869	25.990	0.06831	(*)
17	27.620	19	30.144	27.204	0.09102	(*)
16	28.829	20	31.410	28.412	0.09119	(*)
15	29.393	21	32.671	29.615	0.10488	
14	29.685	22	33.925	30.814	0.12633	
13	30.703	23	35.172	32.007	0.13026	
12	31.792	24	36.414	33.196	0.13223	
11	43.586	25	37.653	34.381	0.01206	(**)
10	44.140	26	38.885	35.563	0.01460	(**)
9	44.576	27	40.114	36.741	0.01801	(**)
8	44.996	28	41.336	37.916	0.02209	(**)
7	59.035	29	42.557	39.088	0.00081	(**)
6	59.765	30	43.772	40.256	0.00098	(**)
5	60.841	31	44.985	41.422	0.00107	(**)
4	61.179	32	46.195	42.585	0.00142	(**)
3	64.534	33	47.400	43.745	0.00084	(**)
2	65.452	34	48.602	44.903	0.00095	(**)
1	111.813	35	49.802	46.058	0.00000	(**)
0	119.980	36	50.999	47.212	0.00000	(**)

(*) -> significant at the 10% level
(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	-3.96647	-3.96497	-3.95672
2	-3.98154	-3.97928	-3.96691
3	-3.98050	-3.97749	-3.96099
4	-3.98020	-3.97643	-3.95580
5	-3.97890	-3.97438	-3.94962
6	-3.97798	-3.97270	-3.94381
7	-3.97690	-3.97087	-3.93783
8	-3.98065	-3.97386	-3.93669
9	-3.97937	-3.97182	-3.93050

10	-3.97814	-3.96984	-3.92438
11	-3.97701	-3.96796	-3.91834
12	-3.97961	-3.96979	-3.91602
13	-3.97861	-3.96804	-3.91012
14	-3.97753	-3.96619	-3.90412
15	-3.97624	-3.96415	-3.89791
16	-3.97510	-3.96224	-3.89185
17	-3.97417	-3.96055	-3.88600
18	-3.97296	-3.95858	-3.87986
19	-3.97321	-3.95807	-3.87518
20	-3.97228	-3.95638	-3.86932
21	-3.97090	-3.95424	-3.86301
22	-3.96982	-3.95239	-3.85698
23	-3.96902	-3.95083	-3.85124
24	-3.96801	-3.94906	-3.84529
25	-3.96803	-3.94831	-3.84036
26	-3.96685	-3.94637	-3.83423
27	-3.96606	-3.94481	-3.82848
28	-3.96466	-3.94265	-3.82213
29	-3.96365	-3.94087	-3.81616
30	-3.96295	-3.93941	-3.81050
31	-3.96376	-3.93945	-3.80634
32	-3.96277	-3.93769	-3.80039
33	-3.96157	-3.93572	-3.79421
34	-3.96163	-3.93501	-3.78930
35	-3.96068	-3.93330	-3.78338
36	-3.95962	-3.93147	-3.77733
Optimal p:	2	2	2

p =2

Variable to be tested:
z(t) = EXRATE
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.0023	-1.9110 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.65000
z(t-1)-z(t-2)	-0.0463	-2.4889
z(t-2)-z(t-3)	0.1261	6.7839
1	0.0746	2.6129
t	0.0000	1.1799
Residual s.e.:	13.62408E-002	
R-square:	0.02256	
n:	2853	

Test result:
H0 is not rejected at the 10% significance level
Wald test that the lag width can be reduced from 2 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
1	46.021	1	3.841	2.705	0.00000 (**)
0	54.241	2	5.991	4.605	0.00000 (**)

(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	-3.96647	-3.96497	-3.95672
2	-3.98154	-3.97928	-3.96691
Optimal p:	2	2	2

p = 36 = [c.n^r], where c=5, r=.25, n=2856

Variable to be tested:
z(t) = LEX
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.0037	-3.5436 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.03000
z(t-1)-z(t-2)	-0.0423	-2.2383
z(t-2)-z(t-3)	0.1987	10.4978
z(t-3)-z(t-4)	0.0075	0.3884
z(t-4)-z(t-5)	-0.0620	-3.2195
z(t-5)-z(t-6)	-0.0189	-0.9787
z(t-6)-z(t-7)	0.0136	0.7052
z(t-7)-z(t-8)	-0.0109	-0.5666
z(t-8)-z(t-9)	0.0560	2.9067
z(t-9)-z(t-10)	-0.0053	-0.2749
z(t-10)-z(t-11)	0.0153	0.7919
z(t-11)-z(t-12)	0.0049	0.2527
z(t-12)-z(t-13)	-0.0590	-3.0632
z(t-13)-z(t-14)	0.0210	1.0870
z(t-14)-z(t-15)	-0.0166	-0.8609
z(t-15)-z(t-16)	-0.0088	-0.4560
z(t-16)-z(t-17)	0.0131	0.6792
z(t-17)-z(t-18)	0.0194	1.0058

z(t-18)-z(t-19)	0.0089	0.4634
z(t-19)-z(t-20)	0.0362	1.8817
z(t-20)-z(t-21)	-0.0384	-1.9945
z(t-21)-z(t-22)	-0.0046	-0.2411
z(t-22)-z(t-23)	-0.0043	-0.2214
z(t-23)-z(t-24)	0.0225	1.1703
z(t-24)-z(t-25)	0.0177	0.9170
z(t-25)-z(t-26)	0.0408	2.1197
z(t-26)-z(t-27)	-0.0209	-1.0842
z(t-27)-z(t-28)	-0.0289	-1.4990
z(t-28)-z(t-29)	0.0091	0.4744
z(t-29)-z(t-30)	0.0087	0.4529
z(t-30)-z(t-31)	-0.0322	-1.6758
z(t-31)-z(t-32)	0.0371	1.9268
z(t-32)-z(t-33)	0.0247	1.2855
z(t-33)-z(t-34)	-0.0138	-0.7161
z(t-34)-z(t-35)	-0.0378	-1.9656
z(t-35)-z(t-36)	-0.0013	-0.0705
z(t-36)-z(t-37)	-0.0158	-0.8401
1	0.0125	3.7676
t	0.0000	2.2091
Residual s.e.:	45.47800E-004	
R-square:	0.07319	
n:	2819	

Test result:
H0 is rejected in favor of H1, at the 5% significance level
Wald test that the lag width can be reduced from 36 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value	
35	0.706	1	3.841	2.705	0.40088	
34	0.707	2	5.991	4.605	0.70225	
33	5.421	3	7.815	6.251	0.14346	
32	5.850	4	9.488	7.780	0.21066	
31	6.776	5	11.071	9.237	0.23782	
30	10.024	6	12.591	10.645	0.12364	
29	12.244	7	14.067	12.017	0.09282	(*)
28	13.207	8	15.507	13.361	0.10492	
27	13.208	9	16.919	14.683	0.15340	
26	15.384	10	18.307	15.987	0.11868	
25	16.582	11	19.675	17.275	0.12085	
24	20.189	12	21.026	18.549	0.06359	(*)
23	20.600	13	22.362	19.812	0.08122	(*)
22	23.570	14	23.684	21.064	0.05161	(*)
21	23.570	15	24.995	22.307	0.07276	(*)
20	23.576	16	26.296	23.541	0.09919	(*)

19	28.449	17	27.588	24.769	0.03996 (**)
18	31.829	18	28.869	25.990	0.02303 (**)
17	31.832	19	30.144	27.204	0.03264 (**)
16	33.517	20	31.410	28.412	0.02959 (**)
15	34.173	21	32.671	29.615	0.03472 (**)
14	34.192	22	33.925	30.814	0.04696 (**)
13	34.690	23	35.172	32.007	0.05582 (*)
12	35.899	24	36.414	33.196	0.05614 (*)
11	48.359	25	37.653	34.381	0.00338 (**)
10	48.551	26	38.885	35.563	0.00466 (**)
9	48.566	27	40.114	36.741	0.00663 (**)
8	48.659	28	41.336	37.916	0.00909 (**)
7	60.647	29	42.557	39.088	0.00051 (**)
6	61.120	30	43.772	40.256	0.00067 (**)
5	63.824	31	44.985	41.422	0.00047 (**)
4	65.795	32	46.195	42.585	0.00040 (**)
3	77.734	33	47.400	43.745	0.00002 (**)
2	77.772	34	48.602	44.903	0.00003 (**)
1	182.227	35	49.802	46.058	0.00000 (**)
0	191.629	36	50.999	47.212	0.00000 (**)

(*) -> significant at the 10% level
(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	-10.72896	-10.72745	-10.71921
2	-10.76456	-10.76230	-10.74993
3	-10.76322	-10.76020	-10.74371
4	-10.76532	-10.76156	-10.74093
5	-10.76444	-10.75992	-10.73516
6	-10.76452	-10.75924	-10.73034
7	-10.76354	-10.75751	-10.72447
8	-10.76699	-10.76021	-10.72303
9	-10.76559	-10.75804	-10.71672
10	-10.76423	-10.75592	-10.71046
11	-10.76311	-10.75405	-10.70444
12	-10.76549	-10.75567	-10.70190
13	-10.76465	-10.75407	-10.69615
14	-10.76334	-10.75201	-10.68993
15	-10.76193	-10.74983	-10.68360
16	-10.76100	-10.74814	-10.67775
17	-10.76042	-10.74681	-10.67225
18	-10.75955	-10.74518	-10.66646

19	-10.75957	-10.74443	-10.66154
20	-10.75984	-10.74395	-10.65688
21	-10.75853	-10.74187	-10.65064
22	-10.75813	-10.74071	-10.64530
23	-10.75830	-10.74011	-10.64052
24	-10.75746	-10.73851	-10.63474
25	-10.75752	-10.73780	-10.62985
26	-10.75658	-10.73610	-10.62396
27	-10.75585	-10.73460	-10.61827
28	-10.75452	-10.73251	-10.61199
29	-10.75396	-10.73118	-10.60647
30	-10.75317	-10.72963	-10.60072
31	-10.75393	-10.72962	-10.59651
32	-10.75406	-10.72898	-10.59168
33	-10.75277	-10.72693	-10.58542
34	-10.75387	-10.72725	-10.58154
35	-10.75370	-10.72632	-10.57640
36	-10.75307	-10.72491	-10.57078
Optimal p:	8	2	2

p =2

Variable to be tested:
z(t) = LEX
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.0030	-3.1533 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.10000
z(t-1)-z(t-2)	-0.0458	-2.4919
z(t-2)-z(t-3)	0.1859	10.1156
1	0.0103	3.3998
t	0.0000	1.7989
Residual s.e.:	45.78278E-004	
R-square:	0.04544	
n:	2853	

Test result:
H0 is not rejected at the 5% significance level
H0 is rejected in favor of H1 at the 10% significance level
Wald test that the lag width can be reduced from 2 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
1	102.325	1	3.841	2.705	0.00000 (**)
0	111.694	2	5.991	4.605	0.00000 (**)

(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	-10.72896	-10.72745	-10.71921
2	-10.76456	-10.76230	-10.74993
Optimal p:	2	2	2

p = 36 = [c.n^r], where c=5, r=.25, n=2856

Variable to be tested:
z(t) = DLEX
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.8540	-8.6217 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.00000
z(t-1)-z(t-2)	-0.1871	-1.9145
z(t-2)-z(t-3)	0.0129	0.1341
z(t-3)-z(t-4)	0.0207	0.2172
z(t-4)-z(t-5)	-0.0414	-0.4411
z(t-5)-z(t-6)	-0.0595	-0.6417
z(t-6)-z(t-7)	-0.0454	-0.4970
z(t-7)-z(t-8)	-0.0557	-0.6187
z(t-8)-z(t-9)	0.0012	0.0133
z(t-9)-z(t-10)	-0.0036	-0.0409
z(t-10)-z(t-11)	0.0123	0.1437
z(t-11)-z(t-12)	0.0176	0.2087
z(t-12)-z(t-13)	-0.0412	-0.4954
z(t-13)-z(t-14)	-0.0192	-0.2356
z(t-14)-z(t-15)	-0.0353	-0.4418
z(t-15)-z(t-16)	-0.0439	-0.5600
z(t-16)-z(t-17)	-0.0306	-0.4000
z(t-17)-z(t-18)	-0.0100	-0.1340
z(t-18)-z(t-19)	-0.0003	-0.0043
z(t-19)-z(t-20)	0.0360	0.5042
z(t-20)-z(t-21)	-0.0025	-0.0362
z(t-21)-z(t-22)	-0.0072	-0.1067
z(t-22)-z(t-23)	-0.0115	-0.1758
z(t-23)-z(t-24)	0.0114	0.1803
z(t-24)-z(t-25)	0.0294	0.4823
z(t-25)-z(t-26)	0.0702	1.1982
z(t-26)-z(t-27)	0.0486	0.8621
z(t-27)-z(t-28)	0.0202	0.3728

z(t-28)-z(t-29)	0.0291	0.5639
z(t-29)-z(t-30)	0.0375	0.7637
z(t-30)-z(t-31)	0.0054	0.1167
z(t-31)-z(t-32)	0.0423	0.9886
z(t-32)-z(t-33)	0.0671	1.7167
z(t-33)-z(t-34)	0.0534	1.5119
z(t-34)-z(t-35)	0.0153	0.4849
z(t-35)-z(t-36)	0.0131	0.4813
z(t-36)-z(t-37)	-0.0022	-0.1186
1	0.0763	3.8731
t	0.0000	-2.9307
Residual s.e.:	45.56744E-002	
R-square:	0.55679	
n:	2819	

Test result:
H0 is rejected in favor of H1, at the 5% significance level
Wald test that the lag width can be reduced from 36 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
35	0.014	1	3.841	2.705	0.90562
34	0.684	2	5.991	4.605	0.71024
33	0.688	3	7.815	6.251	0.87610
32	5.420	4	9.488	7.780	0.24681
31	5.865	5	11.071	9.237	0.31956
30	6.794	6	12.591	10.645	0.34035
29	9.998	7	14.067	12.017	0.18869
28	12.185	8	15.507	13.361	0.14312
27	13.116	9	16.919	14.683	0.15741
26	13.117	10	18.307	15.987	0.21718
25	15.222	11	19.675	17.275	0.17258
24	16.498	12	21.026	18.549	0.16947
23	20.073	13	22.362	19.812	0.09339 (*)
22	20.501	14	23.684	21.064	0.11512
21	23.505	15	24.995	22.307	0.07399 (*)
20	23.505	16	26.296	23.541	0.10089
19	23.511	17	27.588	24.769	0.13334
18	28.383	18	28.869	25.990	0.05646 (*)
17	31.777	19	30.144	27.204	0.03311 (**)
16	31.777	20	31.410	28.412	0.04573 (**)
15	33.616	21	32.671	29.615	0.03981 (**)
14	34.286	22	33.925	30.814	0.04593 (**)
13	34.298	23	35.172	32.007	0.06097 (*)
12	34.749	24	36.414	33.196	0.07221 (*)
11	36.071	25	37.653	34.381	0.07053 (*)
10	48.342	26	38.885	35.563	0.00493 (**)

9	48.561	27	40.114	36.741	0.00664 (**)
8	48.583	28	41.336	37.916	0.00927 (**)
7	48.657	29	42.557	39.088	0.01255 (**)
6	60.993	30	43.772	40.256	0.00070 (**)
5	61.420	31	44.985	41.422	0.00092 (**)
4	64.248	32	46.195	42.585	0.00062 (**)
3	66.061	33	47.400	43.745	0.00055 (**)
2	77.973	34	48.602	44.903	0.00003 (**)
1	78.015	35	49.802	46.058	0.00004 (**)
0	183.570	36	50.999	47.212	0.00000 (**)

(*) -> significant at the 10% level
(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	-1.25078	-1.24927	-1.24103
2	-1.32442	-1.32216	-1.30979
3	-1.34872	-1.34571	-1.32921
4	-1.37679	-1.37303	-1.35240
5	-1.41434	-1.40982	-1.38506
6	-1.42863	-1.42335	-1.39445
7	-1.46011	-1.45407	-1.42104
8	-1.46743	-1.46065	-1.42347
9	-1.47458	-1.46703	-1.42571
10	-1.48105	-1.47275	-1.42728
11	-1.47997	-1.47091	-1.42129
12	-1.48801	-1.47819	-1.42442
13	-1.48981	-1.47923	-1.42131
14	-1.49253	-1.48120	-1.41912
15	-1.49726	-1.48517	-1.41893
16	-1.50246	-1.48961	-1.41921
17	-1.50362	-1.49000	-1.41545
18	-1.50937	-1.49499	-1.41627
19	-1.50800	-1.49286	-1.40997
20	-1.50904	-1.49314	-1.40608
21	-1.50960	-1.49294	-1.40170
22	-1.51449	-1.49707	-1.40166
23	-1.51583	-1.49764	-1.39806
24	-1.51955	-1.50060	-1.39683
25	-1.51827	-1.49855	-1.39060
26	-1.51709	-1.49661	-1.38447
27	-1.51675	-1.49551	-1.37918
28	-1.51792	-1.49591	-1.37539

29	-1.51694	-1.49416	-1.36945
30	-1.51944	-1.49589	-1.36699
31	-1.52098	-1.49667	-1.36356
32	-1.52090	-1.49582	-1.35852
33	-1.51973	-1.49388	-1.35237
34	-1.52001	-1.49340	-1.34768
35	-1.52002	-1.49264	-1.34271
36	-1.52003	-1.49188	-1.33775
Optimal p:	31	24	10

p =10

Variable to be tested:
z(t) = DLEX
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.8463	-15.0390 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.00000
z(t-1)-z(t-2)	-0.1985	-3.6761
z(t-2)-z(t-3)	-0.0005	-0.0095
z(t-3)-z(t-4)	0.0061	0.1238
z(t-4)-z(t-5)	-0.0596	-1.2947
z(t-5)-z(t-6)	-0.0819	-1.9162
z(t-6)-z(t-7)	-0.0614	-1.5713
z(t-7)-z(t-8)	-0.0696	-1.9782
z(t-8)-z(t-9)	-0.0058	-0.1847
z(t-9)-z(t-10)	-0.0122	-0.4472
z(t-10)-z(t-11)	-0.0081	-0.4329
1	0.0755	4.2047
t	0.0000	-3.0578
Residual s.e.:	45.72818E-002	
R-square:	0.54881	
n:	2845	

Test result:
H0 is rejected in favor of H1, at the 5% significance level
Wald test that the lag width can be reduced from 10 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
9	0.187	1	3.841	2.705	0.66508
8	0.225	2	5.991	4.605	0.89350
7	0.293	3	7.815	6.251	0.96135
6	12.248	4	9.488	7.780	0.01560 (**)
5	12.706	5	11.071	9.237	0.02629 (**)
4	15.936	6	12.591	10.645	0.01410 (**)

3	17.823	7	14.067	12.017	0.01279 (**)
2	28.940	8	15.507	13.361	0.00032 (**)
1	28.997	9	16.919	14.683	0.00065 (**)
0	132.345	10	18.307	15.987	0.00000 (**)

(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	-1.25078	-1.24927	-1.24103
2	-1.32442	-1.32216	-1.30979
3	-1.34872	-1.34571	-1.32921
4	-1.37679	-1.37303	-1.35240
5	-1.41434	-1.40982	-1.38506
6	-1.42863	-1.42335	-1.39445
7	-1.46011	-1.45407	-1.42104
8	-1.46743	-1.46065	-1.42347
9	-1.47458	-1.46703	-1.42571
10	-1.48105	-1.47275	-1.42728
Optimal p:	10	10	10

p = 36 = [c.n^r], where c=5, r=.25, n=2856

Variable to be tested:
z(t) = NIFTY
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.0050	-2.8479 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.18000
z(t-1)-z(t-2)	0.0804	4.2463
z(t-2)-z(t-3)	-0.0373	-1.9616
z(t-3)-z(t-4)	0.0642	3.3804
z(t-4)-z(t-5)	0.0086	0.4520
z(t-5)-z(t-6)	-0.0017	-0.0870
z(t-6)-z(t-7)	0.0152	0.7996
z(t-7)-z(t-8)	-0.0373	-1.9567
z(t-8)-z(t-9)	-0.0026	-0.1377
z(t-9)-z(t-10)	0.0535	2.8058
z(t-10)-z(t-11)	-0.0255	-1.3374
z(t-11)-z(t-12)	-0.0234	-1.2260
z(t-12)-z(t-13)	0.0427	2.2365
z(t-13)-z(t-14)	-0.0080	-0.4196
z(t-14)-z(t-15)	0.0473	2.4767

z(t-15)-z(t-16)	-0.0184	-0.9608
z(t-16)-z(t-17)	-0.0072	-0.3748
z(t-17)-z(t-18)	0.0006	0.0299
z(t-18)-z(t-19)	-0.0054	-0.2805
z(t-19)-z(t-20)	0.0048	0.2527
z(t-20)-z(t-21)	0.0238	1.2434
z(t-21)-z(t-22)	-0.0026	-0.1354
z(t-22)-z(t-23)	-0.0339	-1.7709
z(t-23)-z(t-24)	0.0401	2.0988
z(t-24)-z(t-25)	0.0004	0.0200
z(t-25)-z(t-26)	-0.0366	-1.9131
z(t-26)-z(t-27)	0.0018	0.0928
z(t-27)-z(t-28)	-0.0273	-1.4256
z(t-28)-z(t-29)	-0.0264	-1.3811
z(t-29)-z(t-30)	0.0489	2.5522
z(t-30)-z(t-31)	0.0115	0.5979
z(t-31)-z(t-32)	0.0125	0.6515
z(t-32)-z(t-33)	-0.0286	-1.4911
z(t-33)-z(t-34)	0.0026	0.1339
z(t-34)-z(t-35)	-0.0317	-1.6548
z(t-35)-z(t-36)	-0.0088	-0.4590
z(t-36)-z(t-37)	0.0428	2.2442
1	4.2789	2.8397
t	0.0008	1.4178
Residual s.e.:	19.55174E+000	
R-square:	0.03656	
n:	2819	

Test result:
H0 is not rejected at the 10% significance level
Wald test that the lag width can be reduced from 36 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
35	5.036	1	3.841	2.705	0.02482 (**)
34	5.117	2	5.991	4.605	0.07741 (*)
33	8.284	3	7.815	6.251	0.04049 (**)
32	8.302	4	9.488	7.780	0.08112 (*)
31	10.331	5	11.071	9.237	0.06638 (*)
30	10.514	6	12.591	10.645	0.10459
29	11.042	7	14.067	12.017	0.13680
28	17.018	8	15.507	13.361	0.02992 (**)
27	18.570	9	16.919	14.683	0.02910 (**)
26	20.529	10	18.307	15.987	0.02462 (**)
25	20.537	11	19.675	17.275	0.03850 (**)
24	24.662	12	21.026	18.549	0.01651 (**)
23	24.668	13	22.362	19.812	0.02551 (**)

22	29.356	14	23.684	21.064	0.00935 (**)
21	32.497	15	24.995	22.307	0.00551 (**)
20	32.615	16	26.296	23.541	0.00831 (**)
19	34.781	17	27.588	24.769	0.00665 (**)
18	34.817	18	28.869	25.990	0.00997 (**)
17	35.043	19	30.144	27.204	0.01380 (**)
16	35.185	20	31.410	28.412	0.01914 (**)
15	35.401	21	32.671	29.615	0.02550 (**)
14	36.348	22	33.925	30.814	0.02786 (**)
13	42.800	23	35.172	32.007	0.00731 (**)
12	43.006	24	36.414	33.196	0.00993 (**)
11	47.341	25	37.653	34.381	0.00447 (**)
10	48.193	26	38.885	35.563	0.00513 (**)
9	50.590	27	40.114	36.741	0.00389 (**)
8	59.296	28	41.336	37.916	0.00050 (**)
7	59.297	29	42.557	39.088	0.00075 (**)
6	64.296	30	43.772	40.256	0.00027 (**)
5	65.514	31	44.985	41.422	0.00029 (**)
4	65.521	32	46.195	42.585	0.00043 (**)
3	65.527	33	47.400	43.745	0.00064 (**)
2	80.127	34	48.602	44.903	0.00001 (**)
1	84.411	35	49.802	46.058	0.00001 (**)
0	98.133	36	50.999	47.212	0.00000 (**)

(*) -> significant at the 10% level
(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	5.95742	5.95893	5.96717
2	5.95713	5.95939	5.97176
3	5.95371	5.95672	5.97322
4	5.95510	5.95886	5.97949
5	5.95649	5.96101	5.98577
6	5.95756	5.96284	5.99174
7	5.95705	5.96309	5.99612
8	5.95839	5.96518	6.00235
9	5.95692	5.96447	6.00579
10	5.95738	5.96569	6.01115
11	5.95841	5.96747	6.01709
12	5.95847	5.96829	6.02205
13	5.95944	5.97001	6.02793
14	5.95879	5.97012	6.03220
15	5.95979	5.97188	6.03812

16	5.96083	5.97368	6.04408
17	5.96211	5.97573	6.05029
18	5.96338	5.97776	6.05648
19	5.96468	5.97981	6.06271
20	5.96529	5.98119	6.06825
21	5.96645	5.98311	6.07434
22	5.96661	5.98404	6.07945
23	5.96656	5.98475	6.08434
24	5.96796	5.98691	6.09068
25	5.96769	5.98740	6.09536
26	5.96908	5.98956	6.10170
27	5.96967	5.99092	6.10724
28	5.97019	5.99220	6.11272
29	5.96965	5.99243	6.11714
30	5.97095	5.99449	6.12340
31	5.97184	5.99615	6.12925
32	5.97217	5.99724	6.13455
33	5.97360	5.99944	6.14095
34	5.97375	6.00036	6.14608
35	5.97492	6.00230	6.15223
36	5.97462	6.00277	6.15691
Optimal p:	3	3	1

p =1

Variable to be tested:
z(t) = NIFTY
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.0050	-2.9526 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.15000
z(t-1)-z(t-2)	0.0688	3.6818
1	4.3118	3.0212
t	0.0008	1.3497
Residual s.e.:	19.62462E+000	
R-square:	0.00760	
n:	2854	

Test result:
H0 is not rejected at the 10% significance level
Wald test that the lag width can be reduced from 1 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
0	13.556	1	3.841	2.705	0.00023 (**)

(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	5.95742	5.95893	5.96717
Optimal p:	1	1	1

p = 36 = [c.n^r], where c=5, r=.25, n=2856

Variable to be tested:
z(t) = LNIFTY
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.0041	-2.7788 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.21000
z(t-1)-z(t-2)	0.0887	4.6837
z(t-2)-z(t-3)	-0.0153	-0.8040
z(t-3)-z(t-4)	0.0459	2.4164
z(t-4)-z(t-5)	0.0120	0.6300
z(t-5)-z(t-6)	-0.0049	-0.2576
z(t-6)-z(t-7)	0.0048	0.2546
z(t-7)-z(t-8)	-0.0367	-1.9359
z(t-8)-z(t-9)	0.0129	0.6819
z(t-9)-z(t-10)	0.0419	2.2176
z(t-10)-z(t-11)	-0.0239	-1.2623
z(t-11)-z(t-12)	0.0049	0.2570
z(t-12)-z(t-13)	0.0442	2.3398
z(t-13)-z(t-14)	-0.0125	-0.6620
z(t-14)-z(t-15)	0.0525	2.7733
z(t-15)-z(t-16)	-0.0055	-0.2928
z(t-16)-z(t-17)	-0.0054	-0.2835
z(t-17)-z(t-18)	-0.0084	-0.4439
z(t-18)-z(t-19)	-0.0033	-0.1768
z(t-19)-z(t-20)	-0.0008	-0.0424
z(t-20)-z(t-21)	0.0265	1.4018
z(t-21)-z(t-22)	-0.0029	-0.1556
z(t-22)-z(t-23)	-0.0270	-1.4293
z(t-23)-z(t-24)	0.0077	0.4068
z(t-24)-z(t-25)	-0.0090	-0.4791
z(t-25)-z(t-26)	-0.0539	-2.8612
z(t-26)-z(t-27)	0.0261	1.3821
z(t-27)-z(t-28)	-0.0251	-1.3311
z(t-28)-z(t-29)	-0.0405	-2.1514

z(t-29)-z(t-30)	0.0696	3.6897
z(t-30)-z(t-31)	0.0082	0.4331
z(t-31)-z(t-32)	-0.0023	-0.1211
z(t-32)-z(t-33)	-0.0184	-0.9718
z(t-33)-z(t-34)	0.0119	0.6302
z(t-34)-z(t-35)	-0.0328	-1.7395
z(t-35)-z(t-36)	-0.0117	-0.6201
z(t-36)-z(t-37)	0.0308	1.6355
1	0.0275	2.8616
t	0.0000	1.1160
Residual s.e.:	19.02404E-003	
R-square:	0.03684	
n:	2819	

Test result:
H0 is not rejected at the 10% significance level
Wald test that the lag width can be reduced from 36 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
35	2.675	1	3.841	2.705	0.10195
34	2.906	2	5.991	4.605	0.23386
33	6.219	3	7.815	6.251	0.10142
32	6.530	4	9.488	7.780	0.16293
31	7.337	5	11.071	9.237	0.19675
30	7.427	6	12.591	10.645	0.28316
29	7.619	7	14.067	12.017	0.36742
28	21.125	8	15.507	13.361	0.00682 (**)
27	24.586	9	16.919	14.683	0.00347 (**)
26	26.645	10	18.307	15.987	0.00296 (**)
25	28.587	11	19.675	17.275	0.00263 (**)
24	36.580	12	21.026	18.549	0.00026 (**)
23	37.110	13	22.362	19.812	0.00040 (**)
22	37.252	14	23.684	21.064	0.00068 (**)
21	39.908	15	24.995	22.307	0.00047 (**)
20	39.959	16	26.296	23.541	0.00079 (**)
19	42.244	17	27.588	24.769	0.00062 (**)
18	42.283	18	28.869	25.990	0.00101 (**)
17	42.315	19	30.144	27.204	0.00161 (**)
16	42.336	20	31.410	28.412	0.00250 (**)
15	42.623	21	32.671	29.615	0.00351 (**)
14	42.642	22	33.925	30.814	0.00522 (**)
13	50.321	23	35.172	32.007	0.00084 (**)
12	50.988	24	36.414	33.196	0.00106 (**)
11	56.466	25	37.653	34.381	0.00031 (**)
10	56.699	26	38.885	35.563	0.00046 (**)
9	58.582	27	40.114	36.741	0.00040 (**)

8	64.575	28	41.336	37.916	0.00010 (**)
7	65.242	29	42.557	39.088	0.00013 (**)
6	69.796	30	43.772	40.256	0.00005 (**)
5	70.066	31	44.985	41.422	0.00007 (**)
4	70.154	32	46.195	42.585	0.00011 (**)
3	70.169	33	47.400	43.745	0.00017 (**)
2	79.448	34	48.602	44.903	0.00002 (**)
1	80.146	35	49.802	46.058	0.00002 (**)
0	98.816	36	50.999	47.212	0.00000 (**)

(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	-7.89393	-7.89243	-7.88419
2	-7.89307	-7.89082	-7.87844
3	-7.89500	-7.89199	-7.87549
4	-7.89362	-7.88986	-7.86923
5	-7.89243	-7.88791	-7.86314
6	-7.89114	-7.88586	-7.85697
7	-7.89107	-7.88504	-7.85200
8	-7.89073	-7.88394	-7.84676
9	-7.89209	-7.88454	-7.84322
10	-7.89115	-7.88285	-7.83738
11	-7.88998	-7.88092	-7.83130
12	-7.89040	-7.88059	-7.82682
13	-7.89265	-7.88208	-7.82416
14	-7.89394	-7.88260	-7.82053
15	-7.89284	-7.88074	-7.81451
16	-7.89384	-7.88099	-7.81059
17	-7.89360	-7.87998	-7.80543
18	-7.89243	-7.87806	-7.79934
19	-7.89200	-7.87686	-7.79397
20	-7.89291	-7.87701	-7.78995
21	-7.89313	-7.87647	-7.78523
22	-7.89252	-7.87509	-7.77968
23	-7.89113	-7.87295	-7.77336
24	-7.88998	-7.87103	-7.76726
25	-7.89176	-7.87205	-7.76410
26	-7.89137	-7.87089	-7.75875
27	-7.89086	-7.86961	-7.75329
28	-7.89260	-7.87059	-7.75007
29	-7.89604	-7.87326	-7.74855
30	-7.89467	-7.87113	-7.74223

31	-7.89654	-7.87223	-7.73913
32	-7.89716	-7.87209	-7.73478
33	-7.89586	-7.87001	-7.72850
34	-7.89579	-7.86917	-7.72346
35	-7.89561	-7.86823	-7.71830
36	-7.89559	-7.86743	-7.71330
Optimal p:	32	1	1

p =1

Variable to be tested:
z(t) = LNIFTY
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

	OLS estimate	t-value Asymptotic critical regions:
z(t-1)	-0.0048	-3.4541 < -3.40 (5%)
		< -3.13 (10%)
		p-value = 0.04000
z(t-1)-z(t-2)	0.0790	4.2409
1	0.0326	3.5908
t	0.0000	1.1217
Residual s.e.:	19.26025E-003	
R-square:	0.01100	
n:	2854	

Test result:
H0 is rejected in favor of H1, at the 5% significance level
Wald test that the lag width can be reduced from 1 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
0	17.985	1	3.841	2.705	0.00002 (**)

(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	-7.89393	-7.89243	-7.88419
Optimal p:	1	1	1

p = 36 = [c.n^r], where c=5, r=.25, n=2856

Variable to be tested:
z(t) = DLNIFTY
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

OLS estimate t-value Asymptotic critical regions:

z(t-1)	-0.9185	-9.3184 < -3.40 (5%) < -3.13 (10%) p-value = 0.00000
z(t-1)-z(t-2)	0.0092	0.0943
z(t-2)-z(t-3)	-0.0038	-0.0398
z(t-3)-z(t-4)	0.0382	0.4066
z(t-4)-z(t-5)	0.0483	0.5217
z(t-5)-z(t-6)	0.0445	0.4889
z(t-6)-z(t-7)	0.0495	0.5523
z(t-7)-z(t-8)	0.0075	0.0846
z(t-8)-z(t-9)	0.0251	0.2894
z(t-9)-z(t-10)	0.0651	0.7673
z(t-10)-z(t-11)	0.0356	0.4282
z(t-11)-z(t-12)	0.0401	0.4922
z(t-12)-z(t-13)	0.0799	1.0004
z(t-13)-z(t-14)	0.0641	0.8174
z(t-14)-z(t-15)	0.1163	1.5128
z(t-15)-z(t-16)	0.1078	1.4315
z(t-16)-z(t-17)	0.0997	1.3503
z(t-17)-z(t-18)	0.0919	1.2706
z(t-18)-z(t-19)	0.0874	1.2362
z(t-19)-z(t-20)	0.0862	1.2485
z(t-20)-z(t-21)	0.1083	1.6082
z(t-21)-z(t-22)	0.1014	1.5439
z(t-22)-z(t-23)	0.0724	1.1312
z(t-23)-z(t-24)	0.0793	1.2728
z(t-24)-z(t-25)	0.0682	1.1320
z(t-25)-z(t-26)	0.0215	0.3697
z(t-26)-z(t-27)	0.0482	0.8627
z(t-27)-z(t-28)	0.0155	0.2905
z(t-28)-z(t-29)	-0.0266	-0.5206
z(t-29)-z(t-30)	0.0402	0.8333
z(t-30)-z(t-31)	0.0536	1.1885
z(t-31)-z(t-32)	0.0500	1.1896
z(t-32)-z(t-33)	0.0301	0.7784
z(t-33)-z(t-34)	0.0418	1.1932
z(t-34)-z(t-35)	0.0050	0.1606
z(t-35)-z(t-36)	-0.0060	-0.2354
z(t-36)-z(t-37)	0.0305	1.6189
1	0.0900	1.2078
t	0.0000	-0.7170
Residual s.e.:	19.09658E-001	
R-square:	0.47499	
n:	2819	

Test result:
H0 is rejected in favor of H1, at the 5% significance level
Wald test that the lag width can be reduced from 36 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
35	2.621	1	3.841	2.705	0.10547
34	5.840	2	5.991	4.605	0.05394 (*)
33	5.999	3	7.815	6.251	0.11167
32	10.374	4	9.488	7.780	0.03458 (**)
31	10.626	5	11.071	9.237	0.05932 (*)
30	11.593	6	12.591	10.645	0.07168 (*)
29	11.741	7	14.067	12.017	0.10940
28	12.331	8	15.507	13.361	0.13702
27	24.621	9	16.919	14.683	0.00342 (**)
26	28.701	10	18.307	15.987	0.00139 (**)
25	31.847	11	19.675	17.275	0.00081 (**)
24	33.678	12	21.026	18.549	0.00076 (**)
23	40.020	13	22.362	19.812	0.00014 (**)
22	40.622	14	23.684	21.064	0.00020 (**)
21	40.661	15	24.995	22.307	0.00036 (**)
20	43.714	16	26.296	23.541	0.00022 (**)
19	43.865	17	27.588	24.769	0.00036 (**)
18	45.377	18	28.869	25.990	0.00037 (**)
17	45.450	19	30.144	27.204	0.00059 (**)
16	45.506	20	31.410	28.412	0.00094 (**)
15	45.542	21	32.671	29.615	0.00147 (**)
14	45.986	22	33.925	30.814	0.00199 (**)
13	46.060	23	35.172	32.007	0.00294 (**)
12	53.408	24	36.414	33.196	0.00051 (**)
11	54.393	25	37.653	34.381	0.00059 (**)
10	59.126	26	38.885	35.563	0.00022 (**)
9	59.301	27	40.114	36.741	0.00033 (**)
8	61.871	28	41.336	37.916	0.00023 (**)
7	67.427	29	42.557	39.088	0.00007 (**)
6	68.267	30	43.772	40.256	0.00008 (**)
5	74.161	31	44.985	41.422	0.00002 (**)
4	74.450	32	46.195	42.585	0.00003 (**)
3	74.491	33	47.400	43.745	0.00005 (**)
2	74.492	34	48.602	44.903	0.00007 (**)
1	82.873	35	49.802	46.058	0.00001 (**)
0	83.438	36	50.999	47.212	0.00001 (**)

(*) -> significant at the 10% level
(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)

information criteria

p	AC	HQ	SC
1	1.70932	1.71082	1.71907
2	1.57244	1.57470	1.58707
3	1.52188	1.52489	1.54139
4	1.48949	1.49326	1.51389
5	1.46431	1.46883	1.49359
6	1.45649	1.46177	1.49067
7	1.43786	1.44389	1.47693
8	1.41634	1.42312	1.46030
9	1.41267	1.42022	1.46154
10	1.40490	1.41320	1.45866
11	1.39296	1.40202	1.45164
12	1.39193	1.40174	1.45551
13	1.37767	1.38824	1.44616
14	1.37541	1.38675	1.44882
15	1.37535	1.38745	1.45368
16	1.37328	1.38613	1.45653
17	1.37074	1.38435	1.45891
18	1.36980	1.38417	1.46290
19	1.36522	1.38035	1.46324
20	1.36427	1.38017	1.46723
21	1.36447	1.38113	1.47236
22	1.36387	1.38129	1.47670
23	1.36450	1.38269	1.48228
24	1.36590	1.38485	1.48862
25	1.36269	1.38241	1.49036
26	1.36402	1.38450	1.49664
27	1.36517	1.38642	1.50274
28	1.35449	1.37650	1.49702
29	1.35333	1.37610	1.50081
30	1.35407	1.37761	1.50652
31	1.35302	1.37733	1.51044
32	1.35016	1.37524	1.51254
33	1.35139	1.37724	1.51875
34	1.35222	1.37883	1.52455
35	1.34892	1.37630	1.52622
36	1.35019	1.37834	1.53247
Optimal p:	35	32	13

p =13

Variable to be tested:
z(t) = DLNIFTY
H0: Unit root with drift; H1: Linear trend stationarity
ADF model for z(t)-z(t-1):

OLS estimate t-value Asymptotic critical regions:

z(t-1)	-0.8014	-12.9033 < -3.40 (5%) < -3.13 (10%) p-value = 0.00000
z(t-1)-z(t-2)	-0.1123	-1.8681
z(t-2)-z(t-3)	-0.1322	-2.2737
z(t-3)-z(t-4)	-0.0813	-1.4550
z(t-4)-z(t-5)	-0.0771	-1.4437
z(t-5)-z(t-6)	-0.0791	-1.5507
z(t-6)-z(t-7)	-0.0699	-1.4520
z(t-7)-z(t-8)	-0.1082	-2.4008
z(t-8)-z(t-9)	-0.0968	-2.3030
z(t-9)-z(t-10)	-0.0515	-1.3312
z(t-10)-z(t-11)	-0.0756	-2.1564
z(t-11)-z(t-12)	-0.0718	-2.3270
z(t-12)-z(t-13)	-0.0293	-1.1527
z(t-13)-z(t-14)	-0.0521	-2.7718
1	0.1012	1.3787
t	0.0000	-0.8912

Residual s.e.: 19.26360E-001
R-square: 0.46708
n: 2842

Test result:
H0 is rejected in favor of H1, at the 5% significance level
Wald test that the lag width can be reduced from 13 to q:

q	Chi-square test	d.f.	5% crit. value	10% crit. value	p-value
12	7.683	1	3.841	2.705	0.00558 (**)
11	8.628	2	5.991	4.605	0.01338 (**)
10	13.188	3	7.815	6.251	0.00425 (**)
9	13.472	4	9.488	7.780	0.00919 (**)
8	15.174	5	11.071	9.237	0.00964 (**)
7	20.923	6	12.591	10.645	0.00189 (**)
6	21.745	7	14.067	12.017	0.00281 (**)
5	26.639	8	15.507	13.361	0.00082 (**)
4	26.893	9	16.919	14.683	0.00146 (**)
3	26.900	10	18.307	15.987	0.00270 (**)
2	26.900	11	19.675	17.275	0.00476 (**)
1	35.820	12	21.026	18.549	0.00035 (**)
0	36.513	13	22.362	19.812	0.00049 (**)

(**) -> significant at the 5% level

Selection of p under the null hypothesis by
the Akaike (AC), Hannan-Quinn (HQ), and Schwarz (SC)
information criteria

p	AC	HQ	SC
1	1.70932	1.71082	1.71907
2	1.57244	1.57470	1.58707
3	1.52188	1.52489	1.54139
4	1.48949	1.49326	1.51389
5	1.46431	1.46883	1.49359
6	1.45649	1.46177	1.49067
7	1.43786	1.44389	1.47693
8	1.41634	1.42312	1.46030
9	1.41267	1.42022	1.46154
10	1.40490	1.41320	1.45866
11	1.39296	1.40202	1.45164
12	1.39193	1.40174	1.45551
13	1.37767	1.38824	1.44616
Optimal p:	13	13	13