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Raj S. Dhankar

Risk-Return Relationship and Portfolio Management

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Dedicated to all my Teachers

Preface

Risk–return hypothesis, proposed by Hary Markowtiz in the early 1960s, is the bedrock of modern finance. As this new thought process in finance area got ignited over the years, the development of various capital asset valuation models took place such as CAPM APT, Black and Scholes option models, single-index model, Fama–French three-factor model, Carhart four-factor model and several other models.

Around the world, one of the major points of contention, in business schools and amongst the investment decision-makers, is the utility and application of the aforesaid models, more so in emerging and less efficient stock markets. The main motivation of this book, therefore, is to check the relevance of risk–return hypothesis and application of capital market models in less efficient markets like India and Southwest Asia, besides providing deep insights into portfolio construction, selection, diversification and performance evaluation.

This book is divided into five parts: the first part covers the process of valuation of capital assets, particularly the application of CAPM, APT and GARCH models. In the second part, capital market models and market efficiency have been dealt wherein variance ratio test, ARIMA model and multi-factor models have been examined. The third part then examines the risk–return hypothesis, mainly the time series of return and volatility, correlation, uncertainty and investment decision. The fourth part deals with portfolio construction, selection, diversification and performance evaluation in the context of mean–variance approach, market index model and market efficiency. Lastly, the fifth part discusses some of the emerging and contemporary topics such as Islamic finance, value at risk, behavioural finance and adaptive market hypothesis in the field of finance. I believe that this book will fill the vacuum in the current finance literature and also provide clarity and direction to the investors and policy-makers alike in making sound decisions.

I wish to thank the whole Springer team particularly Ms. Sagarika Ghosh, Nupoor Singh and Daniel Joseph Glarance for their support in bringing out this book. I would also like to thank all my co-authors for their scholarly thought process and hard work put in all the writings. I cannot help but put on record my sincere debt of gratitude which I owe to my teachers at UCLA Anderson School of Management, USA, for sharpening my knowledge base in finance area and laying a

strong foundation of research in my early days of academic life. Finally, my heartfelt thanks to my wife Rita for her unconditioned love and support for over forty years in all my ventures, including in writing this book.

New Delhi, India Raj S. Dhankar

About This Book

This book essentially deals with the making of investment decisions in the backdrop of risk–return analysis, a pillar of modern finance proposed by Hary Markowitz. It examines the suitability and relevance of major capital market models evolved in the US markets, for Indian and South Western Asian markets.

This book is divided into five parts: the first part covers the process of valuation of capital assets, particularly the application of CAPM, APT and GARCH models. In the second part, capital market models and market efficiency have been dealt wherein variance ratio test, ARIMA model and multi-factor models have been examined. The third part then examines the risk–return hypothesis, mainly the time series of return and volatility, correlation, uncertainty and investment decisions. The fourth part deals with portfolio construction, selection, diversification and performance evaluation in the context of mean–variance approach, market index model and market efficiency. In the end, the fifth part discusses some of the emerging and contemporary topics such as Islamic finance, value at risk, behavioural finance and adaptive market hypothesis in the field of finance.

This book attempts to provide deep insights into modern finance and highly useful techniques, models and strategies for portfolio managers, mutual fund managers, individual investors and policy-makers.

Raj S. Dhankar

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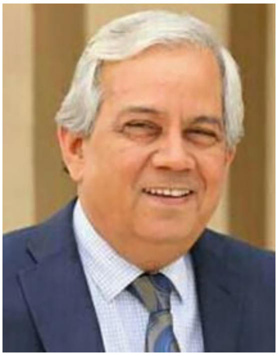
About the Author



Prof. Raj S. Dhankar a thought leader and institution builder, is currently the Chief Executive Officer (CEO) for Higher Education at Appejay Education Society, New Delhi. He is also a Professor of Finance and former Dean of the Faculty of Management Studies (FMS), University of Delhi, India. In the course of his career, he has held various administrative positions like the Vice-Chancellor, Amity University, Raipur; Vice-Chancellor, Ansal University, Gurgaon; Vice-Chancellor, Maharishi Dayanand University, Rohtak, Haryana; and Director of the Centre for Canadian Studies, University of Delhi.

Holding a Ph.D. (1983) and Post-Doctoral Studies degree (PDS) (1987) in Finance, Prof. Dhankar has been actively involved in teaching, research, training and consultancy in the field of finance since 1977. He received a Commonwealth Scholarship for a Ph.D. program in the UK and Post-Doctoral Studies (PDS) Scholarship for the USA from the Government of India. Prof. Dhankar received his PDS in Finance from the John Anderson Graduate School of Management, University of California, Los Angeles (UCLA), USA in 1987, and has taught at several international universities including the University of California, Los Angeles (UCLA), University of Southern California (USC), and Lakehead University, Canada. He has completed several major research projects with financial assistance from national and international agencies. He has six books to his credit, and has published over one hundred research papers in major national and international journals.

Prof. Dhankar serves on the governing bodies/councils of various educational institutions, and as a Director & Trustee on the boards of several public and private sector organizations. He is a member of various committees in the Central and State Governments. In recognition of his contributions to the welfare of society and institution building, he has been honored with several awards, including Best Vice-Chancellor of the Year in 2016 and the "Haryana Ratan" award.

Abbreviations

ACAR	Average cumulative average return
ACF	Autocorrelation function
ADF	Augmented Dickey–Fuller
AIC	Akaike's information criteria
AMH	Adaptive market hypothesis
APT	Arbitrage pricing theory
AR	Autoregressive
ARCH	Autoregressive conditional heteroskedasticity
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
B/M	Book to market
BDS test	Brock, Dechert, and Scheinkman test
BSE	Bombay Stock Exchange
CAPM	Capital asset pricing model
CAR	Cumulative average return
CAViaR	Conditional autoregressive value at risk
CDSL	Central Depository Services Limited
CFRS	Carry forward rolling settlement
CMIE	Centre for Monitoring Indian Economy
CML	Capital market line
DAX	Deutscher Akteinindex
DJGI	Dow Jones Global Index
DPs	Depository participants
DW	Durbin–Watson
ECBs	External commercial borrowing
E-GARCH	Exponential general conditional heteroskedasticity
EMH	Efficient-market hypothesis
EMU	European Monetary Union
EVT	Extreme value theory
EWMA	Exponential weighted moving average

FDI	Foreign direct investment
FIIs	Foreign institutional investors
GAPP	Generally accepted principles and practices
GARCH	General autoregressive conditional heteroskedasticity
GCC	Gulf Cooperation Council
GDP	Gross domestic product
IAS	Indian Accounting Standard
IASB	International Accounting Standards Board
IASC	International Accounting Standards Committee
IFRS	International Financial Reporting Standards
IID	Independent and identical distribution
IPO	Initial public offering
LB statistics	Ljung–Box statistics
LB	Ljung–Box
MA	Moving average
MM	Modigliani and Miller
NAFTA	North American Free Trade Agreements
NOI	Net operating theory
NSCCL	National Securities Clearing Corporation Limited
NSDL	National Securities Depository Limited
NSE	National Stock Exchange
NYSE	New York Stock Exchange
PACF	Partial autocorrelation function
PE	Private equity
PP	Phillips–Perron
RBI	Reserve Bank of India
RWH	Random walk hypothesis
S&P	Standard & Poor's
SIC	Schwarz information criterion
SEBI	Securities and Exchange Board of India
STP	Straight-through processing
TGARCH	Threshold general autoregressive conditional heteroskedasticity
TE	Tracking error
VaR	Value at risk
VR	Variance ratio
WACC	Weighted average cost of capital

Part I
Valuation of Capital Assets

Chapter 1
Capital Asset Pricing Model: An Overview

An investment in knowledge pay the best interest.
Benjamin Franklin

Abstract There is conflicting evidence on the applicability of Capital Asset Pricing Model in the Indian stock market. Data for 158 stocks listed on the Bombay Stock Exchange was analysed using a number of tests from 1991 to 2002, the period which roughly coincides with the period after liberalization and initiation of capital market reforms. Taken in aggregate the various empirical tests show that CAPM is not valid for the Indian stock market for the period studied.

Introduction

It is a well-established fact that risk and return go hand in hand, and asset pricing models attempt to define the relationship between returns and risks. Capital Asset Pricing Model (CAPM) is the most researched as well as critically examined technique in the field of finance. The concepts of Security Market Line (SML) and Capital Market Line (CML) are employed as tools for the estimation of expected return on Securities and Portfolios.

The stock market has always been known for its unpredictability. The uncertainty of reward from stock market investment is referred to as risk, which is expected to be borne by investors for the expectation of earning higher returns.

CAPM has many varied empirical results all over the world. In India too existing literature reveals conflicting evidence on the applicability of Capital Asset Pricing Model (CAPM). This could be due to differences in the type of tests conducted,

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various sizes and constituents of samples, frequency of data and period covered. Economic liberalization, stock market reforms and entry of foreign investors were expected to improve market efficiency and rationality of investors and bring return–risk relationships in line with the CAPM (Dhankar, 1996; Sehgal, 1997). The question of whether or not CAPM is applicable in the Indian stock market is best answered by a comprehensive analysis using a number of tests.

CAPM

The CAPM developed by Sharpe (1964), Linter (1965) and Mossin (1966) is an equilibrium model that explains why different securities have different expected returns. It provides a methodology for quantifying risk and translating the risk into estimates of expected return on equity.

The CAPM explains that every investment carries two distinct risks. One is the risk of being in the market, which is called systematic risk or beta, and the other is unsystematic risk, which is company specific and can be diversified through the creation of portfolios.

The systematic risk, beta, can be estimated by using the market model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} t = 1, \ldots, T \tag{1.1}$$

where ε_{it} is the random error term or the residual of R_{it} which was unexplained by the regression. Investors hold portfolios comprising of the market portfolio and lend or borrow at the risk-free rate depending on individual risk preferences. Securities or portfolios with high betas tend to do better in good times and worse in bad times than those with low betas. This relationship between risk and return is represented by the security market line. The Security Market Line (SML) is expressed by the following equation:

$$E(R_i) = R_f + \{E(R_m) - R_f\} B_i \tag{1.2}$$

where $E(R_i)$ is the expected return on asset i, R_f is the risk-free rate, R_m is the expected return on the market portfolio and B_i is $\mathrm{Cov}(R_i R_m)/\mathrm{Var}\ R_m$, the systematic risk of security i.

In the zero beta CAPM, the lowest risk portfolio or the minimum variance zero beta portfolio which has zero correlation with the market is used in place of the risk-free rate. Investors hold a combination of the market portfolio and zero beta portfolio. The SML in this case has a 'y' intercept equal to the zero beta portfolio.

The zero beta model is characterized by the following equation:

$$E(R_i) = R_z + \{E(R_m) - R_z\} B_i \tag{1.3}$$

where $E(R_i)$ is the expected return on asset i, R_z is the return on the risk-free portfolio (zero beta potfolio), R_m is the expected return on the market portfolio and B_i is Cov(R_jR_m)/Var R_m, the systematic risk of security i. The advantage of the zero beta model as compared to the standard model is that it does not assume risk-free lending and borrowing.

Review of Literature

CAPM has been tested extensively, for over three decades, in various forms primarily in developed capital markets and to some extent in developing markets. Early work in this area including Black, Jenson, and Scholes (1972), Fama and McBeth (1973) and Blume and Friend (1973) supported the standard and zero beta model of CAPM. However, Banz (1981), Reinganum (1981), Gibbons (1982), Shanken (1985) and Fama and French (1992), highlighted the danger of focusing exclusively on mean-beta space. These studies found that the return generation process also depends on other variables like size, book to market ratio and earnings price ratio.

In the Indian context, there have been a number of studies which investigated the validity of CAPM with varying results. Yalawar (1989) studied 122 stocks from 1963 to 1982. He found that results were consistent with CAPM. Maheshwari and Vanjara (1989) analysed returns for 142 stocks from 1980 to 1986. They found that systematic risk and returns were negatively related in bearish markets. Dhankar (1996) studied 50 companies from April 1989 to March 1993, historical betas were adjusted like Blume, and dividend and price expectations of 25 market players were incorporated to get ex-ante average return. A significant linear relationship between beta and return was reported although the intercept and slope were on the higher side. Sehgal (1997) used monthly returns of 80 BSE securities from April 1984 to March 1993 and odd and even month estimation procedure like Ball, Brown and Officer (1976). The two-moment model and three-moment model were used. No significant relationship was found between beta and return. Vipul (1998) examined 114 BSE stocks from July 1986 to June 1993 and used the two factor zero beta model. He reported the existence of time variability of zero beta return and return for risk. The two-factor CAPM explained the returns generating process only marginally better than naïve unit beta model. Ansari (2000) studied 96 stocks from 1990 to 1996 using the BJS methodology with 24-month betas and returns updated each year. He concluded that CAPM was not applicable in India.

Methodology

This study includes frequently traded stocks of large and medium-sized companies listed on the Bombay Stock Exchange (BSE) and included in BSE 200, Nifty and Junior Nifty during the 12-year period, i.e. January 1991–December 2002. Daily adjusted closing prices were mainly extracted from the CMIE database 'Prowess', and supplemented by data from the BSE site. A total of 158 companies satisfied the criteria of at least 75% data points, as compared to BSE 200 index, with not more than 2 months of continuous gaps. The BSE 200 index (1989–90 = 100), a broad-based index comprising of 200 shares was used as the market proxy. Realized returns were used in place of expected return. Fifteen equally weighted portfolios were constructed based on first pass regressions. The sample is limited with respect to the number of securities (158) and the time period (12 years). We have assumed like Ball et al. (1976), that the sample is representative, so as other researchers have done in the past. As pointed out by Levy (1981) in examining the CAPM or in estimating a security's risk one cannot arbitrarily use weekly or monthly data according to availability or convenience since systematic risk and portfolio performance are functions of the assumed investment horizon. An attempt was, therefore, made to use monthly and weekly data to see if conclusions differ based on the interval chosen.

The data was analysed as follows:

1. The entire 12 years and shorter intervals of 1–5 years were studied to see the effect of period length and to decide the number of years to be used for the Black, Jenson and Scholes (BJS) type and other tests. Beta was calculated for each period for formation of portfolios, portfolio betas and average returns were regressed in the second stage.
2. BJS (1972) type analysis using rolling 2-year periods for portfolio formation and subsequent year returns for creation of time series data. Time series tests were performed and standard CAPM and the zero beta model were tested.
3. Fama and Macbeth (1973) type analysis using 2-year betas for portfolio formation revised yearly and 2-year rolling beta updated monthly for cross regression with subsequent month returns. Data was also pooled for eight years.
4. Analysis, using 12-year beta with weekly and monthly cross-sectional analysis, was done. Cross sections were performed using Ordinary Least Squares (OLS) and estimated Generalized Least Squares (EGLS). Monthly data was pooled for 12 years.

   In each section, the entire period is studied and sub-periods are analysed to see if there is any change over the years due to the stock market reforms.

Analysis

Effect of Period Length

Beta was estimated using OLS regressions on weekly and monthly returns for each of the 158 stocks for the 12-year period and the BSE 200 index as the independent variable using Eq. 1.1. Results of the weekly return regressions are given in Table 1.1.

Table 1.1 Summary of regressions of weekly return of 58 securities and BSE 200 for 12 years 1991–2002

Beta		F-statistic		Durbin–Watson statistic		R-square	
Range	Number	Range	Number	Range	Number	Range	Number
0–0.2	0	7	4	<1.65	1	0–0.1	19
0.2–0.4	1	500–100	40	1.65–1.69	0	0.1–0.2	79
0.4–0.6	24	100–200	82	1.69–2.31	152	0.2–0.3	48
0.6–0.8	70	200–300	23	2.31–2.35	3	0.3–0.4	7
0.8–1.0	43	300–400	4	>2.35	2	0.4–0.5	5
1–1.2	16	400–500	2				
1.2–1.4	3	500–600	2				
1.4–1.6	1	600–700	1				
Total	158		158		158		158

Source Compiled from Dhankar and Singh (2005)

The value of the F-statistic is highly significant for all the regressions. The 1% cut-off point at (1. Infinite) degrees of freedom is 6.63, which establishes that the market model holds for the data analysed. The Durbin–Watson Statistic shows no significant autocorrelation in 152 cases. There is positive autocorrelation in one case and negative autocorrelation in two cases and it is indeterminate in three cases. The degree of movement in individual securities explained by the market is in the range of 10–30% for majority of the stocks.

Fifteen equally weighted portfolios of 10–11 stocks were created based on beta calculated in the first pass regressions. OLS regressions were run for each of the portfolios with the BSE 200 as the independent variable. Results of these regressions are given in Table 1.2.

As can be seen that the F-statistics and R-square figures are higher for portfolios than for individual securities. The market factor explains 54–83% of movement in portfolio returns. Also, there is no problem of autocorrelation when portfolios are used. Results using monthly data were similar to weekly data, the F-statistics and R-square figures were higher for portfolios than for individual securities.

The cross-sectional test was performed using the portfolio betas derived from the market model and average weekly and monthly returns for the 12-year period. The results are summarized in Table 1.3.

During this period the weekly T-bill rate ranged between 4.6 and 12.96% (including fixed rate 4.6% before 1993), the T-bill rate averaged on a monthly basis ranged between 4.6 and 11.89%. The average for the 12-year period was 8.02%. The weekly call money rate ranged between 0.24 and 54.5% monthly call money rate ranged between 1.22 and 35.29%. The average call money rate over the 12-year period was 10.32%. Various researchers have considered both of them as proxies for the risk-free rate.

Table 1.2 Summary of regression of weekly return of portfolios and BSE 200 over 12 years 1991–2002

Portfolio no.	Beta	F-statistic	Durbin–Watson	Adjusted R-square
1	1.222	1384.76	1.819	0.795
2	1.036	1190.51	1.772	0.833
3	0.94	839.175	2.005	0.74
4	0.876	910.569	1.77	0.759
5	0.836	1178.564	1.956	0.807
6	0.814	869.917	1.792	0.718
7	0.78	696.033	1.949	0.73
8	0.75	557.837	1.849	0.663
9	0.723	551.859	1.898	0.601
10	0.689	544.139	1.76	0.678
11	0.656	695.231	1.729	0.668
12	0.628	631.896	1.872	0.667
13	0.599	526.777	2.067	0.647
14	0.534	457.588	1.881	0.651
15	0.467	316.793	1.928	0.543

Source Compiled from Dhankar and Singh (2005)

Table 1.3 Cross-sectional test results for the 12-year period 1991–2002

1991–2002	Slope	T-sig	Intercept	T-sig	Annualized intercept (%)	Adjusted R^2	Market return
Weekly	0.34	0.015	0.157	0.121	8.18	0.33	0.26
Monthly	1.61	0.01	0.496	0.147	4.95	0.57	1.32

Source Compiled from Dhankar and Singh (2005)

According to the CAPM, the slope should be positive and equal to excess return over the risk-free rate or zero beta return and intercept should be equal to the risk-free rate or to the zero beta portfolio return. Although the intercept and slope are positive but the intercept is not significant in both cases. The reward for risk is higher than the market rate of return, therefore, higher than excess return. The annualized intercept with weekly returns is very close to the T-bill rate of 8% but when monthly returns are used it is much lower at approximately 5%.

The analysis was repeated using shorter periods of time ranging from 1 year to 5 years. Beta was calculated for each period for formation of portfolios and portfolio betas and average returns were regressed in the second stage. Summarized results for monthly and weekly data are presented in Table 1.4.

The intercepts were very different from the risk-free rate and were negative in 64% of the monthly sub-periods and 44% of the weekly periods. There was no observable relationship between negative slopes and intercepts, and negative return on the market portfolio.

Table 1.4 Summary of cross-sectional test results for one to 5-year period

No. of years	No. of periods	Positive slope	T-sig 5%	Positive intercept	T-sig 5%	Range Adj R^2	Average Adj R^2
Monthly returns							
1	12	11	8	7	7	−0.03 to 0.86	0.36
2	11	9	10	4	5	0.08 to 0.74	0.52
3	10	9	8	3	6	−0.06 to 0.73	0.46
4	9	8	7	2	2	−0.08 to 0.76	0.43
5	8	8	6	2	1	0.13 to 0.72	0.41
Weekly returns							
1	12	9	5	7	6	−0.06 to 0.78	0.26
2	11	9	6	5	6	−0.07 to 0.77	0.35
Weekly returns							
1	12	9	5	7	6	−0.06 to 0.78	0.26
2	11	9	6	5	6	−0.07 to 0.77	0.35
3	10	8	5	5	4	−0.06 to 0.62	0.32
4	9	7	6	6	5	−0.07 to 0.82	0.42
5	8	7	5	5	3	−0.07 to 0.77	0.32

Source Compiled from Dhankar and Singh (2005)

The analysis for shorter periods of time ranging from 1 to 5 years revealed that intercepts and slopes were not always positive. As can be seen from Table 1.4, the slope or reward for risk is positive in all periods only for 5-year periods with monthly data, and there too only six periods are statistically significant at 5%. The slope was positive and significant and higher than the market return in majority of the sub-periods. Negative slopes for beta were basically in 1996 and periods including that year with monthly data and in 1995, 1996 and 2001 with weekly data. The intercept was found to be positive and significant as well as negative and significant in some of the periods for 1–3 year periods; however, both positive and negative slopes were significant in most periods for 4–5 year calculation periods. The intercepts were very different from the risk-free rate and were negative in 64% of the monthly sub-periods and 44% of the weekly periods. There was no observable relationship between negative slopes and intercepts, and negative return on the market portfolio. The sub-periods studied do not show that CAPM is more applicable after liberalization and economic reforms, i.e. towards the second half of the 12 years.

The proportion of variation in return explained by the model also varies over a wide range. For monthly data, the highest average adjusted R-square was 0.52, when 2-year betas and returns were used. For weekly data, the average adjusted R-square was highest at 0.42 for the 4-year analysis. Since the monthly adjusted R-square is higher than the weekly figure and also the period studied was only 12 years, further analysis was done using 2-year periods for calculation of beta.

Test of CAPM Like Balak, Jenson and Scholes (BJS)

Ten overlapping period of 2 years each from 1991 to 2001 were used to estimate alpha and beta using Eq. 1.4 and 24 monthly rates of return on each stock. The stocks were grouped into 15 beta sorted portfolios and rate of return for each portfolio was calculated monthly for the succeeding year resulting in a set of monthly returns from 1993 to 2002. This was the procedure used by BJS to avoid selection bias. Time series tests were done on the monthly returns of portfolios for 10 years and 2-year sub-periods using Eq. 1.4, and results are presented in Table 1.5.

$$R_{it} - R_{ft} = \alpha_i + B_i\left(R_{mt} - R_{ft}\right) + \varepsilon_{it} \tag{1.4}$$

F-statistics for goodness of fit, which is also the t-statistic for Beta, were significant for all at 5%. Unlike BJS, however, no inverse relationship is observed between alpha and beta; alpha is positive for almost all portfolios in 1993–94 and 2001–2002, and negative for all portfolios in 1995–96. Results of the cross-sectional test are presented in Table 1.6.

If the standard CAPM is valid, intercept should not be different from zero and slope should be equal to the average excess return on the market portfolio over the period. As can be seen for the 10-year period, intercept is significantly lower than zero and for the fourth sub-period, it is significantly higher than zero. However, for all other sub-periods, it is negative but not significant. The figures for the slope, on the other hand, are higher than average excess return over the market except in 1999–2000, but are not significant in any period. If the zero beta model holds instead of standard CAPM, and if the return on the zero beta portfolio is higher than the risk-free rate then intercept should be positive and slope should be less than excess return on the market portfolio and vice versa, if risk-free rate is higher than the zero beta portfolio. For the entire period and four of the sub-periods, it appears that $R_z < R_f$, while for 1999–2000 $R_z > R_f$.

The same exercise was repeated without subtracting the risk-free rate to directly test the zero beta model and results are presented in Table 1.7.

As can be seen from Table 1.7, R_z and $E(R_m - R_z)$ are positive in all years except 1995–96. However, none of the relationships are significant except for the intercept in 1999–2000. The zero beta return when annualized ranges from 6 to 20.6% in the 2-year sub-periods and is 0.9% for the 10-year period.

The reward to risk is positive in four sub-periods and for the overall period. Although results vary with the interval chosen, most relationships are not statistically significant with both monthly and weekly returns. The CAPM is not valid when we use the BJS-type tests.

Table 1.5 BJS type time series tests results using monthly returns and the standard CAPM

	1993–2002		1993–94		1995–96		1997–98		1999–2000		2001–2002	
Group	Beta	Alpha	Beta	Alpha	Beta	Alpha	Beta	Alpha	Beta	Alpha	Beta	Alpha
1	1.185	−0.055	1.168	0.403	1.161	−0.053	1.369	−0.769	1.056	−0.119	1.595	0.581
2	1.065	0.318	1.055	1.589	1.119	−1.929	1.199	1.507	0.906	1.162	1.383	1.086
3	0.999	0.219	1.003	1.299	1.108	−1.474	1.119	−0.627	0.871	−0.069	1.241	1.952
4	0.953	0.115	0.973	1.275	1.103	−1.930	1.106	−0.048	0.799	−2.034	1.158	0.958
5	0.918	−0.285	0.928	1.375	1.052	−2.474	1.104	1.693	0.765	−0.264	1.138	1.032
6	0.896	−0.343	0.880	1.276	1.048	−1.946	1.102	0.278	0.735	−1.602	1.103	0.789
7	0.887	−0.593	0.871	1.198	1.021	−1.487	1.059	−0.714	0.664	−0.044	0.976	1.546
8	0.879	−0.362	0.863	0.660	0.986	−1.714	1.023	0.853	0.641	1.194	0.969	0.628
9	0.873	0.071	0.861	0.786	0.979	−2.268	0.981	−0.005	0.639	−0.417	0.886	0.368
10	0.867	−0.202	0.851	1.923	0.959	−0.350	0.981	−1.539	0.639	−1.461	0.879	1.969
11	0.828	0.207	0.847	1.217	0.959	−1.339	0.953	0.049	0.639	−0.417	0.837	2.684
12	0.821	−0.322	0.809	0.330	0.926	−1.820	0.907	1.215	0.625	−0.353	0.821	0.361
13	0.818	−0.418	0.798	0.669	0.918	−1.765	0.822	−0.042	0.602	−1.662	0.773	−0.919
14	0.806	−0.270	0.796	−0.212	0.837	−1.740	0.740	−0.794	0.521	−2.040	0.622	0.278
15	0.687	−0.407	0.764	0.392	0.833	−1.398	0.723	−0.607	0.378	0.920	0.581	0.351

Source Compiled from Dhankar and Singh (2005)

Table 1.6 BJS type cross-sectional test results using monthly returns and standard CAPM

Period	Intercept	t-sig	Slope $E(R_m - R_t)$	t-sig	Actual $R_m - R_t$	Adj R^2
1993–2002	−1.233	0.031	1.046	0.086	−0.1527	0.149
1993–1994	0.365	0.774	2.643	0.077	1.1868	0.162
1995–1996	−2.319	0.216	−1.469	0.423	−2.2085	−0.023
1997–1998	−0.976	0.534	0.772	0.613	−0.2219	−0.055
1999–2000	0.686	0.000	0.038	0.347	1.1685	−0.003
2001–2002	−0.115	0.901	0.293	0.745	−0.6884	−0.068

Source Compiled from Dhankar and Singh (2005)

Table 1.7 BJS type cross-sectional test results using zero beta model and monthly returns

Period	R_z	t-sig	$E(R_m - R_z)$	t-sig	R_m	Adj R^2
1993–2002	0.075	0.897	1.093	0.106	0.545	0.126
1993–1994	1.723	0.105	1.892	0.108	1.895	0.124
1995–1996	−0.501	0.783	−1.476	0.419	−1.304	−0.022
1997–1998	0.518	0.704	0.504	0.703	0.389	−0.064
1999–2000	0.621	0.000	0.044	0.264	1.890	0.025
2001–2002	0.827	0.339	0.202	0.808	−0.143	−0.072

Source Compiled from Dhankar and Singh (2005)

Test of CAPM Like Fama–Mac Beth

The individual stock betas were estimated using the market model over a 2-year period, starting with January 1991–December 1992. The stocks were ranked by beta and fifteen portfolios formed. Portfolio betas and residual standard deviations were estimated over rolling subsequent 2-year periods, starting with January 1993–December 1994. These were regressed with portfolio returns calculated for the following month, i.e. the first month used for cross regression was January 1995. The following cross regression equations were run over each of the 96 months from January 1995 to December 2002.

$$\overline{R}_n = \gamma_{0t} + \hat{\gamma}_{1t}\beta_{it-1} + \hat{\gamma}_{2t}\beta^2_{it-1} + \hat{\gamma}_{3t}s(\varepsilon_{it-1}) + \eta_{it}t \tag{1.5}$$

$$\overline{R}_n = \gamma_{0t} + \hat{\gamma}_{1t}\beta_{it-1} + \hat{\gamma}_{2t}\beta^2_{it-1} + \eta_{it} \tag{1.6}$$

$$\overline{R}_n = \gamma_{0t} + \hat{\gamma}_{1t}\beta_{it-1} + \hat{\gamma}_{3t}s(\varepsilon_{it-1}) + \eta_{it} \tag{1.7}$$

$$\overline{R}_n = \gamma_{0t} + \hat{\gamma}_{1t}\beta_{it-1} + \eta_{it} \tag{1.8}$$

The hypotheses tested were the following:

1. The relationship between risk and return is linear. If this is true, the value of Y_{2t} will be zero.
2. Beta is the relevant measure of risk. If this is true, the value of Y_{3t} will be zero.
3. The relationship between risk and return is positive. If this is true, the value of Y_{1t} will be positive.

In the first pass regressions, t-statistics for beta were significant at 5% for all 15 portfolios in 84 months, for 14 portfolios in 9 months and for 13 portfolios in 4 months. The minimum R-square was 0.041 and maximum was 0.945, and average R-square for 15 portfolios in each month ranged between 0.34 and 0.82. The summary of cross-sectional test results is presented in Table 1.8.

For the 8-year period and sub-periods using Eqs. 1.5–1.8 above, the mean of majority of coefficients are not significantly different from zero except for γ_{3t} which corresponds to the error term.

A detailed look at the results of Eq. 1.8 above revealed that the constant which should correspond to the risk-free rate or the zero beta rate, in this case, is negative in 50 months, and slope which should be positive is negative in 49 months, out of 96 months studied. The R-square or proportion of variation explained by Beta is also less than 10% in 64 months. We sorted the cross-sectional results by monthly market return like Chan and Lakonishok (1993) and examined the ten highest and lowest returns. While they found a nearly monotonic relationship between return and beta, and remarkably high R-square, there was no such relationship for the data

Table 1.8 Summary of Fama–MacBeth-type cross-sectional tests using Monthly returns

	1995–2002		1995–96		1997–98		1999–2002		2001–2002	
	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
Equation 1.5	$\overline{R}_n = \gamma_{0t} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\beta^2_{it-1}\eta_{it}$									
γ_{0t}	−0.14	−0.03	−3.99	−0.43	15.68	1.14	−6.42	−0.73	−5.85	−2.07
γ_{1t}	2.95	0.31	5.67	0.32	−22.66	−0.89	20.55	0.95	8.23	1.14
γ_{2t}	−1.45	−0.30	−2.62	−0.30	9.97	0.83	−9.35	−0.80	−3.75	−0.78
γ_{3t}	−0.24	−2.00	−0.32	−1.35	−0.55	−2.36	−0.51	−2.46	0.41	1.65
Equation 1.6	$\overline{R}_n = \gamma_{0t} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\beta^2_{it-1} + \eta_{it}$									
γ_{0t}	0.67	0.15	−6.19	−0.71	17.05	1.31	−3.62	−0.45	−4.59	−1.64
γ_{1t}	−0.20	−0.02	8.08	0.47	−29.88	−1.25	9.63	0.50	11.36	1.47
γ_{2t}	0.05	0.01	−3.79	−0.46	13.62	1.19	−4.46	−0.42	−5.16	−1.07
Equation 1.7	$\overline{R}_n = \gamma_{0t} + \gamma_{1t}\beta_{it-1} + \gamma_{3t}s(\varepsilon_{it-1}) + \eta_{it}$									
γ_{0t}	1.07	0.89	−2.58	−1.80	6.06	2.02	2.88	1.01	−2.10	−1.45
γ_{1t}	0.08	0.08	1.58	1.48	−2.73	0.1.30	1.28	0.56	0.19	0.08
γ_{2t}	−0.21	−1.82	−0.31	−1.39	−0.59	−2.58	−0.40	−2.21	0.44	1.68
Equation 1.8	$\overline{R}_n = \gamma_{0t} + \gamma_{1t}\beta_{it-1} + \eta_{it}$									
γ_{0t}	0.41	0.41	−3.43	−2.86	3.59	1.38	1.42	0.56	0.09	0.10
γ_{1t}	0.07	0.07	1.50	1.44	−2.52	−1.20	0.21	0.09	1.11	0.43

T-statistics are significant at 5% at 1.98

Source Compiled from Dhankar and Singh (2005)

Table 1.9 Regressions with eight year panel data taken from Fama–MacBeth-type study

		Coeff of dummies			F ratio
No. effects	Beta −0.095	Range	R-square 0.000016	Adj R-square −0.001	
t value	−0.154				
Time period effect	0.198	−14.9 to 29.66	0.778	0.762	50.1 (sig 1%)
t value	0.295	72 out of 95 sig			
Portfolio effect	−0.068	0.68 to 1.81	0.002	−0.008	0.21 (not sig)
t value	−0.109	All 14 not sig			
Time and portfolio effect	0.411	−14.9 to 29.66	0.78	0.762	43.22 (sig 1%)
t value	0.559	72 out of 95 time sig			

Source Compiled from Dhankar and Singh (2005)

studied. While the months with negative returns had negative slopes, half the months with highest returns also had negative slopes. All this shows that beta is not priced and that the non-systematic risk is important, which does not support the CAPM.

The process of combining cross-sectional and time series data to form a panel is called pooling. Pooling may be useful to sort out effects that may not be distinguishable with time series or cross-sectional data alone. Dummies were added to separate the effects of time and portfolio. The significance of the time effect, portfolio effect and time and portfolio effect as compared to the restricted model (no dummies) regressions was calculated as follows:

$$F_{N+T-2,NT-N-T} = \frac{\frac{ESS_1 - ESS_2}{N+T-2}}{\frac{ESS_2}{NT-N-T}} \tag{1.9}$$

where ESS_1 and ESS_2 are the error sum of squares using the restricted model and models with dummies, respectively.

The Fama–MacBeth betas and returns were pooled over the 8-year period. 95 dummy variables were added to segregate the effect of time periods on the intercept and 14 dummies to segregate the portfolio effects. Results are presented in Table 1.9.

As can be seen from the above table, although beta is positive when we introduce dummies to capture the effect of the time period, beta is not significant in any of the regressions. The effect of time period is most significant, whereas the portfolio effect is insignificant. There was no observable pattern in the time period effect.

Test of CAPM with a Single Beta Estimated Over 12 Years

The 12-year results obtained in the first section were analysed further like Vipul (1998). For weekly return, Bartlett's test statistics for checking residual variances between groups was 199.17, which is highly significant (Chi-square at 5% is 7.26), which shows the presence of unequal variances between groups. However, as this test is sensitive to deviations from normality and sometimes may simply be testing the non-normality. Levene's test using the median was also performed. Levene's test statistic is 7.39 (F-test 14,608 at 5% 1.67) which again confirms the presence of heteroscedasticity between groups. Estimated generalized least squares EGLS was performed by dividing portfolio betas and returns by the standard deviation of the residual for each portfolio to correct for inequality of error of variance terms and then performing the cross regression. The slope was 0.25 and intercept 0.077, which is 4.03% on an annualized basis. For monthly returns, Bartlett's test statistics was 91.69, and Levene's test statistic was 3.03, the slope after adjustment for unequal variances using EGLS, was 1.13 and intercept 0.147, which turns out to 1.77% on an annualized basis.

609 OLS cross regressions were performed for weekly returns on estimated betas. Only 167 were found significant at 5%. Slope was negative in 304 periods and intercept was negative in 301 periods. Cross sections were also performed for weekly data using EGLS. Only 123 were found significant at 5%. Slope was negative in 306 (50%) periods and intercept was negative in 314 periods. Slope and intercept were both negative in 96 periods.

144 cross regressions were performed for monthly returns on estimated betas of which only 42 were found significant at 5%. The slope was negative in 72 cases and the intercept was negative in 63 cases. Slope and intercept were both negative in 26 periods.

Cross-sectional regressions for monthly data using EGLS found only 31 significant at 5%, slope was negative in 78 (54%) and intercept was negative in 67 months. Slope and intercept were both negative in 27 months. Average intercept was 0.17, slope was 0.96 and t-statistics were 1.26 and 0.78, respectively, which shows that they are not significantly different from zero. There was no observable relationship between slope and market return when results were sorted by market return.

Results are similar to Vipul (1998), wherein it was found that risk premium (slope) was negative in 43 (53%) months and intercept or zero beta return was negative in 32 out of 81 periods. The conclusions based on weekly and monthly returns are similar, there is time variability in risk premium and zero beta portfolio return for the period under study.

The adjusted monthly returns and betas used for EGLS were pooled across the 12-year period. Variance of error terms across time periods showed inequality when checked with Bartlett's test statistics which was 165.39. The portfolio returns and betas were divided by the standard deviation of the residual for each period to adjust for variance or error terms across time periods, and 143 dummies were added to segregate time effect and 14 dummies for the portfolio effect. The result is presented

Table 1.10 Regressions with 12-year panel data taken from ELGS data

		Coeff of dummies			F ratio
No. dummy variables	Beta −9.397	Range	R-square 0. 119	Adj R-square 0. 119	
t value	−17.105				
Time-effect intercept	−1.517	−9.69 to 8.99	0. 857	0.847	85.08 (sig 1%)
t-value	−3.324	110 of 143 sig 5%			
Portfolio-effect intercept	−11.925	−1.73 to 0.3	0.15	0.144	29.12 (sig 5%)
t value	−19.413	11 of 14 sig 5%			
Time and Portfolio-effect intercept	−8.844	−9.49 to 7.46	0.861	0.85	113.77 (sig 1%)
t-value	−6.533	117 of 157 sig 5%			

Source Compiled from Dhankar and Singh (2005)

in Table 1.10. The coefficient of beta is negative and significant in all the models, which is not consistent with the CAPM.

Summary and Conclusions

First pass regressions show that market returns, stock returns and portfolio returns are significantly related. Cross regression of beta and returns calculated over the entire 12 years period gave positive slopes, which were significant as required by the CAPM, and explained 33% and 57% of variation in returns with weekly and monthly data, respectively. Intercepts were also positive but not significant. The model explains returns to a limited extent for shorter periods from one to five years. Slopes were not always positive or significant and intercepts were often negative and statistically insignificant. For all other tests including standard tests like BJS and Fama–Macbeth over the entire period and sub-periods and pooled data, the CAPM was not found suitable for explaining the return generation process. As regards the effect of interval between data points, the slope and annualized intercept vary with the interval used, however, since most relationships were not significant the broad conclusions were essentially the same. The sub-periods studied showed no evidence that CAPM is more applicable after liberalization and economic reforms. It is, therefore, necessary to look for other factors or models, which may be able to estimate security returns more accurately in Indian stock market.

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Chapter 2
Indian Stock Market and Relevance of Capital Asset Pricing Models

It's not how much money you make, but how much money you keep, how hard it works for you, and how many generations you keep it for.
Robert Kiyosaki

Abstract The arbitrage pricing theory (APT) has been proposed as an alternative to the capital asset pricing model (CAPM). Using principal components analysis to estimate the factors that influence stock returns. Analysis of the Indian stock market using monthly and weekly returns for 1991–2002 shows that APT with multiple factors provides a better indication of asset risk and estimates of required rate of return than CAPM which uses beta as the single measure of risk.

Introduction

Arbitrage Pricing Theory (APT) is essentially a multi-factor model. Multi-factor models attempt to describe asset price returns and their covariance matrix as a function of a limited number of risk attributes. In their general form, factor models posit that the period returns of various assets are explained by some common factors in a linear model. The asset returns are influenced by the factors as per the sensitivity of the individual securities to the factors. These sensitivities, thus, play the role of the beta in CAPM. In addition, the asset return is also influenced by the specific return, which is assumed to be independent of the other factors.

The Capital Asset Pricing Model (CAPM) is widely accepted as an appropriate technique for evaluating financial assets. It is used to construct portfolios, measure the performance of investment managers, develop project screening rates for capital budgeting and value companies. The Arbitrage Pricing Theory (APT), which offers

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an alternative explanation of the relationship between risk and return is yet to receive widespread acceptance in India.

The objective of this study was to compare the CAPM and APT using principal components analysis. This paper briefly reviews the relevant literature and presents evidence that APT may lead to better estimates of risk and expected rate of return than CAPM.

CAPM and APT

The CAPM is an equilibrium model that explains why different securities have different expected returns. It provides a methodology for quantifying risk and translating that risk into estimates of expected return on equity. In particular, it asserts that the expected returns vary because securities have different betas. There is a linear relationship between beta and expected return. The zero beta model is characterized by the following equation:

$$\mathrm{E(R_i) = R_z + \{E(R_m) - R_z\}B_i} \tag{2.1}$$

where $\mathrm{E(R_i)}$ is the expected return on asset *i*, $\mathrm{R_z}$ is the return on the risk-free portfolio (zero beta portfolio), $\mathrm{R_m}$ is the expected return on the market portfolio and $\mathrm{B_i}$ is $\mathrm{Cov(R_iR_m)/Var\ R_m}$, the systematic risk of security i. The advantage of the zero beta model as compared to the standard model is that it does not assume risk-free lending and borrowing.

The systematic risk, beta can be estimated by using the market model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad t = 1\ldots T \tag{2.2}$$

where $\varepsilon_{\mathrm{it}}$ is the random eror term or the residual of $\mathrm{R_{it}}$ which was unexplained by the regression.

The alternative model for asset pricing APT assumes that security returns are generated by a factor model but does not identify the factors. It implies that securities or portfolios with equal factor sensitivities should offer the same expected returns. If not, investors will take advantage of arbitrage opportunities, causing their elimination. The equilibrium expected return on a security is a linear function of its sensitivities to the factors. APT can be described by the following equation:

$$E(R_i) = R_0 + \lambda_i b_{it} + \lambda_2 b_{i2} \lambda_3 b_{i3} + \ = \ldots + \lambda_i b_{ij} \tag{2.3}$$

where $E(R_i)$ is expected return on asset i, R_0 is return on a risk-free asset because all its b_{ijs} are zero, b_{ij} is the reaction coefficient describing the change in asset i's return for a unit change in factor j, and λ_j is the premium for risk associated with factor j. If there are portfolios with identical risk but different return, then investors will push up the prices of undervalued portfolios and vice versa for overvalued portfolios till risk and return are equated.

The sensitivity to factors (like beta in CAPM) are estimated as follows:

$$R_{it} = b_{i0} + b_{i1}\delta_{i1} + b_{i2}\delta_{2t+} b_{i3}\delta_{i3+\ldots} b_{ij}\delta_{jt+} u_{it} t = 1\ldots T \tag{2.4}$$

where R_{it} is the return on asset i in period t, b_{i^2} is the estimated return on asset i when all δ_{jt} values are zero, δ_{jt} is the value at time t of factor j common to the returns of all assets, b_{ij} is the estimated sensitivity of asset i to factor j, and represents residual risk.

Prelude

CAPM has been tested extensively, for over three decades, in various forms primarily in developed capital markets and to some extent in developing markets. Early work in this area, including (Black, Jenson, & Scholes, 1972; Fama & MacBeth, 1973) and (Blume & Friend, 1973) supported the standard and zero beta model of CAPM. However Banz (1981), Reinganum (1981), Gibbons (1982), Shanken (1985) and Fama and French (1992), highlighted the danger of focusing exclusively on mean-beta space. These studies found that the return generation process also depends on other variables like size, book to market ratio and earnings price ratio.

In the Indian context (Dhankar, 1988), used the CAPM to compute risk adjusted cost of capital for public sector undertakings and to measure their performance. There have also been a number of studies which investigated the linearity, slope and intercept of the Security Market Line, with varying results. Some including (Yalawar, 1989), Obaidullah and Mohanty (1994), Dhankar (1996), Ghosh (Dhankar & Singh, 2005) and Vipul (Ghosh, 1997), concluded that evidence supports CAPM to some extent. Others, such as Maheshwari and Vanjara (Vipul, 1998), Madhusoodan (Maheshwari & Vanjara, 1989) and Sehgal (Madhusoodanan, 1997) found that CAPM was not an appropriate tool to be used in Indian markets.

A great deal of research work on APT has been undertaken in developed markets, particularly in the U.S. markets using two approaches. The first approach, i.e. factor analysis, was used by Roll and Ross (Sehgal, 1997) in their classic study of APT, where four or five factors were found to have significant explanatory power. Dhrymes, Friend and Gultekin (Roll & Ross, 1980) found that the number of significant factors increased with the number of securities included in factor analysis. This, Rolls and Ross (Drymes, Friend, & Gultekin, 1984) explained, could be due to new factors depending on the companies included in the sample. The decision as to how many factors are to be extracted depends on the researcher. In the second approach, factors are specified by the researcher in advance. Sharpe (Roll & Ross, 1984) showed that company attributes such as size, dividend yield and sector membership increased the explanatory power of the model. Chen, Roll and Ross (Sharpe, 1982) found that macro variables have a significant explanatory influence on prices. Studies comparing APT and CAPM have used both approaches. Bower et al. (Chen, Roll, & Ross, 1986) used factor analysis to show that APT is a better choice than CAPM for evaluating utility stock returns. Conner & korajczyk (Bower, Bower, & Logue, 1984) used Principal Components Analysis and found five factors that could explain the size and January effect better than CAPM. Lehman and Modest (Connor & Korajczyk, 1988) show that a multi-index model can explain the extra returns associated with high dividend yields and partly explain the size and January effect. Burmeister and McElory (Lehmann & Modest, 1988) concluded that CAPM can be rejected in favour of the APT model, which included factors like default premium and time premium. Vipul and Gianchandani (Burmeister & McElory, 1988) found that the BSE National Index and dollar exchange rate was significant in the first stage, but not properly priced in the second stage. APT is yet to be critically researched in the Indian context, and this study is an effort in this direction.

Methodology Used

The study includes frequently traded stocks of large and medium-size companies, listed on the BSE 200, Nifty and Junior Nifty during the 12-year period, i.e. January 1991–December 2002. Daily adjusted closing prices were mainly extracted from the CMIE data base ‘Prowess’, and supplemented by data from the BSE site. A total number of 158 companies (see Exhibit) satisfied the criteria of at least 75% data points, as compared to BSE 200 index, with not more than 2 months of continuous gaps. The BSE 200 index (1989–90 = 100), a broad-based index comprising of 200 shares was used as the market proxy. The sample is limited with respect to the number of securities (158) and the time period (12 years). We have assumed like Ball, Brown and Officer (Vipul & Gianchandani, 1997), that the sample is representative, as other researchers have done in the past.

Chamberlain and Rothschild (Ball, Brown, & Officer, 1980) showed that principal components is an appropriate technique for finding an approximate factor structure which is all that is needed in empirical work. This technique has been used to extract factors for APT. Equation 2.4 was used for the first stage time series regressions for APT, and Eq. 2.3 for second stage cross regressions. For CAPM, time series regressions Eq. 2.2 was used, and for cross regressions Eq. 2.2 was used. Realized monthly and weekly returns were used in place of expected return.

APT

Before comparing CAPM and APT a preliminary study of number of factors and percentage of variance, that can be explained by them, was done. Monthly returns for all 158 stocks (see Exhibit) were analysed and 32 components were extracted using Eigenvalues of 1 and above. A summary of the magnitude of components is presented in Table 2.1.

As can be seen from the table the first factor is positive for all companies, and ranges between 0.2 and 0.8. Other factors are less than 0.6 and are positive and negative. Further for approximately half the companies, these factors are negative.

The first five factor scores as used by Roll and Ross (Sehgal, 1997), Brown and Weinstein (Chamberlain & Rothschild, 1983), Chen (Brown & Weinstein, 1983) and Trzcinka (Chen, 1983) were used to derive characteristic lines for each security (Eq. 2.4). The results are summarized in Tables 2.2 and 2.3. The first factor explains 39% of the variation and the first five factors explain 50% of the variation. The coefficients of these factor scores were cross regressed with the average return over the 12 year period on a monthly basis to check if they were priced (Eq. 2.3). For the whole period, the constant is negative, the t-test is significant at 5% for four of the factors. In the month-wise analysis, the constant is positive in 77 months and negative in 67 months. Factor premiums are also positive and negative in approximately half of the months, which points to instability over time. Monthly t-statistics are not as significant as the overall period. King (1966) found that one factor out of seven examined, explained a large percentage of the variance of stock prices. This, he interpreted as the market factor which showed high correlation with beta. The correlation between the first factor and Beta for all 158 stocks from the market model is 76.31% for the 12-year period.

Three types of portfolios were formed like Bower et al. (Chen et al., 1986), i.e. alphabetical (essentially random), beta sorted as in CAPM, and industry-based (CMIE classification). Industry classification is expected to reduce the chance of using portfolios with similar factor characteristics. Fifteen portfolios of approximately the same size were formed including some mixed groups (see Annex I). Detailed results of the analysis are given for the industry based portfolios, followed by summarized results for the others.

The first factor explains 80.8% and five factors explain 91% of the variance for industry-based portfolios. These five components also explain 85–97% of variance for the 15 portfolios. If at all these factors are less than the true number of factors, it would not favour APT in a comparative analysis.

The Kaiser–Meyer–Olkin Measure of statistical adequacy (which compares the magnitudes of the observed correlation coefficients to the magnitude of partial correlation coefficients) was very high at 0.968, indicating that factor analysis is very suitable as correlations between pairs of variables can be explained by other variables. For Bartletts test of sphericity also, the chi-square value is highly significant (0.01) rejecting the hypothesis that the matrix is an identity matrix, thus

Table 2.1 Summary of principal components analysis of monthly returns for 158 stocks

Number of firms having standardized component scores in each range						
Factors	<−0.2	−0.2−0	0−0.2	0.2−0.6	0.6−0.8	>0.8
1	0	0	0	65	91	2
2	23	62	44	29	0	0
3	17	53	72	16	0	0
4	15	69	60	14	0	0
5	15	58	69	16	0	0
6	6	79	60	13	0	0
7	8	73	65	12	0	0
8	5	74	70	9	0	0
9	10	68	72	8	0	0
10	9	70	70	9	0	0
11	6	73	73	6	0	0
12	4	81	64	9	0	0
13	5	73	73	7	0	0
14	6	76	67	9	0	0
15	6	76	72	4	0	0
16	4	77	68	9	0	0
17	3	70	79	6	0	0
18	6	73	75	4	0	0
19	5	68	83	2	0	0
20	2	77	74	5	0	0
21	3	76	76	3	0	0
22	2	74	77	5	0	0
23	1	81	70	6	0	0
24	3	75	78	2	0	0
25	4	69	84	1	0	0
26	2	77	77	2	0	0
27	3	73	81	1	0	0
28	2	77	75	4	0	0
29	1	79	76	2	0	0
30	2	82	70	4	0	0
31	2	76	78	2	0	0
32	0	81	75	2	0	0

Source Compiled from Dhankar and Singh (2005)

conforming the correlations. Measures of sampling adequacy for each variable were also very large ranging from 0.936 to 0.984, confirming the suitability of all portfolios for factor analysis.

Principal Components analysis was performed for 1991–2002 and sub-periods to study the portfolio factors over time. Results are presented in Tables 2.4, 2.5 and 2.6.

Table 2.2 Summary of results for cross regression for 158 firms using 5 factors

12 years	Adj R sq 0.451	T-test Sig. for no. of factors 4 factors	F-test significance Sig. at 1%
Monthly range Adj R sq	No. of months	F-test	No. of months
0−0.2	128	1%	23
0.2−0.5	15	5%	72
>0.5	1	Not sig.	49
Total months	144		144

Source Compiled from Dhankar and Singh (2005)

Table 2.3 Summary of factors—cross regression for 158 firms using 5 factors

	Twelve years			144 Months		
				Factor premium		t-test
	% variation explained in the first pass	Factor premium	t-test significance	Months positive	Months negative	Sig. 5%
Constant		−0.183	0.60	77	67	20
Factor 1	39.02	0.198	0	66	78	37
Factor 2	3.69	0.203	0	48	96	56
Factor 3	2.74	0.043	0.04	72	72	43
Factor 4	2.39	−0.041	0.09	80	64	46
Factor 5	2.16	0.097	0	73	71	38
Total	50.00					

Source Compiled from Dhankar and Singh (2005)

Table 2.4 Summary of factors for industry portfolios using monthly returns

Years	KMO measure	Percentage of variance explained					
		First factor (%)	Second factor (%)	Third factor (%)	Fourth factor (%)	Fifth factor (%)	Total (%)
1991–93	0.929	90.15	2.55	1.84	1.20	0.99	96.73
1994–96	0.924	83.00	4.11	2.53	2.11	1.83	93.58
1997–99	0.903	72.80	9.90	3.60	2.64	2.03	90.97
2000–02	0.856	71.40	6.35	4.99	3.74	2.80	89.28
1991–2002	0.968	80.81	4.17	2.55	1.83	1.57	90.93

Source Compiled from Dhankar and Singh (2005)

Table 2.5 Summary of factors for beta-sorted groups using monthly returns

Years	KMO measure	First factor (%)	Second factor (%)	Third factor (%)	Fourth factor (%)	Fifth factor (%)	Total (%)
1991–93	0.937	91.07	3.30	1.15	0.82	0.80	97.15
1994–96	0.939	85.60	2.58	2.19	2.08	1.40	94.01
1997–99	0.932	79.76	4.38	3.18	2.07	1.95	91.33
2000–02	0.919	78.20	6.06	3.03	2.46	2.29	92.08
1991–2002	0.970	85.08	3.45	1.61	1.45	1.18	92.77

Source Compiled from Dhankar and Singh (2005)

Table 2.6 Summary of factors for alphabetically sorted groups using monthly returns

Years	KMO measure	First factor (%)	Second factor (%)	Third factor (%)	Fourth factor (%)	Fifth factor (%)	Total (%)
1991–93	0.915	92.67	1.49	1.17	1.01	0.68	97.03
1994–96	0.854	86.11	2.72	2.06	1.98	1.46	94.30
1997–99	0.905	78.80	4.57	2.98	2.51	2.34	91.20
2000–02	0.893	80.70	3.79	3.23	2.24	1.87	91.88
1991–2002	0.977	85.93	1.94	1.82	1.53	1.26	92.40

Source Compiled from Dhankar and Singh (2005)

Exhibit sector-wise listing of companies: India

GROUP 1—CHEMICAL	**GROUP 6—FOOD and BEVERAGES**	**GROUP 11—MIXED MISC/CHEM. PETRO, PAINT**
Bombay Dyeing & Mfg. Co. Ltd. Colgate-Palmolive(India) Ltd. Gujarat Alkalies & Chemicals Ltd. Hind Lever Chemical Ltd. Monsanto India Ltd. National Organic Chemical Inds. Ltd. Standard Industries Ltd. Supreme Industries Ltd. United Phosphorus Ltd. Wimco Ltd.	Britannia Industries Ltd. Godfrey Phillips India Ltd. Mcdowell & Co. Ltd. Shaw Wallace & Co. Ltd. Tata Tea Ltd. VST Industries Ltd. Bajaj Hindustan Ltd. Glaxosmithkline Consumer Healthcare Ltd. ITC Ltd. Nestle India Ltd.	Asian Paints (India) Ltd. I C I India Ltd. Castrol India Ltd. Deepak Fertilisers & Petrochemicals Corpn. Ltd. Kochi Refineries Ltd. Southern Petrochemical Inds. Corpn. Ltd. Ballarpur Industries Ltd. Titan Industries Ltd. Jaiprakash Industries Ltd. Kodak India Ltd.

(continued)

(continued)

GROUP 2—CHEMICAL PHARMA 1	GROUP 7—MACHINERY 1	GROUP 12—SERVICES
Abbott India Ltd. Aventis Pharma Ltd. Burroughs Wellcome (India) Ltd. Cipla Ltd. Clariant (India) Ltd. Dr. Reddy's Laboratories Ltd. Fullford (India) Ltd. German Remedies Ltd. Glaxosmithkline Pharmaceuticals Ltd. Max India Ltd.	Digital Globalsoft Ltd. Escorts Ltd. Exide Industries Ltd. Himachal Futuristic Communications Ltd. Moser Baer India Ltd. Punjab Tractors Ltd. Rolta India Ltd. Finolex Cables Ltd. Swaraj Engines Ltd. SKF Bearings India Ltd.	Housing Development Finance Corpn. Ltd. Reliance Capital Ltd. State Bank of India Apollo Hospitals Enterprise Ltd. Asian Hotels Ltd. E I H Ltd. Essar Shipping Ltd. Great Hotels Ltd. Hotel Leela Venture Ltd. Indian Hotels Co. Ltd. Thomas Cook (India) Ltd.
GROUP 3—CHEMICAL PHARMA 2	**GROUP 8—MACHINERY 2**	**GROUP 13—TEXTILES**
Merck Ltd. Nicholas Piramal India Ltd. Novartis India Ltd. Parke-Davis (India) Ltd. Pfizer Ltd. Procter & Gamble Hygiene & Health Care Ltd. Ranbaxy Laboratories Ltd. Reckitt Benckiser (India) Ltd. Bayer (India) Ltd. Wyeth Lederle Ltd.	ABB Ltd. Alfa Laval (India) Ltd. Atlas Copco (India) Ltd. Cummins India Ltd. Esab India Ltd. KSB Pumps Ltd. Kirloskar Oil Engines Ltd. Lakshmi Machine Works Ltd. Otis Elevator Co. (India) Ltd. Tata Honeywell Ltd.	Arvind Mills Ltd. Century Enka Ltd. Forbes Gokak Ltd. Futura Polyesters Ltd. Himatsigka Seide Ltd. JCT Ltd. Raymond Ltd. SIV Industries Ltd. SRF Ltd. Trent Ltd. Madura Coats Ltd. Morarjee Goculdas Spg. & Wvg. Co. Ltd.
GROUP 4—CHEMICAL-RUBBER/FERT/INDUSTRIAL	**GROUP 9—MACHINERY 3**	**GROUP 14—TRANSPORT EQUIPMENT**
Apollo Tyres Ltd. Ceat Ltd. J K Industries Ltd. M R F Ltd. Modi Rubber Ltd. Gujarat Narmada Valley Fertilizers Co. Ltd. Gujarat State Fertilizers & Chemicals Ltd. Colour-Chem Ltd. Essel Industries Ltd. Excel Industries Ltd. Finolex Industries Ltd.	Carrier Aircon Ltd. Crompton Greaves Ltd. Ingersoll-Rand (India) Ltd. Philips India Ltd. Samtel Color Ltd. Tata Infotech Ltd. Videocon International Ltd. Wartsila India Ltd. Whirlpool of India Ltd.	Ashok Leyland Ltd. Bajaj Auto Ltd. Bharat Forge Ltd. Hero Honda Motors Ltd. Hindustan Motors Ltd. LML Ltd. Mahindra & Mahindra Ltd. Motor Industries Co. Ltd. T V S Motor Co. Ltd. Tata Engineering & Locomotive Co. Ltd. Sundram Fasteners Ltd.

(continued)

(continued)

GROUP 5—DIVERSIFIED	GROUP 10—METALS	GROUP 15—MINERALS AND ELECTRICITY
Century Textiles & Inds. Ltd. E I D-Parry (India) Ltd. Grasim Industries Ltd. Hindustan Lever Ltd. Indian Rayon & Inds. Ltd. Kesoram Industries Ltd. Larsen & Toubro Ltd. Rallis India Ltd. Reliance Industries Ltd. Tata Chemical Ltd. Voltas Ltd.	Essar Steel Ltd. Gillette India Ltd. Hindalco Industries Ltd. Indian Aluminium Co. Ltd. Indo Gulf Corpn. Ltd. (Merged) Ispat Industries Ltd. Jindal Strips Ltd. Mukund Ltd. Saw Pipes Ltd. Sterlite Industries (India) Ltd. Tata Iron & Steel Co. Ltd.	Ahmedabad Electricity Co. Ltd. CESC Ltd. Tata Power Co. Ltd. BESC Ltd. Sesa Goa Ltd. India Cements Ltd. Birla Corporation Ltd. Madras Cements Ltd. Associated Cement Cos. Ltd. Gujarat Ambuja Cements Ltd.

As can be seen from Tables 2.4, 2.5 and 2.6, there is one major factor which decreases slightly in the later period. The results suggest that the relative importance of factors acting on security returns changes over time, and may be the factors also change. The grouping procedure also has an impact on the factors extracted. The first factor is more important in beta sorted and alphabetically sorted portfolios, which could be due to its correlation with beta.

APT Versus CAPM

APT monthly factor scores for five factors were used to estimate characteristic lines for each of the industry portfolio (Eq. 2.4). All portfolios had at least two coefficients with significant t-statistics. In fact, 10 of the portfolios had 4 or more significant coefficients. Characteristic lines for the same portfolios were also estimated for CAPM using the market model (Eq. 2.2), with the BSE 200 index as the independent variable. A comparison is given in Table 2.7. The adjusted R-square and F-statistics show that APT factors can explain more variation than beta. The correlation between the first factor and beta is 85% for the 15 industry groups.

Cross regression was performed to derive the APT equation (Eq. 2.3) using the factors derived from characteristic lines as the independent variable and average return over the period as the dependent variable. The Security Market Line for CAPM (Eq. 2.2) was derived using beta as the independent variable and average return over the period as the dependent variable. As can be seen, the proportion of variation explained by the APT equation is much higher and t-statistics more significant than with CAPM (Table 2.8).

Table 2.7 APT and CAPM characteristic lines—industry portfolios using monthly returns

Portfolio	APT factor 1	Beta	Adjusted R-square		No. of APT factors	Error sum of squares		F-test**
	APT	CAPM	APT	CAPM	t-test sig.*	APT	CAPM	APT versus CAPM
1	10.98	0.877	0.919	0.682	4	1523.8	6187.6	105.58
2	10.79	0.906	0.908	0.604	4	2092.1	9267.3	118.32
3	9.11	0.761	0.924	0.659	5	1115.9	5171.5	125.37
4	11.40	0.913	0.884	0.666	3	2425.9	7212.0	68.06
5	11.04	0.948	0.895	0.768	4	2053.6	4695.5	44.38
6	9.534	0.816	0.875	0.714	4	1948.5	4599.6	46.93
7	10.34	0.9	0.969	0.674	4	624.6	6758.4	338.75
8	9.38	0.766	0.847	0.678	2	2216.8	4801.4	40.22
9	10.89	0.879	0.887	0.616	4	2383.2	8307.7	85.76
10	11.40	0.919	0.908	0.649	5	1999.4	7879.6	101.46
11	10.67	0.866	0.895	0.695	3	1903.5	5655.6	68.00
12	11.26	1.038	0.93	0.748	4	1684.9	6254.4	93.56
13	11.09	0.867	0.875	0.622	4	2519.8	7861.2	73.12
14	9.95	0.82	0.977	0.64	4	400.3	6533.6	528.58
15	11.60	0.989	0.898	0.75	4	2237.4	5631.3	52.231

Source Compiled from Dhankar and Singh (2005)
Note *t-test was significant for beta for all portfolios; **F-test (4,138) df is significant at 1% for all (value above 3.32)
Factors were also derived and cross regressions performed with individual securities, and with the three types of portfolios, using various number of factors (3, 5, 7, 9). The summary of results is presented in Table 2.8

APT Equation

$$\begin{array}{llllll} 0.28 + 0.17\mathrm{b}_1 & + 0.132\mathrm{b}_2 & + 0.04\mathrm{b}_3 & + 0.107\mathrm{b}_4 & + 0.08\mathrm{b}_5 & (\bar{\mathrm{R}}'^2 = 0.537) \\ (t = 0.198) & (1.18) & (3.45) & (1.22) & (2.29) & (1.46) \end{array}$$

CAPM equation

$$\begin{array}{ccc} 1.282 & + & 0.757\beta \\ (t = 0.925) & & (0.485) \end{array} \quad \left(\bar{R}^2 = 0.06\right)$$

The adjusted R-square for APT is higher than CAPM and error sum of squares is significantly lower for individual stocks and for alphabetical and industry portfolios. However, the adjusted R square is higher with CAPM for all the beta-sorted groups. The industry-based portfolios had the highest adjusted R-square and significant factors like (Bower et al., 1984). It appears that inter portfolio dissimilarity is important in estimating common factors designed to maximize explanation of returns. Although the comparison is in favour of APT, the conclusion must be

Table 2.8 Summary of cross regression results—APT and CAPM using monthly returns

Model used	Constant	Coeff f1/beta	Adj RSq	Sig. factors	APT versus CAPM F-Statistic
158 stocks					
APT 5 Factors	−0.183	0.198	0.451	f 1,2,4,5	24.5*
CAPM beta	0.589	1.504	0.104	beta	
15 alphabetical portfolios					
APT 5 Factors	1.05	0.08	0.316	none	14.0*
CAPM beta	1.37	0.619	0.03	none	
15 Industry portfolios					
APT 3 Factors	0.979	0.091	0.294	f2	26.6*
APT 5 Factors	0.28	0.157	0.537	f2,4	79.0*
APT 7 Factors	0.561	0.13	0.58	f2,4	126.2*
APT 9 Factors	0.657	0.121	0.487	f2	149.6*
CAPM beta	1.282	0.787	0.06	none	
15 Beta portfolios					
APT 3 Factors	1.356	0.048	0.53	none	Not sig.
APT 5 Factors	1.371	0.046	0.479	none	Not sig.
APT 7 Factors	1.716	0.013	0.358	none	Not sig.
APT 9 Factors	2.57	0.071	0.186	none	Not sig.
CAPM beta	0.196	1.614	0.578	beta	

Source Compiled from Dhankar and Singh (2005)
Note *Comparison of unadjusted error sum of squares of CAPM and APT, F significant at 1%

qualified as APT factor scores were drawn out of the results arrived at from the explanation provided by these factor scores.

To take care of this reservation, three portfolios at a time were removed from the 15 portfolios (first portfolio, 1,2,3, then 4,5,6). Factor scores derived from the remaining 12 portfolios were used to derive characteristic lines for the 3 excluded portfolios. This was repeated for subsequent sets of 3 portfolios. Results are presented in Table 2.9.

The R-square is still higher for 14 out of 15 portfolios using APT factors and F-test is also significant at 1% for 14 out of 15 portfolios. This shows that APT can explain the return generating process better than CAPM, and this result needs no qualification, as factors are not generated from the same data. The coefficient of correlation between CAPM betas and the first factor even after excluding the relevant portfolios is 82.7%.

Characteristic lines were also estimated for individual stocks using five factors that were derived after excluding the corresponding portfolios. The results are summarized in Table 2.10.

For 136 firms, the R-square is higher with APT. It appears that APT can explain the return generating process better than CAPM even in case of individual firms.

Table 2.9 APT and CAPM characteristic lines for excluded portfolios (there at a time) for industry portfolios using monthly returns

Portfolio	APT factor 1	Beta	Adjusted R square		t-test sig.	Error sum of squares		F-test
	APT	CAPM	APT	CAPM	APT factors*	APT	CAPM	APT versus CAPM
1	10.857	0.877	0.868	0.682	2	2494.46	6187.653	51.07
2	10.333	0.906	0.733	0.604	4	6079.87	9267.325	18.08
3	8.778	0.761	0.785	0.659	5	3159.43	5171.54	21.97
4	11.255	0.913	0.85	0.666	2	3154.83	7212.016	44.36
5	10.918	0.948	0.858	0.768	2	2784.79	4695.573	23.67
6	9.405	0.816	0.808	0.714	2	2996.33	4599.673	18.46
7	10.023	0.9	0.698	0.674	2	6073.25	6758.462	3.89
8	9.219	0.766	0.807	0.678	1	2799.87	4801.419	24.66
9	10.577	0.879	0.759	0.616	2	5064.79	8307.72	22.08
10	11.133	0.919	0.826	0.649	3	3789.07	7879.698	37.24
11	10.476	0.866	0.851	0.695	2	2695.79	5655.683	37.87
12	10.937	1.038	0.709	0.748	3	7014.99	6254.437	−3.74
13	10.897	0.867	0.824	0.622	2	3551.94	7861.282	41.85
14	9.674	0.82	0.745	0.64	2	4490.58	6533.632	15.69
15	11.387	0.989	0.843	0.75	3	3438.23	5631.329	22

Source Compiled from Dhankar and Singh (2005)
Note *t-test was significant for beta for all portfolios; F-test for APT versus CAPM (4,138) df is significant at 1% at 3.32 for 14 portfolios; Adj R square is higher for APT for 14 portfolios

Table 2.10 Summary of results for characteristic lines of individual firms excluding relevant portfolios using monthly returns

Firms in	Total no. of firms	APT Adj R sq higher than CAPM	F ratio sig. 5% for APT versus CAPM
1, 2, 3	31	29	25
4, 5, 6	32	28	26
7, 8, 9	29	24	22
10, 11, 12	33	24	21
13, 14, 15	33	30	27
Total	158	135	121

Source Compiled from Dhankar and Singh (2005)

The correlation between beta and the first factor was 93.1% for individual securities, again pointing to the fact that the first factor is probably a market related factor.

For the 12-year period, we also forecast the required/expected return for each stock using APT and CAPM. This was done using the CAPM betas and the APT factors estimated for the excluded portfolios. A naïve model, simply using the average return of all stocks, as the forecast over the 12-year period was also used. The quality of the forecast was assessed using Theil's U^2.

where

$$U^2 = \sum \frac{\left(\bar{R}_i - \widehat{R}_i\right)^2}{\Sigma\left(\bar{R}_i - \hat{R}\right)^2}$$

Theil's U^2 is the ratio of the sum of squared differences of each stock's average return for the 12-year period from the APT or CAPM forecast of return, and the sum of squared differences of average return of each stock from the average return of all stocks. The smaller the ratio the better the model forecast, as compared to the naïve forecast. Theil's U^2 was 0.56 for APT and 0.88 for CAPM. As forecasting models, both the APT and CAPM are better than the naïve model. The APT forecast is superior to CAPM even though the market index represents all stocks while calculating beta, and for APT the relevant portfolios are excluded while calculating factors. It is also possible that the exclusion of these portfolios may have biased the findings against APT since the most relevant factors may not have been represented.

Analysis Using Weekly Returns

The analysis with three types of portfolio was repeated using weekly returns to check if results differ with a change in the intervening period. The grouping procedure impacts the factors extracted, as was observed with monthly returns. APT weekly factor scores for five factors were used to estimate the characteristic lines for each of the industry portfolios Table 2.11.

All portfolios had at least four coefficients with significant t-statistics, which is higher than the result of monthly data. F-statistics for APT versus CAPM are significant at 1% for all portfolios (Table 2.11). The correlation between the first factor and beta is 81% for the weekly returns of 15 industry groups.

Result Using Cross Regressions

APT equation

$$0.20 + 0.59\mathrm{b}_1 + 0.077\mathrm{b}_2 + 0.007\mathrm{b}_3 + 0.058\mathrm{b}_4 + 0.003\mathrm{b}_5 (\overline{\mathrm{R}}^2 = 0.896)$$
$$(t = 1.52) \quad (1.72) \quad (7.63) \quad (-0.68) \quad (5.72) \quad (0.29)$$

Table 2.11 APT and CAPM characteristic lines—industry portfolios using weekly returns

Portfolio industry	b1	Beta	Adjusted R-square		No. of APT factors	Error sum of squares		F-test**
	APT	CAPM	APT	CAPM	t-test sig.*	APT	CAPM	APT versus CAPM
1	3.927	0.757	0.828	0.52	4	1998.27	5615.1	62.44
2	3.803	0.763	0.867	0.445	5	1825.14	7688.62	110.83
3	3.158	0.64	0.889	0.474	5	1011.86	4804.81	129.32
4	3.847	0.736	0.808	0.484	4	2256.58	6112.44	58.95
5	4.009	0.851	0.834	0.614	4	2069.76	4831.14	46.02
6	3.267	0.686	0.827	0.53	5	1622.21	4429.37	59.7
7	4.081	0.894	0.912	0.552	5	1335.89	6873.25	143
8	3.428	0.649	0.816	0.458	5	1781.7	5276.95	67.68
9	4.228	0.847	0.801	0.523	4	2870.86	6934.51	48.83
10	4.295	0.851	0.835	0.513	4	2461.14	7293.4	67.73
11	3.943	0.773	0.853	0.548	4	1686.32	5231.15	72.52
12	3.767	0.894	0.949	0.649	4	661.52	4578.24	204.26
13	3.919	0.759	0.826	0.455	5	2312.83	7297.33	74.35
14	3.676	0.722	0.838	0.485	5	1834.86	5863.69	75.75
15	3.981	0.827	0.849	0.549	5	1986.4	5966.89	69.13

Source Compiled from Dhankar and Singh (2005)
Note * t-test was significant for beta for all portfolios; **F-test for (4,138) df is significant at 1% for all (value above 3.32)

CAPM equation

$$\underset{(t = 0.151)}{0.358} \quad + \quad \underset{(0.772)}{0.89\beta} \quad \left(\bar{R}^2 = 0.07\right)$$

The comparison with weekly returns is highly in favour of APT, and variation explained is much higher than with monthly data. The summarized results for cross regressions with weekly returns using various number of factors, types of groups and individual securities are presented in Table 2.12.

As was the case with monthly returns, the adjusted R square for the APT is higher than CAPM and error sum of squares is significantly lower for individual stocks and all groups including the beta-sorted groups. A comparison of the monthly and weekly return analysis for 158 stocks reveals that the adjusted R-square is very similar and the significant factors are also the same. For the industry portfolios, the adjusted R-square is much higher with weekly data and also in some of the cases, the constant and factor 1 is significant in addition to factor 2 and 4, which are significant for both. For the beta-based portfolios, unlike the monthly data, weekly data shows APT to be superior to CAPM. This could be because group constituents are not the same.

Table 2.12 Summary of cross regression results—APT and CAPM using weekly returns

Model used	Constant	Coeff f1/ beta	Adj RSq	Sig. factors	APT versus CAPM F-statistic
158 stocks					
APT 5 Factors	0.122	0.079	0.466	f 1,2,4,5	29.03*
CAPM beta	0.229	0.216	0.041	c, beta	
15 alphabetical portfolios					
APT 5 Factors	0.039	0.1	0.378	none	50.84*
CAPM beta	0.386	0.047	−0.07	c	
15 industry portfolios					
APT 3 Factors	0.089	0.89	0.603	f2	74.91*
APT 5 Factors	0.2	0.077	0.896	f2,4	512.57*
APT 7 Factors	0.233	0.005	0.913	f2,4	922.8*
APT 9 Factors	0.07	0.092	0.921	f2,4	1242.0*
CAPM beta	0.358	0.089	−0.07	none	
15 beta portfolios					
APT 3 Factors	−0.611	0.275	0.63	c,f1,2	40.37*
APT 5 Factors	−0.332	0.2	0.659	none	66.04*
APT 7 Factors	−0.332	0.2	0.633	none	82.8*
APT 9 Factors	−0.373	0.21	0.714	none	185.4*
CAPM beta	0.157	0.34	0.334	beta	

Source Compiled from Dhankar and Singh (2005)
Note *Comparison of unadjusted error sum of squares of CAPM and APT, F significant at 1%

Analysis with weekly data and factors generated excluding relevant portfolios is presented in Table 2.13. The table shows that adjusted R-square is still higher for 14 out of 15 portfolios using APT factors, and F-test is also significant at 1% for 14 out of 15 portfolios. Moreover, the same portfolios are significantly better with APT whether data used is monthly or weekly.

However, compared to monthly figures, the adjusted R-square is lower. The coefficient of correlation between CAPM betas and the first factor even after excluding the relevant portfolios is 79.35%, as compared to 82.7% with monthly returns.

Table 2.13 APT and CAPM characteristic lines for excluded portfolios (three at a time) for industry portfolios using weekly returns

Portfolio industry	b1	Beta	Adjusted R square		t-test sig.*	Error sum of squares		F-test**
	APT	CAPM	APT	CAPM	No. of APT factors	APT	CAPM	APT versus CAPM
1	3.834	0.757	0.766	0.52	3	2716.00	5615.10	36.82
2	3.563	0.763	0.619	0.445	4	5253.89	7688.62	15.98
3	2.962	0.64	0.657	0.474	5	3116.27	4804.81	18.69
4	3.752	0.736	0.74	0.484	3	3084.49	6112.44	33.86
5	3.905	0.851	0.765	0.614	4	294.08	4831.14	22.19
6	3.177	0.686	0.672	0.53	3	3093.55	4429.37	14.89
7	3.911	0.894	0.614	0.552	4	5885.74	6873.25	5.78
8	3.309	0.649	0.691	0.458	3	2990.91	5276.95	26.36
9	4.085	0.847	0.701	0.523	2	4315.2	6934.51	20.94
10	4.153	0.851	0.725	0.513	4	4085.49	7293.40	27.08
11	3.836	0.773	0.797	0.548	2	2337.23	5231.15	42.71
12	3.635	0.894	0.614	0.649	1	5003.09	4578.24	-2.92
13	3.787	0.759	0.678	0.455	2	4282.09	7297.33	24.29
14	3.563	0.722	0.683	0.485	3	3581.06	5863.69	21.99
15	3.84	0.827	0.711	0.549	3	3791.42	5966.89	19.79

Source Compiled from Dhankar and Singh (2005)
Note *t-test was significant for beta for all portfolios; **F-test for APT versus CAPM (4,138) df is significant at 1% at 3.32 for 14 portfolios; R square is higher for APT for 14 portfolios

Table 2.14 Summary of results for characteristic lines of individual firms excluding relevant portfolios using weekly returns

Firms in	Total no. of firms	APT Adj R sq higher than CAPM	F ratio sig. 5% for APT versus CAPM
1, 2, 3	31	30	21
4, 5, 6	32	28	32
7, 8, 9	29	25	19
10, 11, 12	33	27	22
13, 14, 15	33	32	24
Total	158	142	118

Source Compiled from Dhankar and Singh (2005)

Characteristic lines were estimated for individual stocks using weekly returns and factors that were derived after excluding the corresponding portfolios. The results are summarized in Table 2.14. For 136 firms, the adjusted R-square is higher with APT and the error sum of squares is significantly lower for 121 firms when APT is used. The correlation between beta and the first factor for individual securities with weekly returns was 93.6%. Forecasts using weekly data yielded Theil's U^2 of 0.56 for APT and 0.82 for CAPM.

Conclusion

Evidence suggests that APT may lead to better estimates of expected rate of return than CAPM. In the tests conducted, APT explains the return generation process and forecasts return better than CAPM. The amount of variance explained in the first stage regressions to derive characteristic lines, and in the second stage cross regressions, to check if factors were priced, was consistently higher with APT. Monthly and weekly returns gave similar results. Forecasts were also better with APT as compared to CAPM and the naïve model. It is, however, premature at this stage to conclude that APT is superior to CAPM in the Indian context as results may vary depending on the sample, time period and estimation methods used. We can only suggest that decision makers should give due consideration to multi-factor models like APT and not rely solely on beta and CAPM.

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Chapter 3
Non-linearities, GARCH Effects and Emerging Stock Markets

In investing, what is comfortable is rarely profitable.
Robert Arnott

Abstract Up to the beginning of the last decade, financial economics was dominated by linear paradigm, which assumed that economic time series conformed to linear models or could be well approximated by a linear model. However, there is increasing evidence that asset returns may be better characterized by a model which allows for non-linear behaviour. Though more efforts are now being directed towards the Asian stock markets in the light of their increasing importance to the investment world and the world economy, there is an extremely sparse literature, which utilizes recent advances in non-linear dynamics to examine the data generating process of the South Asian stock markets. This study investigates the presence of non-linear dependence in three major markets of South Asia: India, Sri Lanka and Pakistan. It was, however, realized that merely identifying non-linear dependence was not enough. Previous research has shown that the presence of non-linear characteristics usually takes the form of ARCH/GARCH (Autoregressive Conditional Heteroscedasticity or Generalized Autoregressive Conditional Heteroscedasticity) type conditional heteroscedasticity. Keeping this in view, this study investigates whether the non-linear dependence is caused by predictable conditional volatility. It has been found that the simple GARCH (1, 1) model has fitted all the market return series adequately and accounted for the non-linearity found in the series.

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Introduction

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are invariably applied in financial time series. It helps in making financial decisions which are generally influenced by the trade-off between risk and return. The non-linear models allow us to capture volatility and serial correlation in the series. Heteroscedasticity describes the irregular pattern of variation of an error term, or variable, in a statistical model. Essentially where there is heteroscedasticity, observations do not conform to a linear pattern. Instead, they tend to cluster. It has been proven by many studies that if variables are significantly skewed, linear versions of these models are not sufficient for both explaining the past volatility and forecasting the future volatility.

Structural changes and financial liberalization policies were undertaken by many emerging countries during the last decade, along with economic and financial globalization, promoted an accelerated growth of stock exchanges around the world. This led to an increased interest in determining the opportunities of investing in the emerging markets to enhance portfolio returns. Despite the potential benefits of portfolio diversification in South Asian region,[1] there is a lack of research and relatively much less is known about the stock markets of the region.

The available research has primarily focused on detecting linear structure in the financial data.[2] Employing traditional statistical tests such as autocorrelation most empirical tests of the Efficient Market Hypothesis (EMH) have looked into the linear predictability of future share price changes. If the share price changes turn out to be uncorrelated, the EMH is accepted and the stock market in question is deemed informationally efficient, and if they are found to be serially correlated, the EMH is rejected and the market is considered inefficient. However, Brock, Hsieh, and LeBaron (1991) and Brock, Lakonishoi, and LeBaron (1992) point out that '… lack of linear dependence does not rule out non-linear dependence, which, if present, would contradict the random walk model'. Evidence of this possibility is provided by Granger and Andersen (1978) and Sakai and Tokumaru (1980), who demonstrate that non-linear models may exhibit no serial correlation while containing strong non-linear dependence. Hence, recently, several researchers have focused their attention on the Independent and Identical Distribution (IID) assumption of Random Walk Hypothesis (RWH), which implies that not only are the increments in prices linearly uncorrelated, but that any non-linear functions of the increments are also uncorrelated.

The traditional tests of serial correlation, which checks for linear predictability, cannot explicitly test for the IID assumption implied by RWH. In fact, as Campbell, Lo, and MacKinlay (1997) argue, many aspects of economic behaviour may not be linear, and may cause rejection of IID. There may be several reasons behind the non-linear behaviour of financial markets. First, market imperfections and some features of market microstructure may lead to delays of response to new information, implying non-linearity in share price changes.[3] For instance, transaction costs may make investors unwilling to respond rapidly to the arrival of new information. In turn, they would rather wait until their expected excess profits (net of transaction cost) are high enough to allow for positive returns. This delay in adjustment may lead to non-linearity in share price changes. Further, as Shleifer and Summers (1990) argue, there are two types of investors in the market; rational arbitrageurs or speculators who trade on the basis of reliable information, and noise traders who trade on the basis of imperfect information. Given that a significant number of traders in emerging markets may trade on the basis of imperfect information, share prices are likely to deviate from their equilibrium values. In addition, given the informational asymmetries and lack of reliable information, noise traders may also lean towards delaying their responses to new information in order to assess informed traders' reaction, and then respond accordingly. The moot point, therefore, is that there could be enough reasons for economic systems to be non-linear. In this backdrop, it need not come as a surprise if the results of this study report the existence of non-linear dependence in South Asia too. The presence of non-linear dependence may have short-term, if not long-term, forecasting potential, provided the actual generating mechanism is known. Previous research has shown that the presence of non-linear characteristics usually takes the form of ARCH/GARCH (Autoregressive Conditional Heteroscedasticity or Generalized Autoregressive Conditional Heteroscedasticity) type conditional heteroscedasticity. Essentially, it implies non-linearity in the variance, allowing for correlated second moments.

Several studies across the world, especially in the developed countries, have reported that asset returns may be better characterized by a model, which allows for non-linear behaviour. For value-weighted, size-decile portfolios of weekly stock returns from 1963 to 1987, Hsieh (1991) found that these returns exhibited non-linear serial dependencies and that conditional heteroscedasticity could be the source of these non-linearities, but that none of the ARCH models seem to adequately describe the data. Al Loughani and Chappell (1997) applied the BDS test to the daily changes of FTSE 30 share index of the London Stock Exchanges and found evidence of non-linear dependence which they could successfully capture with a GARCH M (1, 1) model. In another study on the UK, Opong, Mulholland, Fox, and Farahmand (1999) examined the non-linear behaviour of the London Financial Times Stock Exchange (FTSE) All Share, 100, 250 and 350 equity indices. The results rejected the hypothesis that the index series examined in this study are random, independent and identically distributed. The results suggested that the FTSE stock index returns series is not truly random since some cycles or patterns show up more frequently than would be expected in a true random series. GARCH (1, 1) process seemed to explain the behaviour of the return series.

Abhyankar, Copeland, and Wong (1997) found evidence of non-linearity for the data set consisting of real-time observations for the period 1 September–30 November 1991 at 1 min frequency in the case of FTSE-100, Deutscher Aktein Index (DAX), and Nikkei-225 and 15-s frequency for the S&P 500 futures. Booth, Martikainen, Sarkar, Virtanen, and Yli-Olli (1994) found evidence of non-linear dependence in the Finnish stock returns and confirm that a simple GARCH model was able to capture the dependence. Non-linear dependence has also been reported in returns for another European market by Poshakwale and Wood (1998) using daily data from two main indices and an equally weighted portfolio of 17 stocks in the emerging Polish market. Hamill, Opong, and Sprevak (2000) also reported non-linear dependence of Irish stock returns and indicated that the series could not be modelled by GARCH (1, 1) process.

Sewell, Stansell, Lee, and Pan (1993) reported evidence of dependency in the market index series in Japan, Hong Kong, Korea, Singapore and Taiwan. However, they accepted IID as the characterization for the S&P 500 for the US. Errunza, Hogan, Kini, and Padmanabhan (1994) indicated non-linear dependence in returns for Germany, Japan, and the emerging markets of Argentina, Brazil, Chile, India and Mexico. Pandey, Kohers, and Kohers (1997) reported evidence of non-linear dependence in the index returns of Hong Kong, Japan and the US. In one study on Indian stock market, by Poshakwale (2002), there has been evidence of non-linear dependence in the index as well as some individual stocks. It has also been found that GARCH models could successfully capture these dependencies.

Curiously enough, while such studies have been in the limelight in the developed markets over the last few years, the literature pertaining to South Asia is extremely sparse. Hence, the objective of this paper is to examine whether the market return series of three countries in the South Asian region, viz. India, Sri Lanka and Pakistan are characterized by non-linearities and, if so, to investigate whether the same can be modelled applying GARCH techniques. The findings of the study will be useful to those involved in investment decision-making in South Asian stock markets. Others keen to pursue international diversification will increase their understanding of the pricing process in the region before committing significant amounts of capital to the market. The implication of the study may, thus, be appealing to both researchers and practitioners, and the findings will provide additional evidence to the existing literature.

Stock Markets in South Asian Countries

The stock markets in South Asian countries have developed remarkably over the last two decades, although there is much heterogeneity among the markets in terms of size, liquidity, profitability, etc. However, there are concerted efforts on the part of the authorities concerned to improve the functioning of the markets. All the markets have adopted the automated trading system. Trading in these markets is done in a dematerialized form and on rolling settlement basis. The regulatory front has also been strengthened with the establishment of securities exchange boards/commissions in each of the countries, which oversees and regulates the activities of the stock exchanges. Presently, there are 24, 1 and 4 stock exchanges in India, Sri Lanka and Pakistan, respectively.

However, there is still a long way to go. The growth of the markets can be assessed from Table 3.1, which presents the various statistics for the year 2003, in respect of the different markets along with that of Japan, the UK and the US to provide a comparative study of the markets. The size of the market in terms of market capitalization is small for all the South Asian countries as compared to the

Table 3.1 Comparative statistics of stock markets of South Asian countries and the UK, the USA and Japan for 2003

Serial No.	Country	Market capitalization ($ million)	Turnover ratio (value of shares traded as (% of market capitalization)	Listed domestic companies	S&P/IFS investable index (% change in price index)
1	India	2,79,093	14.1	5,644	76.5
2	Sri Lanka	2,711	1.2	244	35.6[a]
3	Pakistan	16,579	40.11	701	50.4[a]
4	UK	18,64,134	135.42	1,701	26.3[c]
5	USA	1,10,52,403	202.5	5,685	26.4[d]
6	Japan	21,26,075	71.0	3,058	37.8[b]

Source 2004 World Development Indicators published by World Bank
Notes a. Data refer to the S&P/IFC Global Index
b. Data refer to the Nikkei 225 Index
c. Data refer to the FT 100 Index
d. Data refer to the S&P 500 Index

three advanced countries. Liquidity as measured by the value of shares traded to market capitalization, also does not show much impressive performance. However, in terms of number of companies listed, India stands second only to the US, while the rest of the countries are way behind. Interestingly, the returns in most of the South Asian markets have been impressive and hence provide an immense opportunity to investors, both local and foreign, to increase their potential gains.

Data and Methodology

The data used in the present study are the major daily indices of the three South Asian countries provided by the respective stock exchanges. The indices that are considered for the different countries are BSE Sensex for India, Milanka price index[4] for Sri Lanka, and KSE-100 Index for Pakistan. The time period of the study spans from 1 January 1996 to December-end 2005.

With the data set described above, the daily returns have been calculated as follows:

$$r_t = I_n(P_t/P_{t-1})100 \tag{3.1}$$

where

r_t is the continuously compounded percentage change of share price index for the period *t*
P_t is the price index at *t*

P_{t-1} is the same for preceding period
I_n is the natural logarithm.

The study tests for the non-linear dependence in stock returns, by applying the BDS test developed by Brock, Dechert, Scheinkman, and LeBaron (1996), which is based on the null hypothesis of Independent and Identical Dstribution (IID).

To perform the BDS test, a distance, ε, has to be chosen. If the observations of the series are truly IID, then for any pair of points, the probability of the distance between these points being less than or equal to epsilon will be constant. This probability is denoted by $c_1(\varepsilon)$. Sets consisting of multiple pairs of points can also be considered. One way to choose sets of pairs is to move through the consecutive observations of the sample in order. That is, given an observation s, and an observation t of a series X, a set of pairs can be constructed of the form

$$[\{X_s X_\tau\}\{X_{s+1}X_{\tau+1}\}\{X_{s+2}X_{\tau+2}\},\ldots\{X_{s+m-1}X_{\tau+m-1}\}] \tag{3.2}$$

where m is the number of consecutive points used in the set, or *embedding dimension.* The joint probability of every pair of points in the set satisfying the epsilon condition can be denoted by the probability $c_m(\varepsilon)$.

The BDS test proceeds by noting that under the assumption of independence, this probability will simply be the product of the individual probabilities for each pair. That is, if the observations are independent,

$$c_m(\varepsilon) = c_1^m(\varepsilon) \tag{3.3}$$

When working with sample data, $c_1(\varepsilon)$ or $c_m(\varepsilon)$ are not directly observed. They can only be estimated from the sample. As a result, this relationship is not expected to hold exactly, but only with some error. The larger the error, the less likely it is that the error is caused by random sample variation. The BDS test provides a formal basis for judging the size of this error.

To estimate the probability for a particular dimension, one can simply go through all the possible sets of that length that can be drawn from the sample and count the number of sets which satisfy the condition. The ratio of the number of sets satisfying the condition divided by the total number of sets provides the estimate of the probability. Given a sample of n observations of a series X, this condition can be stated in mathematical notation,

$$c_{m,n}(\varepsilon) = \frac{2}{(n-m+1)(n-m)} \sum_{s=1}^{n-m+1} \sum_{t=s+1}^{n-m+1} \prod_{j=0}^{m-1} I_\varepsilon(X_{s+j'}X_{t+j}) \tag{3.4}$$

where I_ε is the indicator function:

$$I_\varepsilon(x,y) = 1, \textit{if } |x-y| \leq \varepsilon \text{ and } I_\varepsilon(x,y) = 0 \text{ otherwise.} \tag{3.5}$$

It may be noted that the statistics $c_{m,n}$ are often referred to as correlation integrals.

These sample estimates of the probabilities can be used to construct a test statistic for independence:

$$b_{m,n}(\varepsilon) = c_{m,n}(\varepsilon) - c_{1,n-m+1}(\varepsilon)^m \tag{3.6}$$

where

the second term discards the last observations from the sample so that it is based on the same number of terms as the first statistic. In this study, we have reported $b_{m,n}(\varepsilon)$ as the BDS statistic.

Under the assumption of independence, this statistic would be expected to be close to zero. In fact, it is shown in Brock et al. (1996) that

$$(n-m+1)^{1/2} - b_{m,n}(\varepsilon)/\sigma_{m\,n}(\varepsilon) \rightarrow N(0,1) \tag{3.7}$$

where

$$\sigma^2_{m,n}(\varepsilon) = \left[k^m + 2\sum_{j=1}^{m-1} k^{m-j}c_1^{2j} + (m-1)^2 c_1^{2m} - m^2 k c_1^{2m-2}\right] \tag{3.8}$$

and where c_1 can be estimated using $c_{1.n,}$ k as the probability of any triplet of points lying within ε of each other, and is estimated by counting the number of sets satisfying the sample condition:

$$k_n(\varepsilon) = \frac{2}{n(n-1)(n-2)} \sum_{\tau=1}^{n}\sum_{s=\tau+1}^{n}\sum_{r=s+1}^{n}\{I_\varepsilon(X_{\tau'}\,X_s)I_\varepsilon(X_{s'}\,X_\tau) + I_\varepsilon(X_{\tau'}\,X_\tau)I_\varepsilon(X_{\tau'}\,X_s) + I_\varepsilon(X_{s'}\,X_\tau)I_\varepsilon(X_{\tau'}\,X_\tau)\} \tag{3.9}$$

If the BDS test identifies non-linearity in the series, it may well be due to changes in the volatility of the series and in order to investigate this, an attempt shall be made to fit in a GARCH model to the return series.

Since the GARCH methodology is, by now, well known, only a brief description of the model along with its application to the data used in this study is provided. The GARCH (p, q) model can be represented by the following system of equations:

$$r_\tau = \mu + \varepsilon_\tau \tag{3.10}$$

$$\frac{\varepsilon_\tau}{\psi_{t-1}} \sim N(0, h_\tau) \tag{3.11}$$

$$h_\tau = \alpha_0 + \alpha_1\varepsilon^2_{\tau-1} + \alpha_2\varepsilon^2_{\tau-2} \cdots + \alpha_q\varepsilon^2_{\tau-q} + \beta_1 h_{\tau-1} + \beta_2 h_{\tau-2} + \cdots + \beta_p\varepsilon_{\tau-p} \tag{3.12}$$

where

$$\alpha_0 > 0$$
$$\alpha_1, \alpha_{2'} \ldots \alpha_{q'} \geq 0,$$

$$\beta_1, \beta_2 \ldots \beta_p \geq 0$$

where r_τ represents the continuously compounded return on the market portfolio as defined in (3.1), the conditional mean, is constant and the residual term, ε_τ, given the information available $\psi_{\tau-1'}$ is normally distributed. The conditional variance, is a function not only of the last period's error but also of the last period's conditional variance with the parameters, α and β, indicating the propensity of volatility shocks to persist over time.

However, it is rarely necessary to use more than a GARCH (1, 1) model which has just one lagged error square and one autoregressive term and is given by

$$h_\tau = \alpha_0 + \alpha_1 \varepsilon_{\tau-1}^2 + \beta_1 h_{\tau-1} \tag{3.13}$$

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

The stationary condition for GARCH $(1, 1)$ is $\alpha_1 + \beta_1 < 1$.

Empirical Findings

Descriptive Statistics

Some of the stochastic characteristics of the market return series of all the three countries under consideration is presented in Table 3.2, which sheds some light on the behaviour of stock prices in these markets. The average return is positive for all the indices, implying the fact that prices have increased over time. The statistics show that returns are negatively skewed for all the markets, implying that the return distribution of the shares traded in these markets have a higher probability of earning returns greater than the mean. The value of the kurtosis is greater than 3 in all the markets, which indicates that the returns series have a heavier tail than the standard normal distribution. Finally, the calculated Jarque–Bera statistics and corresponding p-values have been used to test the null hypotheses that the daily returns are normally distributed. All p-values are smaller than the 0.01 level of significance suggesting the rejection of the null hypothesis. None of these returns are thus well approximated by the normal distribution.

Table 3.2 Summary statistics of market return series

Statistics	India	Sri Lanka	Pakistan
Mean	0.0448	0.0277	0.0768
Standard deviation	1.6116	1.4814	1.7903
Skewness	−0.2676	−0.9852	−0.2703
Kurtosis	6.6064	19.569	8.3534
No. of observation	2464	2399	2432
J-B test of normality	1364.71	27830.9	2933.72
p-value	0	0	0

Source Compiled from Dhankar and Chakraborty (2007)

Test for IID Hypothesis

In order to test whether the return series is characterized by non-linear dependence, the BDS test developed by Brock et al. (1996) is applied. The null hypothesis for the BDS test is that the return series is Independently and Identically Distributed (IID). Following Brock et al. (1991), Hsieh (1991) and Sewell et al. (1993), the value of α used in the study equals 0.5σ, σ, 1.5σ and 2σ. The value σ represents the standard deviation of the series. As for the choice of the relevant embedding dimension m, Hsieh (1989) suggests consideration of a broad range of values from 2 to 10 for this parameter. Following recent studies of Barnett et al. (1995), we implement the BDS test for the range of m-values from 2 to an upper bound of 8.

Table 3.3 reports the BDS statistic for the returns series for embedding dimension 2–8 and for epsilon values starting from 0.5 to 2 times the standard deviation of the index returns series of India, Sri Lanka and Pakistan. The results strongly reject the null hypothesis of independently and identically distributed index price changes at 5% and 1% significance level. The alternative hypothesis of the test includes, in addition to serial correlation, non-stationarity, higher order dependences specified by GARCH as well as other unspecified non-linear forms. Since the results have rejected the IID assumption of RWH, we now, focus on uncovering the structure of dependency in the series.

As the BDS test has a good power against linear as well as non-linear systems, we use a filter to remove the serial dependence in the return series and the resulting residual series are retested for possible non-linear hidden structures. We use an autoregressive moving average, i.e. ARMA (p, q) model to take out all the linearity in the series. One may be cautious that linear filtering may change either the asymptotic or the finite sample distribution of the test statistic. However, as Brock (1987) proves, the asymptotic distribution of the BDS test is not altered by using residuals instead of raw data in 'linear' models.

Through trial and error, it has been found that the ARMA models which fit the return series of each country are as follows: India (9, 0), Sri Lanka (5, 0) and Pakistan (3, 0). On diagnostic checking, it has been found that the sum of the 20 squared autocorrelations as shown by Ljung–Box statistic[5] LB = 29.099, p-value = 0.086 for India, LB = 28.606, p-value = 0.096 for Sri Lanka and 22.450 with probability 0.317 for Pakistan) are not statistically significant, indicating that

Table 3.3 BDS statistics for raw return series

Country/ε		2	3	4	5	6	7	8
India	0.5σ	0.0069*	0.0063*	0.0038*	0.0020*	0.0010*	0.0005*	0.0002*
	1.0σ	0.0164*	0.0261*	0.0284*	0.0267*	0.0235*	0.0198*	0.0162*
	1.5σ	0.0176*	0.0349*	0.0487*	0.0580*	0.0639*	0.0673*	0.0682*
	2.0σ	0.0127*	0.0279*	0.0441*	0.0589*	0.0721*	0.0839*	0.0939*
Sri Lanka	0.5σ	0.0303*	0.0329*	0.0263*	0.0183*	0.0121*	0.0077*	0.0048*
	1.0σ	0.0482*	0.0825*	0.1001*	0.1048*	0.1024*	0.0949*	0.0864*
	1.5σ	0.0390*	0.0777*	0.1097*	0.1337*	0.1519*	0.1629*	0.1710*
	2.0σ	0.0251*	0.0539*	0.0809*	0.1054*	0.1294*	0.1496*	0.1687*
Pakistan	0.5σ	0.0190*	0.0181*	0.0126*	0.0077*	0.0046*	0.0027*	0.0015*
	1.0σ	0.0349*	0.0567*	0.0659*	0.0656*	0.0614*	0.0546*	0.0471*
	1.5σ	0.0293*	0.0591*	0.0849*	0.1032*	0.1159*	0.1224*	0.1246*
	2.0σ	0.0191*	0.0429*	0.0678*	0.0909*	0.1116*	0.1286*	0.1423*

Source Compiled from Dhankar and Chakraborty (2007)
*Indicates significance at 1% level

the residuals of the ARMA models are white noise, and that the model accounts for all the linear dependence in the series.

The BDS statistics for the ARMA residuals are reported in Table 3.4. Even after the removal of linear dependence, the statistics are still significant at 1 per cent level for all the dimensions up to 8 for the ARMA residuals of each of the countries. The results suggest the rejection of IID for the residual series, too. Since, linear dependence is ruled out in the residual series, the possible causes for rejection of IID could be either non-stationary or non-linearity in the returns series (Hsieh, 1991). We explore the possibility of non-stationarity in the data by applying tests capable of detecting the presence of unit roots. The presence of unit roots in the series implies non-stationarity. Two well-known tests, the Augmented Dickey Fuller (ADF) test and the Phillip Perron (PP) test have been applied. To start with, ADF unit root test of the null hypothesis of non-stationarity is conducted, which consists of a regression of the first difference of the series against the series lagged k times

$$\Delta r_t = \alpha + \delta_{t-1} + \Sigma\beta_s r_{t-s} + \varepsilon_t$$

Where $\Delta r_t \models r_t - r_{t-1}$

$$r_t = I_n(R_t)$$

The null and alternative hypotheses are

Null and Alternative hypothesis

$H_0 : \delta = 0;$

Alternative hypothesis

$H_1 : \delta < 0.$

Table 3.4 BDS statistics for ARMA residual series

Country/ε		2	3	4	5	6	7	8
India	0.5σ	0.0067*	0.0061*	0.0038*	0.0021*	0.0011*	0.0005*	0.0003*
	1.0σ	0.0168*	0.0271*	0.0290*	0.0270*	0.0238*	0.0198*	0.0162*
	1.5σ	0.0184*	0.0372*	0.0511*	0.0599*	0.0657*	0.0682*	0.0684*
	2.0σ	0.0136*	0.0303*	0.0471*	0.0617*	0.0751*	0.0863*	0.0955*
Sri Lanka	0.5σ	0.0235*	0.0276*	0.0225*	0.0158*	0.0104*	0.0066*	0.0042*
	1.0σ	0.0389*	0.0724*	0.0902*	0.0960*	0.0948*	0.0887*	0.0814*
	1.5σ	0.0320*	0.0692*	0.1005*	0.1245*	0.1431*	0.1542*	0.1628*
	2.0σ	0.0225*	0.0511*	0.0785*	0.1032*	0.1273*	0.1468*	0.1655*
Pakistan	0.5σ	0.0188*	0.0181*	0.0125*	0.0076*	0.0045*	0.0026*	0.0015*
	1.0σ	0.0357*	0.0581*	0.0667*	0.0661*	0.0617*	0.0548*	0.0472*
	1.5σ	0.0304*	0.0613*	0.0872*	0.1056*	0.1178*	0.1241*	0.1261*
	2.0σ	0.0192*	0.0432*	0.0679*	0.0908*	0.1111*	0.1279*	0.1415*

Source Compiled from Dhankar and Chakraborty (2007)
*Indicates significance at 1% level

Table 3.5 Unit root test for index returns

Country	ADF test	PP test
India	−45.6476*	−45.6476*
Sri Lanka	−39.2977*	−35.6531*
Pakistan	−45.1813*	−46.28

Source Compiled from Dhankar and Chakraborty (2007)
*Indicates significance at 1% level

The rejection of the null hypotheses implies stationarity. MacKinnon's critical values are used in order to determine the significance of the test statistic. The PP test incorporates an alternative (non-parametric) method of controlling for serial correlation when testing for a unit root by estimating the non-augmented Dickey-Fuller test equation and modifying the test statistic so that its asymptotic distribution is unaffected by serial correlation. It is based on the following model:

$$\Delta r_t = \mu + \delta r_{t-1} + \varepsilon_t$$

The results of both the ADF and PP test, presented in Table 3.5, reject the null hypothesis of unit root thereby, implying stationarity in the return series. This confirms the presence of significant non-linear dependence in the returns of South Asian markets.

Now that we know that there is significant non-linear dependence in the return series of all the three markets, we try to identify the nature of this non-linearity. For this purpose, we first investigate the presence of volatility clustering in the returns, which means that large changes in the return series tend to be followed by large changes and small changes by small changes. Figures 3.1, 3.2 and 3.3 provide the plot of daily returns for the three countries. From the figures, it appears that there are stretches of time where the volatility is relatively high and certain stretches of time where the volatility is relatively low which suggests an apparent volatility

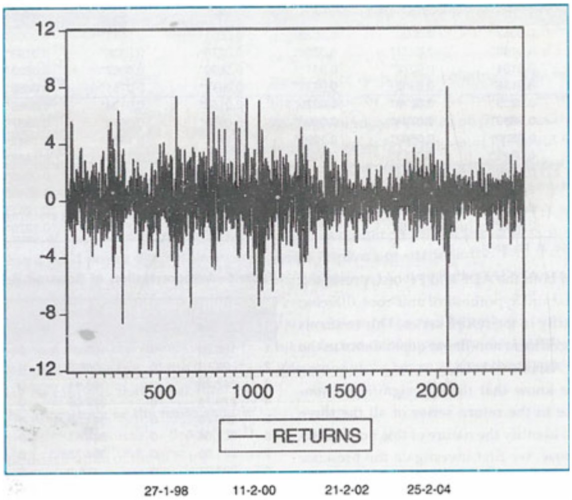


Fig. 3.1 Daily returns of BSE Sensex depicting volatility clustering in India. *Source* Compiled from Dhankar and Chakraborty (2007)

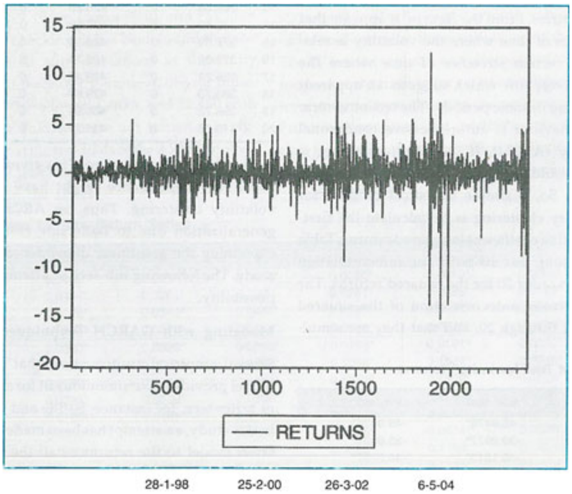


Fig. 3.2 Daily returns of Milanka price index depicting volatility clustering in Sri Lanka. *Source* Compiled from Dhankar and Chakraborty (2007)

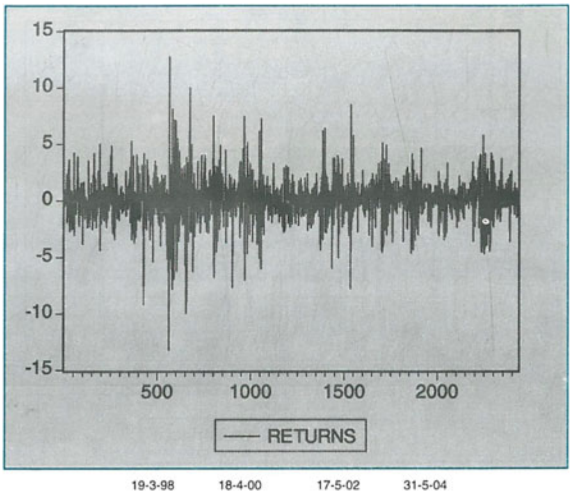


Fig. 3.3 Daily returns of KSE-100 index depicting volatility clustering in Pakistan. *Source* Compiled from Dhankar and Chakraborty (2007)

Table 3.6 Autocorrelation of squared returns

Lags	India		Sri Lanka		Pakistan	
	LB stat	*p*-value	LB stat	*p*-value	LB stat	*p*-value
1	185.25	0	155.91	0	85.314	0
2	227.3	0	268.2	0	326.55	0
3	247.26	0	308.41	0	380.12	0
4	279.71	0	322.05	0	483	0
5	309.78	0	341.59	0	503.65	0
6	321.64	0	348.41	0	531.29	0
7	331.95	0	394.78	0	572.37	0
8	338.21	0	408.2	0	603.42	0
9	344.95	0	409.03	0	654.74	0
10	350.94	0	415.32	0	684.66	0
11	354.5	0	417.58	0	713.75	0
12	356.45	0	422.89	0	743.48	0
13	365.66	0	426.28	0	759.68	0
14	376.49	0	427.62	0	772.26	0
15	377.69	0	428.12	0	792.72	0
16	379.06	0	428.16	0	845.04	0
17	386.24	0	429.48	0	878.02	0
18	386.73	0	429.66	0	914.72	0
19	398.72	0	430.84	0	944.28	0
20	413.08	0	435.21	0	967.81	0

Source Compiled from Dhankar and Chakraborty (2007)

clustering in some periods. The technical term given to this behaviour is autoregressive conditional heteroscedasticity (ARCH). If volatility clustering is present, there would be a strong autocorrelation in squared returns. So, a simple statistical method for detecting volatility clustering is to calculate the first-order autocorrelation coefficient in squared return. Table 3.6 provides the Ljung–Box statistics for autocorrelation coefficients up to order 20 for the squared returns. The results suggest strong autocorrelation of the squared returns for lags 1 through 20, and that they are simultaneously not equal to zero. This gives the hint that the non-linear dependence might have been caused by volatility clustering. Thus, an ARCH process or its generalization due to Bollerslev (1986) may help in explaining the non-linear dependence reported in this study. The following subsection attempts to explore this possibility.

Modelling with GARCH Techniques

Several empirical studies show that a GARCH (1, 1) model provides a parsimonious fit for share price changes series (see, for instance, Baillie and Bollerslev, 1989). In this study, an attempt has been made to fit the GARCH (1, 1) model to returns of all the three markets.

The following equations a, b and c have been obtained for the conditional variances for the returns of India, Sri Lanka and Pakistan, respectively:

$$h_\tau = 0.0858 + 0.1117\,\varepsilon_{\tau-1}^2 + 0.8601\,h_{\tau-1} \tag{a}$$

$$h_\tau = 0.2095 + 0.4423\,\varepsilon_{\tau-1}^2 + 0.5255\,h_{\tau-1} \tag{b}$$

$$h_\tau = 0.1229 + 0.1689\,\varepsilon_{\tau-1}^2 + 0.7997\,h_{\tau-1} \tag{c}$$

where ε_τ is the residual term and h_τ is the conditional variance. The parameters with their respective *t*-statistics and *p*-values are reported in Table 3.7. The α_0, α_1 and β_1, coefficients of the variance equations are highly significant for all return series, favouring the appropriateness of the model. Figures 3.4, 3.5 and 3.6 plot the conditional volatility obtained from the GARCH (1, 1) model for India, Sri Lanka and Pakistan, respectively. It may be observed that the conditional variance varies over time and that period of high and low volatility tend to cluster.

It is also important to interpret the sizes of the parameters α and β. The coefficient β determines the persistence in volatility: irrespective of what happens in the market, a high β indicates that if volatility was high yesterday, it will still be high today. Alternatively, large error coefficient means that volatility reacts quite intensely to market movements resulting in 'spike' volatility. The closer β is to one, the more persistent is volatility following a market shock. Thus, a high β gives little reaction to actual market events, but great persistence in volatility, and a large α gives highly reactive volatility that quickly dies away.

It appears from Table 3.7 that β_1 is close to one and α_0 and α_1 are small for India and Pakistan. Large value of lag coefficient β_1, here, indicates that shocks to conditional variance take a long time to die out, so volatility is 'persistent' as can be seen in Figs. 3.4 and 3.6. These two markets thus take some time to fully digest the recent price shocks. The relatively small value of error coefficient α_1 implies that volatility reacts relatively less intensely with large market surprises in these two countries. Reaction and persistence coefficients of Sri Lanka indicate that volatility is less persistent and more reactive than India and Pakistan. Hence the GARCH volatility of Sri Lanka appears to be spiky, which can also be observed from Fig. 3.5. The results thus suggest that markets behave differently for different countries in terms of reaction and persistence in volatility.

Further, it can be observed from the Figs. 3.4, 3.5 and 3.6 that the volatility in the figures behaves qualitatively like the apparent volatility variation in the returns as in Figs. 3.1, 3.2 and 3.3. At this point, it may be worthwhile to trace the most

Table 3.7 GARCH (1, 1) parameter estimates

Country	α_0	α_1	β_1
India	0.0858 (z = 6.381) (p = 0.000	0.1117 (z = 12.526) (p = 0.000	0.8601 (z = 87.128) (p = 0.000
Sri Lanka	0.2095 (z = 18.8086) (p = 0.000)	0.4423 (z = 23.187) (p = 0.0000	0.5255 (z = 34.025) (p = 0.000)
Pakistan	0.1229 (z = 11.246) (p = 0.00)	0.1689 (z = 15.662) (p = 0.00)	0.7997 (z = 100.085) (p = 0.00)

Source Compiled from Dhankar and Chakraborty (2007)

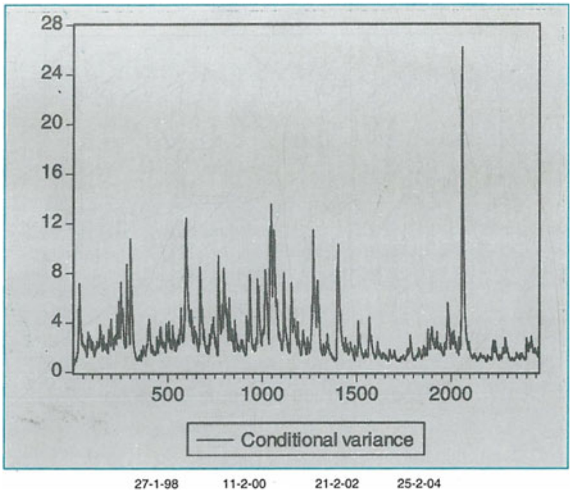


Fig. 3.4 Conditional variance of returns of BSE Sensex. *Source* Compiled from Dhankar and Chakraborty (2007)

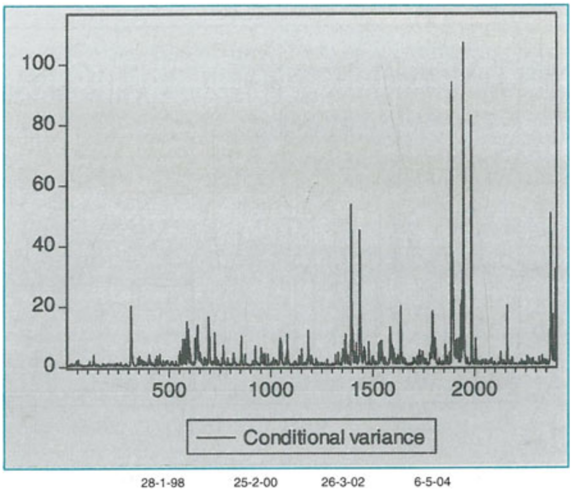
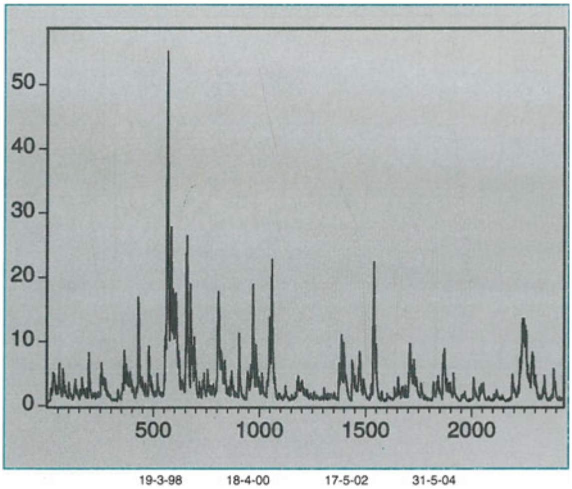


Fig. 3.5 Conditional variance of returns of Milanka price index. *Source* Compiled from Dhankar and Chakraborty (2007)

Fig. 3.6 Conditional variance of returns of KSE-100 index. *Source* Compiled from Dhankar and Chakraborty (2007)



volatile periods in the markets and locate the reasons as to why the markets showed high conditional heteroscedasticity during those periods. From Fig. 3.4, which has plotted the conditional volatility of the Indian stock market, it appears that during mid-2004, the volatility was highest over the period under study. The BSE Sensitivity Index (Sensex) declined from about 5,900 on 22 April 2004 to around 4,500 on 17 May 2004. On 17 May (also referred to as Black Monday), it registered a record 800 point decline, which is the steepest fall in the 130-year-old history of the stock exchange, before recovering to close 564 points lower than the previous close. The Sensex started a recovery from 18 May. Several reasons have been cited for such dramatic movements. For instance, Krishnamurthy (2005) points to the unexpected election verdict[6] in May 2004 as a possible reason for the excessive volatility during the period. Ram Mohan (2006) puts forth that FII sale in the Indian market following election results caused prices to plummet sharply. He opines, ‘FII flows have a significant impact on prices which may not be on account of the trading they do themselves; it could be that FII investment decisions tend to get magnified by influencing decisions of domestic investors and lead to overshooting in the market’. These shocks in the Indian market caused the conditional heteroscedasticity to rise sharply during the middle of 2004 as is evidenced in Fig. 3.4.

Although no major market crash or scam has been reported for the Colombo Stock Exchange, from Fig. 3.5, it can be perceived that there has been higher volatility in the later part of the year 2001 and in 2004. The Sri Lankan economy went through a turbulent phase in 2001. The country recorded a negative growth rate of 1.3% in 2001, for the first time in the country’s history. Drought conditions resulted in the output decline of the country’s major commodities. Moreover, the country has been suffering badly from the terrorist attacks of LTTE, which weakened business confidence and prospects. These had their impact on the stock market, which saw a bearish phase till October 2001. However, since mid-October, the prices saw a reversal, with the then forth-coming elections and the possibility of some decisive steps in ending terrorism. The market looked more confident, but elections being an uncertain game, prices also fluctuated on the basis of the day-to-day news and rumours, causing a higher volatility during the period.

The market was volatile again in 2004 with the dissolution of the Parliament in February, followed by the general elections in April and the change in the Government. Towards the end of the year, the unprecedented natural disaster in the form of *Tsunami* which hit on 26 December 2004 also had a negative effect on the market.

From Fig. 3.6, it may be observed that the Pakistan stock market experienced the maximum volatility in the year 1998. In that year, the nuclear test followed by severe foreign exchange crunch and international economic sanctions had devastating effects on the Pakistan stock market. The investor's confidence was badly shaken leading to highly irregular and frenzied price movements. These shocks have been reflected in the graphs of conditional volatility of the markets.

Does the GARCH (1, 1) Model Explain Non-linearity?

Having fitted the GARCH (1, 1) model, it is important to test for the adequacy of the model. The results of the diagnostic tests in Table 3.8 show that the model is correctly specified. If the GARCH (1, 1) model describes the data, then the standardized residuals $\varepsilon_t/(h_t)^{1/2}$ should have zero mean and unit variance. More importantly, there should be an absence of serial correlation in the standardized squared residuals $\varepsilon_t^2/(h_t)$. Some diagnostic information on the estimation is presented in Table 3.8. The mean and variance of the standardized residuals are found to be approximately zero and one, respectively, for all the countries.

The Ljung–Box statistic is computed for the standardized squared residuals to test the null hypothesis of no autocorrelation up to order twenty. The Q^2 statistic (20 lags were looked into) suggests no serial correlation in the squared standardized residuals of the three countries. This suggests that the GARCH (1, 1) model is successful in modelling the serial correlation structure in the conditional variance and is an adequate description of the volatility process of all of these countries.

To evaluate if the GARCH (1, 1) model could capture the non-linear structure in the return series, the BDS test can be used again on the standardized residuals as a misspecification test. The acceptance of the IID hypothesis will imply that the conditional heteroscedasticity is responsible for the non-linearity in index returns.

There are two ways to apply the BDS test to GARCH standardized residuals: one is to apply the BDS test directly to the standardized residual and the other is to apply it to the logarithms of squared standardized residuals. In general, the asymptotic distribution of the BDS test is not altered by using residuals of 'linear' models, however, when applied to standardized residuals from a fitted ARCH/GARCH model, earlier studies (for example, Brock et al., 1991) suggest that the

BDS statistic needs to be adjusted to have the right size and Monte Carlo simulations are usually relied upon to derive the adjustment factor for specific GARCH models. However, following suggestions in Brock and Potter (1993) and De Lima (1996), recent studies (for example, Caporale, Ntantamis, Pantelidis, and Pittis (2004) and Fernandes and Preumont (2002)) show that if applied to the logarithms of squared standardized residuals from a fitted GARCH model, the BDS test is more reliable. Following these recent advances, we apply the BDS test to the logarithm of the squared standardized residuals from the GARCH process the

Table 3.8 Diagnostics for GARCH (1, 1) model

Statistics	India	Sri Lanka	Pakistan
Mean of standard residuals variance of standard residuals Ljung–Box stat, and p-values in parentheses for Autocorrelation of squared standard residuals	−0.0385 0.99868	0.05e −05 1.00028	6.63e −05 1.00003
$\sigma^2(1)$	1.7923 (−0.181)	0.5151 (−0.473)	0.2138 (−0.644)
$\sigma^2(2)$	1.8223 (−0.402)	1.0931 (−0.579)	0.3663 (−0.833)
$\sigma^2(3)$	1.8347 (−0.607)	1.5934 (−0.661)	0.4028 (−0.94)
$\sigma^2(4)$	1.8584 (−0.762)	2.555 (−0.635	0.9043 (−0.924)
$\sigma^2(5)$	1.9311 (−0.859)	3.1002 (−0.685	1.1564 (−0.949)
$\sigma^2(6)$	1.9311 (−0.926)	3.3676 (−0.761)	4.9814 (−0.546)
$\sigma^2(7)$	1.9324 (−0.963)	5.9132 (−0.55)	4.9973 (−0.66)
$\sigma^2(8)$	4.1653 (−0.842)	5.9132 (−0.657)	5.405 (−0.714)
$\sigma^2(9)$	7.3306 (−0.603)	6.4076 (−0.699)	7.1181 (−0.625)
$\sigma^2(10)$	1.7336 (−0.693)	6.4621 (−0.775)	7.1581 (−0.71)
$\sigma^2(11)$	8.6189 (−0.657)	6.4985 (−0.838)	8.0391 (−0.71)
$\sigma^2(12)$	12.007 (−0.445)	7.6377 (−0.813)	8.2053 (−0.769)
$\sigma^2(13)$	13.011 (−0.447)	9.3730 (−0.744)	8.7473 (−0.792)
$\sigma^2(14)$	13.075 (−0.521)	11.123 (−0.676)	8.8425 (−0.841)

(continued)

Table 3.8 (continued)

Statistics	India	Sri Lanka	Pakistan
$\sigma^2(15)$	13.348 (0.575)	11.24 (−0.735)	9.208 (0.866)
$\sigma^2(16)$	13.883 (0.607)	11.254 (−0.794)	9.3619 (0.898)
$\sigma^2(17)$	13.935 (0.672)	12.07 (0.796)	9.3634 (0.928)
$\sigma^2(18)$	16.991 (0.524)	12.387 (0.827)	10.434 (0.917)
$\sigma^2(19)$	17.085 (0.584)	12.41 (0.868)	11.064 (0.922)
$\sigma^2(20)$	26.686 (0.144)	18.058 (0.584)	11.951 (−0.918)

Source Compiled from Dhankar and Chakraborty (2007)

results of which are reported in Table 3.9. The BDS test fails to reject the null hypothesis that the logarithm of the squared standardized residuals are IID random variables at 5% degree of significance. This confirms that the GARCH process is capable of capturing the non-linearity in the series, and that the conditional heteroscedasticity is the cause of the non-linearity structure uncovered in the returns series.

Conclusion

In this study, we have tested the IID behaviour of stock return series of three major South Asian countries, namely, India, Sri Lanka, and Pakistan. The BDS test applied for investigating the same has strongly rejected the null hypothesis of independent and identical distribution of the return series. The same has been rejected for the ARMA residuals as well. This implies that the rejection of IID is not caused by linear dependence. The study also shows that the rejection is not caused by non-stationarity either. This suggests the presence of non-linear dependence in the return series. The findings are consistent with the previous research that has shown evidence of non-linear dependence in the stock returns of the developed markets. In order to examine whether the non-linear dependence is attributable to GARCH effects, the study has applied GARCH (1, 1) model, which has been found to fit the data adequately. On reapplication of the BDS test to logarithm of GARCH squared standardized residuals, it has been found that GARCH (1, 1) successfully accounted for all the non-linearity in the returns series. The results suggest the rejection of random walk hypothesis for the markets under study.

Table 3.9 BDS statistics for log of GARCH squared standardized residuals

Country/ε	1	2	3	4	5	6	7	8
India	0.5σ	0.00035	0.00059	0.00044	0.00025	0.00011	4.22E−05	9.63E−06
	1.0σ	0.00017	0.00174	0.00259	0.00251	0.0191	0.00135	0.00065
	1.5σ	0.00053	0.00291	0.00475	0.00548	0.00507	0.00422	0.00271
	2.0σ	0.00094	0.00299	0.00437	0.00508	0.00493	0.00441	0.00355
Sri Lanka	0.5σ	−7.58E−05	0.00044	0.00019	−8.53E−05	−1.63E−05	−1.39E−05	−2.06E−06
	1.0σ	0.00095	0.00064	0.00117	−0.000881	−0.00051	−0.00051	−0.00046
	1.5σ	0.00174	0.00023	0.00125	−0.00184	−0.00126	−0.00146	−0.00179
	2.0σ	0.0015	0.00067	0.00127	−0.00266	−0.00235	−0.00278	−0.00325
Pakistan	0.5σ	8.43E−06	0.00015	0.00012	7.58E−05	4.52E−05	4.53E−05	1.71E−06
	1.0σ	−0.00067	0.00042	−6.28E−05	8.95E−05	0.0002	1.80E−06	−3.38E−05
	1.5σ	−0.001469	0.00199	0.00206	−0.00279	−0.00307	−0.00359	−0.00344
	2.0σ	−0.00151	0.00308	0.00431	−0.00637	−0.00783	−0.00926	−0.00971

Source Compiled from Dhankar and Chakraborty (2007)

Though the present study rejects the random walk hypothesis for the South Asian stock market, and finds evidence of non-linear dependence in the index returns series, the results are not necessarily inconsistent with efficient market hypothesis, simply because non-linearity does not essentially mean predictability. As noted by Abhyankar et al. (1997), the future price changes can be predictable but only with a time horizon too short to allow for excess profits. Moreover, because of the relatively high transaction costs in emerging markets, the excess profit from forecasting is likely to be nil, if not negative.

Further, the implications of rejecting the IID Hypothesis go beyond the issue of market efficiency. The evidence of non-linearity is continuingly reshaping our traditional views of modelling asset prices, and portfolio and risk management, as well as forecasting techniques. For instance, Bera, Bubnys, and Park (1993) question the ability of the Ordinary Least Square Model in estimating the optimal hedge ratio using futures contracts and find that, compared to ARCH hedge ratio, the conventional model leads to too many or too few short sellings of future contracts. Hence, we can say that the common assumption of constant variance underlying the theory and practice of option pricing, portfolio optimization, and value at risk (VaR) calculations are definitely subject to question, in view of the increasing evidence of non-linearity and conditional heteroscedasticity. If the assumed stochastic processes do not adequately depict the full complexity of the true generating processes, then any derivatives in question may be mispriced. This implies that investors and institutions may have imperfect hedges, which expose them to unwanted risks.

To conclude, the prevalence of non-linearity in financial time series, particularly in the stock market data of the South Asian countries, should be taken seriously and should not at all be neglected. For researchers in the developing countries, it is time to embrace the shift to non-linearity, which offers both great excitement and challenges. It is exciting in a sense that it will provide a better understanding of the underlying dynamics of financial time series. On the other hand, they reveal how much work still remains to be done, especially on the financial markets of the emerging countries.

End Notes

1. See Table 3.1 for the percentage change of S & P/IFC Investable Index for the year 2003, which presents the generally high positive changes.
2. See, for example, Ray (1976) Barua (1981), Chaudhury (1991), Elyasiani, Perera, and Puri (1996), Madhusoodanan (1998), Karmakar and Chakraborty (2000a and 2000b), Mobarek and Keasey (2000).
3. Schatzberg and Reiber (1992) suggest that share prices do not always adjust instantaneously to new information.
4. The Milanka Price Index (MPI) was introduced in January 1999, replacing the Sensitive Price Index (SPI). Hence, in this study, we consider the Sensitive Price

index from January 1996 to December 1998 and Milanka Price index from January 1999 to December 2005.

5. The Ljung–Box statistic is defined in the following way:

$$\mathrm{LB} = n(n+2)\sum_{k=1}^{m} r_k^2/(n-k) \sim x^2(m\,d.f.),$$

where

n= sample size
m=lag length

6. The UPA took over as the ruling party which was apparently not as per the predictions reported in the media.

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Chapter 4
Stock Market Overreaction

Every once in a while, the market does something so stupid it takes your breath away.
Jim Cramer

Abstract Overreaction Effect can be traced back to 1980s when DeBondt and Thaler (The Journal of Finance XL:793–805, 1985) argued that there existed a strong tendency for both low- and high-performing securities in one period to experience a reversal in the following years. Since then, it has become one of the grey areas in finance and leads to an ongoing debate on its existence. The study critically evaluates the work of various authors discussing the possible causes of the effect and its behavioural aspects.

Introduction

Overreaction is an emotional response to new information about a security, which is led either by greed or fear. Investors, overreacting to news, cause the security either over brought or oversold, until it returns to its intrinsic value. Investors are not always rational. Instead of pricing all publicly known information perfectly and instantly, as the efficient market hypothesis assumes, they are often affected by cognitive and emotional biases (Kenton, 2018).

In 1670, Isaac Newton concluded that 'What goes up must come down'. Centuries later DeBondt and Thaler (1985) came out with the same conclusion in stock market proposing that there is a strong tendency for high-performing securities in one period to experience a reversal in the following years, referring it as 'Overreaction Effect'. Since then, it has become one of the grey areas in finance.

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Overreaction Hypothesis asserts that stock market is subject to the waves of optimism and pessimism. Stock prices tend to deviate temporarily from their fundamental values; prices shoot up over good news and drops over bad news. However, over a period of time, stock prices gradually reverts back to their fundamental values thereby suggesting that prices have overreacted in the initial period and it subsequently corrects itself. The most interesting application associated with Overreaction Hypothesis is the potential to earn abnormal profits by implementing contrarian strategy that is purchasing low-performing securities and selling high-performing securities in advance of any subsequent reversals. This possibility acts as a serious blow to Efficient Market Hypothesis (EMH) (Fama, 1970) that claims that stock prices accurately reflects all the available information at all times, and hence there is no possibility to earn excess returns in the market. Subsequent studies focussed on testing the overreaction hypothesis and explaining the overreaction effect. This has resulted in theee development of several theoretical and behavioural models.

The purpose of the study is to review the available literature on the overreaction effect. Section "Overreaction Effect: An Overview" gives the brief review of the effect. Sections "Critiques of the Overreaction Effect" and "The Overreaction Hypothesis Restored" discuss the various arguments in favour and against the presence of the overreaction effect. Section "Behavioural Finance: A New Perspective" provides the possible explanation of overreaction effect based on behavioural models. Section "International Empirical Evidences of Overreaction Effect" provides empirical evidences on overreaction effect in various international stock markets and finally section "Inferences" concludes.

Overreaction Effect: An Overview

Overreaction Hypothesis

DeBondt and Thaler (1985) argued that stock market overreacts to information in past earnings and/or security prices, at the expense of longer run trends. As a result of this, investors can earn abnormal profits in the longer horizon by buying up undervalued stocks and selling overvalued stocks. The motivation behind the research of DeBondt and Thaler (1985) was to investigate the relationship and link between the market behaviour and psychology of individual decision making. Based on the work of Kahneman, Slovic, and Teversky (1982), they suggested that investors do not follow Baye's rule and most people 'overreact' to unexpected and dramatic news events.

DeBondt and Thaler (1985*)* explained the Overreaction effect as follows:

> If stock prices systematically overshoot, then their reversal should be predictable from past return data alone, with no use of any accounting data such as earnings. Specifically, two hypotheses are suggested:

(1) Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction.
(2) The more extreme the initial price movement, the greater will be the subsequent adjustment.

To verify these hypotheses, they observed the NYSE monthly return data for the period 1926–1982 by focusing on stocks that have experienced either extreme capital gain or losses over the period of last 5 years. The methodology used by DeBondt and Thaler (1985) involved the construction of two portfolios: Winner and Loser. Winner portfolio was composed of extreme high return securities and Loser portfolio was composed of extreme low return securities. Empirical results of the study shows that on an average, the loser portfolio outperformed the market by 19.6% and winner underperform the market by 5%. Hence, the average cumulative residual between the extreme portfolios (Winner–Loser) equals to significant gain of 24.6%. This work of DeBondt and Thaler (1985) was the first attempt to apply a test for a behavioural principle to the stock market. This phenomenon is also known as Winner–Loser Effect. The overreaction hypothesis generated much of the interest in subsequent years. Brown and Harlow (1988) further extended the study of DeBondt and Thaler (1985) by studying the relationship between the magnitudes of the reaction with the amount of time of initial price change. They formulated the 'Overreaction Hypothesis' as the following three propositions:

Directional Effect: Extreme Movements in equity prices will be followed by movements in the opposite direction.

Magnitude Effect: The more extreme the initial price change, the more extreme the offsetting reaction.

Intensity Effect: The shorter the duration of the initial price change, the more extreme the subsequent response.

Subsequent research by Fama and French (1988) and Poterba and Summers (1988) also finds results consistent with the predictability in stock returns, supporting the Debondt and Thaler (1985) findings. Fama and French reported in 1988 that 25–45% of the variations in monthly returns over a period of 3–5 years are predictable using past returns. Jegadeesh and Titman (1993) had thrown new light on the influential work of Debondt and Thaler (1985) and found evidence in favour of short-term momentum effect and long-term reversals.

In addition to long-term overreaction documented by DeBondt and Thaler (1985), many studies have documented the existence of short-term overreaction effect. Brown and Harlow (1988) also stated that the tendency of stock market to overreact is best regarded as asymmetric short-term phenomenon. Howe (1986) proved that based on large price depreciation over a period of 1 week, the winners exhibit abnormal negative returns up to 1-year post portfolio formation. Bowman and Iversan (1998) argued that even though the evidence on the cause of long-run return reversal are conflicting, the evidences are more consistent in favour of overreaction as short-term reversals.

Stock Overreaction and Implication to EMH

Efficient Market Hypothesis (EMH), is perhaps the most interesting, well studied and controversial topic in all the social sciences. Fama in 1970 summarised EMH as 'prices fully reflect all available information' and markets are rational and efficient. On the basis of relevant information, market is divided into three stages: weak form, semi-strong form and strong form. According to EMH, stocks will always trade at their fair value and will give normal returns only. Hence, it is impossible to get abnormal returns based on the information available about the past. In the first decade after its formation, EMH was widely accepted by financial economists. This had made investors to believe that EMH restricts their ability to earn abnormal profits. However, in the recent years, researchers have started challenging the weak form of market efficiency. Overreaction Hypothesis proposes that stocks that perform best (worst) over an initial period tend to perform worst (best) in the subsequent period. This behaviour is generally recorded due to market participants, who overreact to the new dramatic event in a way that extremely negative news pulls the stock prices much below their true value and extraordinary positive news pushes the stock prices well above their fundamental value. Over a period of time, investors realize their mistakes and take corrective actions. This leads to the change in the prices in the opposite direction of the initial movement and prices revert back to their true fundamental levels. Hence, it is possible to earn abnormal profits by adopting contrarian strategy of purchasing past low-performing securities and selling past high-performing securities. This suggests that, there exists some predictability in the stock market and hence violating the weak form of market efficiency. This has led to an ongoing debate on stock market efficiency and researchers have not yet reached a consensus about whether financial markets are efficient or not.

Critiques of the Overreaction Effect

The proposition of the overreaction hypothesis by DeBondt and Thaler (1985) has generated much interest and controversy in the subsequent years. DeBondt and Thaler (1985) suggested that the results of the study evidence the irrationality or irrational behaviour shown by the investors in stock markets. They suggested that when investors revise their prospects, they tend to overweight recent information and underweight past information. This leads to excessive optimism about good news and extreme pessimism over bad news. This causes stock prices to depart from their fundamental values. However, different authors were sceptical about the hypothesis and have presented different explanations for the same.

Overreaction or Time-Varying Risk

DeBondt and Thaler (1985) assumed that the risk level does not change between portfolio formation and test period. However, Chan (1988), Ball and Kothari (1989) and others have argued that the prior performance do changes the risk of winner and loser firms and the risk does not remain constant over the period of time.

Chan (1988) argued that both winner and loser portfolio experiences large changes in market value during the rank period. He argued that the stocks with the series of negative abnormal returns will experience an increase in their equity betas and thus increased expected returns. The results of the study were consistent with the risk change explanation as large changes in betas from rank period to the test period were observed. The loser's beta increases after a period of abnormal loss and the winner's beta decreases after a period of abnormal gain. Further, after accounting for the changes in betas of losers and winner portfolios from rank period to test period, contrarian strategy earns only small, non-economical significant abnormal returns.

Similar and confirmatory evidence was presented by Ball and Kothari (1989), who although using a different methodology as compared to Chan (1988), finds that negative serial correlation in returns are entirely due to variation in relative risks. They presented a novel argument for negative serial correlation by taking into consideration the changes in leverage. They argue that as leverage is a decreasing function of past equity returns, and equity betas, in turn, are increasing function of leverage, hence a series of negative abnormal returns will increase the leverage which will increase the equity beta of the firm leading to increased expected return on the stock. The results of the study showed severe changes in betas, between formation and the test period. Their results proved the importance of time-varying risk as an explanation behind the mean reversion of returns.

Jones (1993) reconciled the work of DeBondt and Thaler (1985, 1987), Chan (1988) and Ball and Kothari (1989) and suggested that the simple leverage effect as reported by Chan (1988) could not account for the positive covariance. Instead, the evidence of overreaction could be attributed to the pattern of market movements. Assuming stocks returns as described by market model, asymmetric risk exposure was observed, that is, the winner betas tends to be relatively higher in up markets and lower in down markets. Jones suggested that the apparent pattern in US stock returns and contrarian profits were consistent with rational time-varying expected returns.

Overreaction: A Manifestation of Size Effect

Zarowin (1989, 1990) challenged the DeBondt and Thaler's (1985) findings and evidence on stock market overreaction in the light of size phenomenon. Size effect is a well-known anomaly in the academic literature. Size effect refers to the tendency of small-capitalization shares to outperform the large-capitalization shares over the longer horizons. Zarowin (1990) proposed that it is the differential size that drives the Winner versus Loser phenomenon rather than the assumed investor overreaction. When DeBondt and Thaler (1985) study was replicated, results were found to be consistent with the hypothesis as poorest earners were found to outperform the best earners stocks. However, when size was controlled, losers outperformed winners only in the month of January. He further analyses the periods when losers were smaller than winners; and periods when losers were bigger than winners. The results indicated that when losers were smaller, they outperformed the winners and when winners were bigger, they outperformed the losers. This was consistent with size phenomenon but inconsistent with the overreaction phenomenon. Hence, Zarowin (1990) concluded that the Winner–Loser phenomenon observed by DeBondt and Thaler is another manifestation of size effect documented by previous studies.

Microstructure Effects or Overreaction

Another attack on overreaction effect comes from those who studied bid–ask effect. Kaul and Nimalendrum (1990) and Conrad and Kaul (1993) attempted to show that most of the returns claimed by overreaction effect are caused by measurement errors in prices in the form of bid–ask spread. Loser firms being small and low priced firms have higher bid–ask spread as well as higher chances of non-trading. This leads to spurious autocorrelation. The above authors also criticized the use of cumulative abnormal returns methodology adopted by DeBondt and Thaler (1985) as this cumulates the upward biases along with the returns and exaggerate the observed mean reversion in stock prices. Instead, they recommended the use of buy and hold return metric. Ball, Kothari, and Shankeen (1995) also argued that the losers stocks picked by DeBondt and Thaler (1985, 1988) were low priced. The low-priced loser stocks were found to be extremely sensitive to microstructure and liquidity effects. They further criticized DeBondt and Thaler (1985) choice of December as the portfolio formation month. They reported that when June and August were used as portfolio formation month, the results were found to be inconsistent with the overreaction hypothesis.

Overreaction or January Effect

Starting from the study of DeBondt and Thaler (1986), Zarowin (1990), Jegadeesh (1991), Conrad and Kaul (1993), Pettengill and Jordan (1990), Chopra, lakonishok, and Ritter (1992) observed strong January seasonal in the price reversals. Pettengill and Jordan (1990) reported that all the reversals observed by overreaction hypothesis were restricted to the month of January. In fact, when losers and winner portfolios were matched with comparable size portfolios, Zarowin (1990) observed that the performance differentials only exist in the month of January. Conrad and Kaul (1992) using buy and hold strategy also claimed that all the observed abnormal returns in the month of January was due to January effect rather than any past performance of the securities.

The Overreaction Hypothesis Restored

The critiques of Chan (1988), Ball and Kothari (1988), Zarowin (1990), Conrad and Kaul (1993) and others have not gone unchallenged. De Bondt and Thaler (1987) revaluate the overreaction hypothesis to study the size, January effect as well as time-varying risk premia. They provided an additional support in favour of overreaction hypothesis and reported evidences that were inconsistent with two alternative explanations based on firm size and the difference in risk as measured by CAPM beta. They argue that though the estimated beta for loser portfolio was 0.22, greater than the winner beta, this risk difference was insufficient to explain the average annual return of 9.2% of arbitrage portfolio. This rejects the plausible difference in risk explanation for Winner–Loser effect. Further, they also reported that as the firm in both extreme quintiles were smaller than those in middle portfolio but were found not to be unusually small. The average market value for quintile was thirty times larger than average market value for the smallest quintile as ranked by market value. This rejected the small firm effect as a plausible explanation of overreaction effect.

Chopra, Lakonishok, and Ritter (1992) further presented evidence consistent with overreaction hypothesis and dismissed size based explanations. They confirmed that the statistically significant degree of overreaction exists of about 5–10% per year even after controlling for risk and size. Focussing initially on the risk adjustments, Chopra et al. critically examined the work of Ball and Kothari (1989) and pointed out that the Ball and Kothari estimates of degree of overreaction were underestimated due to sample selection bias. Chopra et al. approaches the problem of controlling for risk by grouping companies into equivalent risk class beta for the test period of 1926–1981. After adjusting for size when calculating abnormal returns, they observe the presence of an economically significant overreaction effect. The effect was found to be much stronger in small firms compared to large firms. This was due to predominant individual investors in small firms, who might overreact. Alonso and Rubio (1990), Albert and Henderson (1995) and Ahmad and Hussain (2001) also dismissed the notion that the return reversal is explained by the firm size effect. Albert and Henderson (1995) claims that the ‘size matching methodology’ used by Zarowin (1990) was biased in a way the firms were ranked. Using different methodology to construct control portfolios, they observed an overreaction effect that was distinct from the size effect.

With regard to bid–ask spread, Loughram and Ritter (1996) challenged the findings of Conrad and Kaul (1993). Authors provided direct evidence showing that the DeBondt and Thaler (1985) findings were not driven by the use of cumulating single period returns as compared to buy and hold returns. With the help of direct tests, they further found little differences in test period returns whether CAR (Cumulative Abnormal Returns) as proposed by DeBondt and Thaler or buy and hold returns were used. Loughram and Ritter further claimed that the buy and hold method provides a sharper distinction between the portfolios, but once portfolios are selected, both CAR strategy and buy and hold Strategy will provide similar results. Furthermore, they also suggested that the differences in loser and winner 36th CAR results as reported by Conrad and Kaul (1993) were different from DeBondt and Thaler (1985) mainly due to survivorship bias in Conrad and Kaul (1993) sample.

Further, Dissanaike (1997) using the methods employed by Chan (1988) and Ball and Kothari (1989) to control for time-varying risk, finds little evidence supporting the claim that changes in betas leads to price reversals. Moreover, by restricting the sample to large and better known companies to minimize the biases created by bid–ask effect and infrequent trading, significant abnormal returns were observed. This shows that the existence and the causes of the overreaction effect are still open to debate.

Behavioural Finance: A New Perspective

Behavioural finance offers unconventional explanations on the most important question of, why prices deviate from their fundamental values. According to Hirshleifer (2001), behavioural finance is based on the claim that human behaviour and perceptions represents the two crucial elements of financial decision making. In addition, it focussed an application of psychological and economic principles for the improvement of financial decision making. This has led to the search for new models and ideas that may be able to predict and explain various market anomalies and behaviour from various psychological biases. The following section provides some of the behavioural explanations the short term under reaction and long term reversals in stock prices.

In order to explain the long term overreaction, Barberis et al. (1998) presented a model that combines conservatism bias with representative heuristic. Barberis et al. argued that representative heuristic may lead investors to mistakenly conclude that firms realizing extraordinary growth will continue to experience such growth in future. This behavioural tendency will lead to long-horizon negative returns for stocks with consistently high returns in the past.

Daniel, Hirshleifer, and Subrahmanyam (1998) assumed that investors are overconfident about their private information and overreacts on that. Due to self-attribution bias, investor's overconfidence increases following the arrival of confirming news. The increase in overconfidence promotes the initial overreaction and generates the return momentum. The overreaction in prices will eventually be corrected in the longer run as investors observed future news and realized their mistakes, leading to long-run reversals.

Hong and Stein (1999) presented a model that was based on the initial under-reaction to information and subsequent overreaction that eventually leads to stock price reversal in the long run. The model defines two types of investors: news watchers and momentum- traders; news watchers rely purely on their private information and momentum traders rely exclusively on the information in past price changes. The prices are initially driven by news watchers and then the news gradually gets transmitted to the market where momentum traders react to the news. This leads to initial under-reaction till the time momentum traders didn't react to the news and subsequent overreaction when they react. In long run this overreaction disappeared and price reverts back to their fundamentals in long run.

As it can be seen there exist a number of theories in behavioural sciences that tries to give an explanation on the presence of positive long term reversals. According to behaviourist, contrarian profits are due to market inefficiency and investors non-rational behaviour. However, Locke and Gupta (2009) has pointed out that it is still unclear whether such violations of market efficiency can be given a behavioural explanation or these are the results of rational response of investors towards the market constraints. Hence, a lot of research is needed on the behavioural explanation of investor's overreaction and the kind of behavioural patterns that generates such reaction.

International Empirical Evidences of Overreaction Effect

The empirical evidences presented so far were concentrated mainly on the US stock market. However, as the case in most other financial studies, once the phenomenon has been detected in the US market, it is further tested in other financial markets. It is important to examine the overreaction effect in international equity markets as the strength of overreaction effect may depends on various market characteristics and the evidences of overreaction effect in different markets and time periods would make for a strong argument against data mining.

In the UK Stock market, Campbell and Limmack (1997) and Dissanaike (1997) found evidence in favour of overreaction hypothesis. However, Clare and Thomas (1995) examined the Overreaction using the UK data for the period from 1955 to 1990 showed a very weak overreaction effect in the UK stock market. They concluded that these abnormal returns were due to the size effect, as claimed by Zarowin (1990). In stock markets other than the US and UK, Alonso and Rubio (1990) reported the presence of strong overreaction in the Spanish equity market for the time period between 1967 and 1984. Overreaction in the Spanish stock market was found to be systematic, with winners losing as much as losers winning and the effect gets stronger when longer formation and testing periods were used. In contrast, Forner and Marhuenda (2000) reported the results against the overreaction effect in the Spanish equity market for the sample period from January 1963 to

December 1997. The discrepancies between the studies were due to different methodology and sample period used. Alonso and Rubio used both non-overlapping formation and test period, in contrast to non-overlapping test periods only by Forner and Marhuenda. Stock (1990) for German, Swallow and Fox (1998) for the New Zealand stock market also confirmed the presence of overreaction effect. Bacmann and Dubois (1998) also reported that the standard contrarian strategy in all states of nature, lead to smaller yet significant profits in France. They further reported that the profits computed were stronger when the market was strongly bullish.

However, in Australian and Canadian stock markets, the evidence in favour of overreaction effect was found to be weak. Brailsford (1992) using the Australian stock market data revealed that there exists no mean reversion in the returns of extreme portfolios. Kryzanowski and Zhang (1992) investigated the overreaction effect in the Canadian Stock Market and found results inconsistent with overreaction effect using the test and formation period of 1, 2, 3, 5, 8 and 10 years. Unlike DeBondt and Thaler (1985), there exists insignificant reversal behaviour for winner and loser over longer formation and test periods.

Richard (1997) conducted quite a different study by using total returns of 16 national market indices to form loser and winner portfolio, assuming the markets are well integrated with common international risk factors. He found statistically insignificant positive autocorrelation in short horizon of 1 year or less. However, for longer horizon of 3–4 years, losers outperformed winners. Further, winner–loser reversals were found to be larger among smaller markets; this may be due to market imperfections in smaller and emerging markets. Baytas and Cakici (1999) examined the seven developed US, Canadian, Japanese, French, Italian, German and UK stock markets and found strong evidence of overreaction effect in 2 and 3 year period for all countries except the USA and Canada.

Most of the previous Overreaction Hypothesis testings were concentrated on developed stock markets. In fact, only a few studies included emerging markets in their samples. Da Costa (1994) came up with the findings in agreement to overreaction hypothesis in the Brazilian stock market. The empirical results were found to be consistent with overreaction effect. Moreover, the overreaction effect in the Brazilian stock market was found to be asymmetric in nature, as only the values of winner portfolio have reverted. Strong evidence in favour of the effect was also observed in Asian stock markets that include India, Malaysia, Sri Lanka and China stock markets. Ahmad and Hussain (2001) and Ali, Nassair, Hassan, and Abidin (2011) reported the overreaction effect and seasonality in the stock returns of Malaysia Kuala Lumpur Stock Exchange (KLSE). Ali et al. (2011) study also highlighted that the overreaction behaviour in the Malaysian stock market was more pronounced in the period prior to 1997 Asian financial crises and had gradually diminished and became insignificant during the recent time period. Strong asymmetric overreaction effect was also observed by Wu (2004) in the Chinese stock market, Gunasekarage and Power (2005) for the Colombo stock exchange (Sri Lanka), Locke and Gupta (2009) and Tripathi and Aggarwal (2009) for the Indian stock market. In addition, a small number of studies also reported evidences in favour of overreaction effect in Africa and Middle-East stock exchanges. These includes Page and Way (1992) and Hsieh and Hodnett (2011) for South Africa, Dhouib and Abaoub (2007), Bildik and Gulay (2007) for Turkey, Saleh (2007) for Jordan and Ismail (2012) for the Egyptian stock market. Hsieh and Hodnett (2011) test results also suggested that there exists a saturation point for the past winners and a loser to continue their trends and the mean reversal takes place once that saturation point is reached. In addition, the authors performed a correlation analysis that revealed that winner and loser portfolio accumulates abnormal returns in the opposite direction that were negatively correlated even when the returns of winners, losers and markets were positively correlated. The regression analysis supported the argument that mean reversals were more likely to take place when investors are less confident about the future prospects of the economy.

Overall the results of these studies violate the weak version of EMH and confirm the possibility of stock returns on the basis of historical recordings without using any accounting data in respective stock markets. However, there are some important caveats to this conclusion. First, many of the studies in emerging markets reported non-significant results in favour of overreaction effect; still, they claimed them to be economically significant. Second, small sample composition of several studies including Dhouib and Abaoub (2007) of 30 stocks and Bildik and Gulay (2007) of less than 100 stocks, raises doubts on the reliability of the results. Further, studies such as Ahmad and Hussain (2007), Bildik and Gulay (2007) and Dhouib and Abaoub (2007), includes 10 years or less data, are also unlikely to yield reliable results.

Inferences

Scope for Future Research

This paper discusses the literature review of overreaction effect and its various causes. One of the major limitations observed in the literature is that most of the statistical overreaction evidences are concentrate mainly in the highly developed markets and very few focussed on less developed markets. However, less developed and emerging markets are characterized by more predictability, thin trading and are dominated by less sophisticated investors who do not respond to information instantaneously. This leads to more profitable contrarian strategy. Further, the evidence of contrarian profits on such markets would be of more interest to investors as it leads to higher abnormal profits. Hence, there exists a huge gap in the existing literature. We need more empirical research to re-examine the robustness of the overreaction effect not only in developed markets but in less developed and emerging markets as well. The overreaction effect could also be further tested in financial markets other than equity. Also, a comparative study on the strength of such contrarian profits between developed and emerging markets could be undertaken as a future course of research to understand if significant difference exist in the investing behaviour of investors in the two different types of markets. This provides great opportunities for researchers to look into the area with a new outlook and different perspective.

Conclusion

In the stock market literature, a very well-known and widely accepted proposition claims that the movement of a change in share prices is best characterized by random walk. However, contrary to the argument of the hypothesis, a great deal of evidence has been discovered that future prices are predictable. There exists an unusual occurrence or abnormality in a smooth pattern of stock market. EMH has been unable to explain the existence of such anomalies. DeBondt and Thaler (1985) observed one such anomaly and referred it as 'Overreaction Effect' and was claimed as one of the most important anomalies investigated during 1980s. Since its existence, overreaction effect has been re-examined frequently and has been challenged on various factors. Despite the various challenges the overreaction effect has been recognized as an unresolved dispute. Nevertheless, the overreaction and opposite to it the under-reaction phenomena constitute examples of possible violations of market efficiency since these ideas assert that investors are likely to make profits either by buying past losers and selling past winners in the long run, or by buying past winners and selling past losers in the short run, respectively.

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Part II
Market Efficiency and Capital Market Models

Chapter 5
Single-Factor Model and Portfolio Management

Know what you own, and know why you own it.
Peter Lynch

Abstract Modern portfolio theory began with the postulation of Capital Asset Pricing Model (CAPM). It provides how a risky security is priced in competitive capital market. It is the theory of equilibrium between risk and return. It postulates a positive and linear relationship between risk and return, and maintains that non-market risk successively declines with the process of diversification. The study examines the monthly return of composite portfolio of 100 stocks of BSE 100 for the period from June 1996 to May 2005. The findings are in favour of the model by asserting a positive and linear relationship between risk and return. The study also reports that as diversification is carried out, non-market risk successfully declines. The findings support CAPM in Indian stock market in establishing a trade-off between risk and return.

Introduction

A portfolio is a collection of investments held by an investment company, hedge fund, financial institution or individual. An investor who constitutes a portfolio wish to make as much return as possible at the lowest risk compared to the money parked in a single asset. The portfolio theory explains the correlation between the expected return and the risk of the portfolio. There are several models that are used to analyse a portfolio such as the Markowitz model, factor model and single-index model.

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The single-index model is also known as the market model. In this model, the portfolio risk depends on the sensitivity of the security associated to the changes of the portfolio market return. The portfolio analysis is done on the basis of two parameters, i.e. expected return and risk of the portfolio. This model analyses the movement of the stocks caused by the market index.

Modern portfolio theory began with the postulation of Capital Asset Pricing Model (CAPM). It provides how a risky security is priced in competitive capital market. It is the theory of equilibrium between risk and return. It postulates a positive and linear relationship between risk and return, and maintains that non-market risk successively declines with the process of diversification.

The mean–variance model of Markowitz (1952), establishes a positive relationship between risk and return. It is the cornerstone of modern finance theory and a powerful tool for effective allocation of wealth in different investment alternatives. Sharpe (1964), Lintner (1965), and Mossin (1966) further extended Markowitz's work by integrating the return of a stock with the return of market. The modern Capital Asset Pricing Model (CAPM) is extensively used to address many practical problems in a number of areas of finance, including asset pricing, cost–benefit analysis, portfolio formulation and to measure the performance of a security and portfolio. One of its important applications is the construction of market portfolio for investors. This paper examines the relevance of CAPM in the Indian stock market, whether it is a suitable measure to determine the expected rate of return of a security.

CAPM: Some Conceptual Issues

CAPM suggests that the formulation of portfolio is an effective measure of diversification of portfolio risk. Diversification eliminates non-market risk which results in decline of total portfolio risk. Markowitz (1952) argues that portfolio risk is not simply weighted average risk of individual securities but it is an aggregation of co-variability of the return of different securities in the portfolio. A market portfolio includes riskless securities along with risky securities. Symbolically, it can be written as

$$E(R_p)w(R_m) + (1 - w)Ri \tag{5.1}$$

where $E\left(R_p\right)$ is expected portfolio return, w is proportion of total money invested in risky security R_m, and $1 - w$ is rest of money, which is invested in riskless securities R_f. For ease of testing, the study assumes here, portfolio includes only risky securities. Symbolically, it can be written as

$$E(R_p) = w(R_m) \tag{5.2}$$

According to CAPM, the required rate of return of a marketable security in competitive capital market can be written as

$$R_i = R_f + \beta_i[E(R_m) - R_f] + e_i \tag{5.3}$$

where R_i is expected rate of return on security, i, β_i is slope or sensitivity of security i, e_i is random variable of stock i with constant variance and zero mean value. Beta is a source of market risk. It integrates the return of a stock to the return of market, and has a significant impact upon the determination of the required rate of return of a stock. Return, expected by investors should logically be related to market risk, as opposed to total risk of the security. Klemlosky and Martin (1975) maintain that the market risk of each security in the portfolio should be assumed an appropriate measure of portfolio risk, since non-market risk can be eliminated or goes on declining with diversification. The CAPM has been stated in terms of expected return, however, it is possible to use realized return for the test of the theory. When CAPM is tested in realized return, the model symbolically, becomes

$$R_i = R_f + \beta_i(R_m - R_f) + e_i \tag{5.4}$$

To test the model further, Eq. 5.4 can be symbolically, written as

$$\bar{R}_i = y_o + y_1\beta + e_i \tag{5.5}$$

If, CAPM holds well, y_o should not be significantly different from zero and it should be equal to its theoretical value R_i. On the other hand, y_1 should be significantly different from zero and it should be equal to its theoretical value ($R_m - R_f$). In testing the model, two-phase regression techniques have been used. The first phase regression involves the estimation of the characteristic lines of all stocks passing through the observations taken from each period, variance and coefficient of determination. The second phase regression, on the other hand, is cross-sectional in nature, wherein the slope of the first regression is used in the second phase regression. This phase regression involves, return of each portfolio, which is treated as dependent variable, is regressed to the beta of each portfolio, which is treated as independent variable. The line of best-fit pass through the observations in this phase is an estimate of the security market line.

Review of Select Related Works

The CAPM has been extensively tested in the developed stock markets. Jacob (1971) study deals with 593 New York Exchange stocks for the period from 1946 to 1965. Regression analysis is performed for the periods from 1946 to 1955 and from 1956 to 1965 using both monthly and annual security return. The results show a significant positive relationship between realized return and risk during each of the 10-year period. Although the relationships estimated by the study are all positive, they are not stronger than predicted by the CAPM.

Fama and Macbeth (1973) study included the construction of 20 portfolios of securities to estimate betas from a first pass regression. Then they performed one-second pass regression for each month over the time period 1935–1968. By estimating CAPM (in cross section) for each month, they studied how the parameters change over time. The study found a significant positive relationship between realized returns and market risk. However, the slope of the relationship was found less steeper than that predicted by a CAPM model. The relationship between risk and return appears to the linear. Both market and non-market risks seem to be positively related to stock returns. The study partially supported CAPM. The empirical tests do not support the view that beta is a standard measure of risk, and high beta stocks tend to be priced so as to yield corresponding high rates of return.

Srinivasan (1988) uses a two-phase regression, to test the relationship, and the effect of diversification in Indian stock market. The first phase consists of the time series regression of 85 companies listed on the Bombay Stock Exchange (BSE), where stocks return is regressed to the market return. The second phase involves cross-sectional regression of portfolio return to portfolio beta. He finds a significant relationship between portfolio return and portfolio market risk.

Sehgal (1997) study does not support the CAPM in determining the required rate of return of an asset in the Indian stock market, thereby, does not support any relationship between return and risk. Rao et al. (1998) signify the time interval of return in maintaining the relationship between return and risk. Dhankar and Kumar (2006) examine BSE 100 stocks monthly adjusted opening and closing prices for the period 1996–2005. The study involves the formulation of ten portfolios and thereafter estimation of their expected return, market risk, and non-market risk by applying the CAPM. The study reports a high, positive significant relationship between portfolios expected return and market risk. They found that with increasing market risk of portfolios, investors get increasing returns, and so concluded that the efficient capital market theory holds well in the context of the Indian stock market.

However, Dhankar and Kumar (2007a, 2007b) study does not report the corresponding relationship between the portfolios expected return and their P/E ratios. The study, first, involves in the formulation of ten portfolios on the basis of P/E ratio, and thereafter estimates their expected return, market, and non-market risk. The ten portfolios are tested in the pooled period (1996–2005) and three sub-periods (1996–99, 2000–02 and 2003–05). The study does not report consistency between portfolios P/E and expected return. It documents that stock market does not reflect the instantaneous response to earnings announcements. However, it shows a significant relationship between portfolios expected return and market risk.

Methodology

This paper measures the relationship among risk, return, and effect of diversification on the portfolio risk in the Indian stock market by using CAPM. For this purpose, monthly adjusted opening and closing prices of composite portfolio of 100 companies' stocks of BSE 100, representing all the sectors of the economy, have been taken. These prices are adjusted with the bonus issue, right issue, and other corporate actions. The data, covers the period from June 1996 to May 2005, has been taken from PROWESS, a database maintained by CMIE Ltd. For calculating the return of the stocks, natural logarithmic mode has been used. The logarithmic difference between the prices is symmetric between up and down movements. It is expressed in percentage terms for ease of comparatability. It can be written as

$$\dot{R}_{it} = Log_{tt}\left(\frac{P_t}{P_{t-1}}\right) * 100 \tag{5.6}$$

where R_{it} is return on stock i in time period t, Log_t, is natural logarithm, P_t is closing price and P_{t-1} is the opening price.

The same method has been used for calculating the return on market index (BSE 100), symbolically, it can be written as

$$X_i = Log_i\left(\frac{I_t}{I_{t-1}}\right) * 100 \tag{5.7}$$

where X_i is return on index, I_t, is closing number and I_{t-1} is the opening number.

The CAPM asserts that return on security i, R_{it} in time period t is a linear function of market return x_i and independent factor unique to security i e_{it}. Symbolically, it can be written as

$$E(R_{it}) = \alpha_i\beta_i X_i + e_{it} \tag{5.8}$$

Beta (β) can be estimated by regressing the monthly security return to the return of index. It is calculated as

$$(\beta_i) = \frac{n\sum XR - \sum X\sum R}{n\sum X^2 - (\sum X)^2} \tag{5.9}$$

Alpha (α) is a constant intercept indicating a minimum level of return that is expected from security i, if market remains flat (neither going up not coming down), calculated as under:

$$\alpha_i = \bar{R} - \beta_i\bar{X} \tag{5.10}$$

where α_i is a constant intercept of security i, $\bar{R}$ is mean return of security i, $\bar{X}$ is mean market return of index and β_i, is slope of security i. The e_{it} is an error term representing the residuals (non-market risk) of security *i.* Given the assumptions that (1) cov (e_{it}, e_{it}) = 0 for all, i $\neq$ j, (2) cov (X_i, e_{it}) = 0 and (3) constant variance of error term (e) $\sigma_{it} = \frac{\sum e_1^2}{n-k}$, where n is the total number of observations, k is the total parameters in the equations. Total risk of a security is the sum of total market risk and total non-market risk. Symbolically, it can be written as

$$\sigma_i^2 = \beta_1^2 \sigma_{x_1}^2 + e_{it}^2 \tag{5.11}$$

where σ_i^2 is variance of stock i representing the total risk, $\beta_{it}^2 \sigma_{x_i}^2$ is total market risk and e_{it}^2 is non-market risk. By merely taking the weighted average return of individual securities, one can construct the portfolio. Here, it is assumed that equal weights have been given to each security in the portfolio. Symbolically, portfolio return can be obtained as

$$E(R_i) = \sum_{t-i}^{N} w_i(\alpha_i + \beta_1 X) \tag{5.12}$$

where R_i is portfolio return, w_i is the weight given to security i in the portfolio. For a portfolio w = 1. In the same fashion, the total risk of a portfolio is the weighted average of total risk of individual securities, which is composite of market, and non-market risk. Block (1969) argues that if the diversification is carried out effectively, the portfolio risk will be significantly less than the weighted average risk of individual stocks. For easy compatibility of risk (market risk) and return, all the securities have been arranged in the ascending order on the basis of beta value, and thereafter, ten portfolios have been formulated. The first portfolio contains ten securities having the least value of betas. The second portfolio, in the same way, covers the next ten securities having the second least value of betas and so on. From all the ten portfolios, the first portfolio can be categorized as defensive portfolio, as it shows the least response to the market. The return of this portfolio is not significantly related to the return of the market. Portfolio, on the other hand, comes on the tenth place, can be categorized as the most aggressive portfolio showing a greater degree of response to the market. The return of this portfolio is highly integrated to the return of the market. The weighted average of portfolios beta can be written as

$$\beta_p = \sum_{t=1}^{N} w_1 \beta_i \, \text{where w} = 1 \tag{5.13}$$

So far, the main objective is to test the relationship between risk (systematic risk) and return, and effect of diversification on the portfolio risk. Thereafter, the hypotheses to be tested are the following:

First phase Regression Hypotheses:

H1: The intercept alpha is not significantly different from zero.

H2: The slope beta is significantly different from zero.

Second Phase Regression Hypotheses:

H3: Intercept (y_0) is not significantly different from zero, and it is equal to its theoretical value R_f

H4: Slope (y_1) is significantly different from zero, and it is equal its theoretical value $R_m - R_f$

H5: A positive relationship exists between portfolios beta and portfolios return, i.e. the coefficient of correlation between the two is statistically significant.

H6: Process of diversification leads to reduction of non-market risk of portfolio.

To measure statistical reliability of the above hypotheses, 'Z' test is used at 5% level of significance, where the numbers of observations are less than 30, there 't' test has been applied and the calculated value of t* of both the parameters are compared with the tabular t-value (Koutsoyiannis, 1977). If t falls in the critical region ($-t_{0.025} > t^* > + t_{0.025}$) with $n - 2$ degrees of freedom, we reject the null hypotheses, and accept that estimates are statistically significant. If, on the other hand, t* falls in the acceptance region ($-t_{0.025} < t^* < + t_{0.025}$) with $n - 2$ degrees of freedom, the null hypothesis can be accepted, and it can also be admitted that estimates are not statistically significant. To calculate the expected return of the securities and portfolios, the study assumes that market will give 2% (24% annual) monthly return in the near future, and monthly interest on fixed deposit (0.44) has been taken as risk-free return.

Regression Estimates for First Phase Hypotheses

It is clear from Table 5.1 that out of 100 stocks, beta for 90 stocks are statistically significant. Likewise, most of the intercepts are not significantly different from zero. Spearman correlation coefficient between the stock beta and expected return (0.75), and the total market risk and expected return (0.62) signify the high degree of relationship between risk and stock return. The proposition of CAPM seems to be correct here. High risk yields high return, and low risk yields low return to the investors. Diversification has been carried out on the basis of the arranging of securities according to the beta value. Stocks, which come in the first end of ranking, can be categorized as less volatile. They remain less responsive to the market ups and downswings. On the other hand, stocks in the second end of ranking are highly volatile, showing a high degree of market sensitivity. Beta of a stock integrates the stock to the market developments. The ups or downswings in the market rate of return bring less or more proportional change in the return of security depending upon the beta value.

To determine, how much variation in stock return is explained by the index return, coefficient of determination (R^2) is calculated for this purpose.[1] If the value

[1]It is defined as the ratio of explained variation to the total variation. Such that $1 - R^2$ indicates the percentage of variation in the security return that is not explained by the index return.

Table 5.1 Individual stocks' return and risk

Sl. No.	Company	Var_{xy}	β_1	α_1	$\beta_i^2 * \sigma_{xi}^2$	e_{ti1}^2	β_{SE}	α_{SE}	R^2	E (R)
1.	Reliance Capital	20.00	0.12*	−3.07*	2.08	17.82	0.04	0.38	0.10	−2.85
2.	MICO	6.21	0.12	0.40	0.05	6.16	0.13	0.24	0.00	0.64
3.	Pizer Ltd.	11.20	0.22	0.10	0.16	11.09	0.18	0.32	0.01	0.54
4.	MRPL	17.90	0.23	−0.29	0.17	17.74	0.22	0.41	0.00	0.17
5.	Matrix Lab	24.80	0.24	0.13	0.20	24.61	0.26	0.48	0.00	0.61
6.	Container Corp	9.86	0.27*	−0.19	0.24	9.62	0.16	0.30	0.02	0.35
7.	Indian Rayon	7.61	0.29*	0.20	0.28	7.33	0.14	0.26	0.03	0.78
8.	Wockhardt	7.96	0.30*	−0.21	0.30	7.66	0.14	0.27	0.03	0.39
9.	Indian overseas bank	9.21	0.32	−0.51	0.25	8.97	0.26	0.42	0.02	0.13
10.	Patni Computer	2.15	0.32	−0.09	0.11	2.04	0.36	0.39	0.02	0.55
11.	HDFC Bank	4.79	0.33*	0.41	0.36	4.44	0.11	0.20	0.05	1.06
12.	IDBI	9.99	0.37*	−0.81*	0.46	9.53	0.16	0.30	0.07	-0.07
13.	Indian Oil Corp.	7.02	0.38*	0.03	0.49	6.54	0.14	0.25	0.04	0.79
14.	Cummins India.	6.80	0.39*	0.16	1.05	5.75	0.13	0.24	0.06	0.94
15.	Novartis India	7.49	0.41*	0.13	0.55	6.94	0.14	0.25	0.07	0.95
16.	Asian Paints	3.89	0.42*	0.02	0.58	3.31	0.10	0.18	0.07	0.86
17.	VSNL	8.80	0.43*	−0.32	0.61	8.19	0.15	0.28	0.02	0.54
18.	HDFC	9.00	0.46*	0.02	0.72	8.28	0.15	0.28	0.07	0.94
19.	Raymond Ltd.	8.38	0.47*	−0.51	0.72	7.65	0.14	0.27	0.08	0.43
20.	Cadila Health Centre	7.81	0.48*	−0.61	0.55	7.26	0.22	0.35	0.07	0.35
21.	Bharat Forge	12.50	0.51*	−0.06	0.88	11.60	0.18	0.33	0.07	1.08
22.	Nicholas Pirmal	7.58	0.51*	0.48	0.86	6.71	0.14	0.25	0.11	1.50
23.	Vijaya Bank	11.10	0.51*	−1.40	0.63	10.45	1.14	1.86	0.05	−0.38
24.	Blocon Ltd.	3.26	0.52*	−0.68	0.31	2.95	0.29	0.49	0.09	0.36
25.	GE Shipping Co.	7.71	0.52*	−0.53*	0.92	6.79	0.14	0.25	0.11	0.51
26.	ABB Ltd.	8.73	0.54*	0.48	0.99	7.75	0.07	0.27	0.11	1.56
27.	J & K Bank	14.50	0.55*	−0.08	1.01	13.51	0.22	0.41	0.06	1.02
28.	Nestle India	6.93	0.57*	0.31	1.08	5.85	0.13	0.23	0.15	1.45
29.	Bajaj Auto	4.48	0.59*	0.22	1.17	3.31	0.10	0.18	0.26	1.40
30.	Glaxosmith	5.97	0.59*	0.23	1.06	4.91	0.12	0.21	0.17	1.41
31.	HLL	5.23	0.60*	0.19	1.21	4.02	0.11	0.19	0.23	1.39
32.	SCI	1.50	0.60*	−0.37	1.18	10.31	0.17	0.31	0.10	0.83
33.	ITC Ltd.	5.94	0.61*	0.09	1.23	4.71	0.12	0.21	0.20	1.31
34.	Kochi Refinery	9.76	0.61*	−0.50	1.22	8.54	0.16	0.28	0.12	0.72
35.	Colgate Palmolive	4.48	0.62*	−0.29	1.29	3.19	0.09	0.17	0.28	0.95

(continued)

Table 5.1 (continued)

Sl. No.	Company	Var_{xy}	β_1	α_1	$\beta_i^2 * \sigma_{xi}^2$	e_{ti1}^2	β_{SE}	α_{SE}	R^2	E (R)
36.	Ashok Leyland	12.30	0.63*	−0.73*	1.32	10.98	0.18	0.32	0.10	0.53
37.	Lupin Ltd.	18.30	0.63*	−0.52	1.33	17.01	0.21	0.38	0.09	0.74
38.	Tata Tea Ltd.	6.73	0.63*	0.01	1.34	5.39	0.12	0.22	0.19	1.27
39.	United Phosphor	45.60	0.64	1.13	1.37	44.17	0.35	0.64	0.03	2.41
40.	Hero Honda Motor	9.29	0.65*	0.01	1.43	7.86	0.15	0.27	0.07	1.31
41.	Chennai Petroleum	11.70	0.66*	−0.36	1.46	10.22	0.17	0.31	0.12	0.96
42.	Tata Chemical	9.23	0.66*	−0.58*	1.45	7.77	0.14	0.27	0.15	0.74
43.	Sun Pharmaceutical	7.69	0.67*	−0.26	1.51	6.20	0.13	0.24	0.19	1.08
44.	Bharat Petroleum	11.70	0.68*	−0.28	1.53	10.53	0.17	0.31	0.13	1.08
45.	Hindalco Industries	6.38	0.68*	−0.01	1.54	4.84	0.12	0.21	0.24	1.35
46.	KM Bank	12.6	0.68*	0.58	1.53	11.08	0.18	0.32	0.12	1.94
47.	Ranbaxy Lab	5.67	0.69*	0.08	1.60	4.08	0.10	0.20	0.28	1.46
48.	Dr .Reddy's Lab	6.03	0.71*	0.09	1.67	4.37	0.11	0.20	0.27	1.51
49.	Rashtirya Chemical	21.60	0.71*	−0.87	1.68	19.92	0.23	0.43	0.28	0.55
50.	TVS Motor	10.50	0.71*	−0.14	1.71	8.75	0.15	0.29	0.16	1.28
51.	M &M	7.22	0.72*	0.24	1.72	5.49	0.12	0.23	0.23	1.68
52.	ONGC	8.28	0.72*	−0.21	1.72	6.56	0.14	0.25	0.20	1.23
53.	OBC	8.48	0.72*	−0.17	1.72	6.73	0.14	0.25	0.20	1.27
54.	Indian Hotels	7.98	0.74*	−0.18	1.84	6.14	0.13	0.24	0.23	1.30
55.	National Alum.	1.70	0.74*	−0.25	1.83	15.13	0.21	0.37	0.10	1.23
56.	Siemens Ltd.	9.08	0.74*	0.30	1.84	7.24	0.14	0.26	0.20	1.78
57.	Cipla Ltd.	7.02	0.78*	0.24	2.01	5.01	0.13	0.23	0.28	1.80
58.	Moser Baer	18.50	0.78*	−0.46	2.05	16.47	0.22	0.39	0.11	1.10
59.	GAIL India	7.53	0.79*	−0.08	1.86	5.66	0.14	0.24	0.24	1.50
60.	MTNL	9.61	0.79*	0.13	3.07	7.54	0.15	0.27	0.21	1.71
61.	Divi's Laboratory	12.70	0.80*	0.07	1.08	11.57	0.51	0.68	0.08	1.67
62.	Neyveli Lignite	41.50	0.81*	−0.25	2.26	39.19	0.31	0.58	0.10	1.35
63.	Hind. Petroleum	11.90	0.83*	−0.42	2.18	9.73	0.17	0.30	0.18	1.20
64.	Tata Motors	8.48	0.84*	−0.12	2.30	6.19	0.15	0.24	0.27	1.54
65.	G. Ambuja Cement	8.22	0.84*	−0.11	2.36	5.86	0.13	0.23	0.28	1.57
66.	Tata Power	8.72	0.85*	−0.50*	2.36	6.39	0.10	0.24	0.26	1.18

(continued)

Table 5.1 (continued)

Sl. No.	Company	Var_{xy}	β_1	α_1	$\beta_i^2 * \sigma_{xi}^2$	e_{ti1}^2	β_{SE}	α_{SE}	R^2	E (R)
67.	Arvind Mills	9.00	0.86*	−0.72*	2.43	6.56	0.16	0.30	0.27	0.98
68.	Reliance Energy	8.33	0.87*	−0.39	2.45	6.56	0.16	0.24	0.27	0.98
69.	Tata Iron & Steel	8.16	0.88*	0.10	2.51	5.64	0.12	0.23	0.30	1.84
70.	Maruti Udyog Ltd.	5.48	0.88*	0.21	1.330	4.15	0.33	0.45	0.24	1.97
71.	Grasim Industries	9.13	0.89*	0.09	2.64	6.49	0.14	0.25	0.28	1.87
72.	Infosys Technology	11.10	0.90	0.54	2.71	8.38	0.15	0.28	0.24	2.34
73.	Sterlite Industries	12.10	0.90*	−0.08	2.78	9.35	0.16	0.30	0.22	1.72
74.	I-Flex Solutions	13.60	0.91	−0.54	1.17	12.24	0.49	0.61	0.08	1.28
75.	UTI Bank	14.00	0.92*	−0.80*	2.88	11.11	0.20	0.38	0.20	1.04
76.	Larsen & Tubro	7.93	0.93*	−0.11	2.86	5.07	0.12	0.22	0.36	1.75
77.	Reliance Industries	7.51	0.94*	0.26	2.90	4.54	0.11	0.21	0.39	2.14
78.	Bank of Baroda	13.50	0.97*	−0.44	3.30	10.23	0.17	0.32	0.24	1.50
79.	ICICI Bank	11.10	0.97*	−0.54	2.87	8.26	0.17	0.30	0.25	1.40
80.	SAIL	17.60	0.97*	−0.87	3.16	14.38	0.20	0.37	0.18	1.07
81.	BHEL	12.10	0.98*	−0.65*	3.22	8.90	0.16	0.29	0.26	1.31
82.	Satyam Computer	13.80	0.98*	0.50	3.22	10.57	0.17	0.31	0.23	2.46
83.	Indian Petrochemical	10.90	1.01*	−0.24	3.41	7.50	0.17	0.26	0.31	1.78
84.	Bharti Televenture	10.00	1.02*	−0.27	1.92	8.10	0.34	0.46	0.19	1.77
85.	Corporation Bank	11.70	1.02*	−0.45	3.22	8.51	0.18	0.31	0.27	1.59
86.	PNB	11.40	1.03*	−0.16	1.47	9.96	0.43	0.53	0.12	1.90
87.	Bank of India	9.87	1.04*	−0.63*	3.22	6.65	0.90	0.26	0.32	1.45
88.	State Bank of India	8.42	1.05*	−0.26	0.71	4.70	0.11	0.21	0.44	1.84
89.	Tata Teleservice	10.60	1.11*	−1.74*	2.99	7.56	0.23	0.38	0.26	0.48
90.	ACC	11.70	1.14*	−0.13	4.32	7.33	0.14	0.26	0.37	2.15
91.	Wipro	13.40	1.16*	0.48	4.52	8.86	0.15	0.29	0.33	2.80
92.	Jaiprakash Asso.	11.10	1.20	0.35	1.78	9.35	0.84	0.96	0.15	2.75
93.	Zee Telefilm	20.40	1.21*	0.52	4.86	15.48	0.20	0.38	0.23	2.94

(continued)

Table 5.1 (continued)

Sl. No.	Company	Var_{xy}	β_1	α_1	$\beta_i^2 * \sigma_{xi}^2$	e_{ti1}^2	β_{SE}	α_{SE}	R^2	E (R)
94.	HCL Infosystem	18.00	1.28*	0.33	5.45	12.55	0.19	0.34	0.30	2.89
95.	Polaris Software	18.20	1.30*	−0.10	5.83	12.34	0.23	0.43	0.32	2.50
96.	Andhra Bank	13.80	1.45*	−1.06*	4.01	9.80	0.32	0.46	0.29	1.84
97.	Bharat Electronics	16.90	1.48*	−0.48	7.44	9.49	0.17	0.31	0.43	2.48
98.	HCL Technology	19.90	1.53*	−0.25	7.70	12.24	0.24	0.44	0.38	2.81
99.	Canara Bank	13.23	1.70*	−1.09	4.19	9.13	0.45	0.22	0.31	2.80
100.	Union Bank	10.90	1.70*	−0.60	4.19	6.70	0.37	0.47	0.38	2.80
Weighted Average		11.12	0.74	−0.20	1.93	9.17	0.20	0.34	0.18	129

Source Compiled from Dhankar and Kumar (2007)
Note *Significant at 5% level of significance; Var_{xy} = Variance of stocks; β_u = Standard error of beta; and α_x Standard error of alpha

of r_{RX} is 0.9, R^2 will be 0.81 and this would mean that 81% variation in the stock return is explained by index return.

Regression Estimates for Second Phase Hypotheses

It can be observed from Table 5.2 that correlation coefficient between portfolios' beta $r(E(R)\beta)$ and portfolio expected return, and between total portfolios' market risk $(r_{E(R)\beta^2\sigma_x^2})$ and portfolio expected return, which are supposed to be positive according to CAPM, are 0.98, and 0.96, respectively. Both the correlation coefficients are significant at 5% level of significance indicating positive and linear relationships. Rao et al. (1998) find positive relationship between portfolio return and portfolio beta when monthly return is used in the Indian stock Market.

Bruno (1974) also finds that the prices of a long array of stocks move together by showing a relationship to market. The rate of return on any reasonably well-diversified portfolio will be highly correlated with that of the market as a whole. The increasing value of R^2 with each successive portfolio exhibits that non-market risk is declining with the process of diversification.

From Table 5.2, it is obvious that an investor has ten alternative portfolios with different levels of returns subject to different levels of risks. However, the kind of portfolio that an investor may pick up depends on his risk-return trade-off. He will choose that portfolio, where his risk and return preferences will intersect each other.

Table 5.2 Testing of portfolio risk and return

Portfolio	Var_p	β_t	α_t	$\beta_p^2 * \sigma_x^2$	e_i^2	β_{SE}	α_{SE}	R^2	E (R_p)	R_p-R_p	t_β	$t\alpha$
P1	11.69	0.24	−0.35	0.39	11.30	0.18	0.34	0.03	0.13	−0.31	1.33	−1.02
P2	7.39	0.41	−0.15	0.60	6.78	0.14	0.26	0.08	0.68	0.24	2.94*	−0.57
P3	8.27	0.54	−0.09	0.89	7.38	0.25	0.45	0.12	0.99	0.55	2.16**	−0.20
P4	12.91	0.62	−0.09	1.29	11.64	0.16	0.30	0.14	1.14	0.70	3.87*	−0.30
P5	10.30	0.68	0.17	1.56	8.77	0.15	0.28	0.19	1.20	0.76	4.53	−0.60
P6	10.06	0.75	−0.04	1.96	8.19	0.15	0.27	0.20	1.46	1.02	5.00*	−0.14
P7	12.24	0.83	−0.21	2.12	10.12	0.21	0.35	0.22	1.47	1.03	3.95	−0.60
P8	11.76	0.93	−0.25	2.72	9.00	0.19	0.32	0.24	1.61	1.17	4.89*	−0.78
P9	11.05	1.04	−0.4	2.77	7.97	0.28	0.33	0.28	1.67	1.23	3.71	–1.21
P10	15.58	1.40	−0.19	4.98	10.59	0.32	0.47	0.31	2.60	2.16	4.37*	−0.40
Average	11.12	0.74	−0.20	1.93	9.17	0.20	0.34	0.18	1.29	0.85	3.89*	−0.05

Source Compiled from Dhankar and Kumar (2007)
Note *Significant at 5% level
**Significant at 10% level

Security Market Line (SML)

The estimates of CAPM coefficients are reported in Table 5.3. The intercept value is −0.15 with a standard error 0.10. Null hypothesis, that is, intercept term is equal to zero, is accepted. However, in case of slope, which has the value of 1.94 with a standard error of 0.12, the alternative hypothesis, that is, slope is significantly different from zero, is accepted. Srinivasan (1988) found that the intercept term was not significantly different from zero, and slope was significantly different from zero supports the above results.

When the CAPM is depicted graphically, it is called the Security Market Line. It signifies the relationship between portfolios beta and expected return. It exhibits the expected return that an investor should earn in the market for any level of market sensitivity (β). Empirical SML can be obtained by joining the portfolios' beta to the corresponding portfolios' expected return. Figure 5.1, provides the empirical SML representing various combinations of portfolios, return, and portfolios' beta, is observed to be very close to the linear theoretical SML, asserting the positive and linear relationship.

The empirical capital market line, as shown in Fig. 5.2, depicts closeness to theoretical CML, and signifies the positive and linear relationship between total market risk of portfolio and portfolio expected return. Diversification, generally, involves holding more than one stock in the portfolio, which differs from each other on some common attributes. But for the sake of convenience, here diversification was carried out on the basis of beta value of each stock.

Table 5.3 Testing of CAPM coefficients

	Regression results				Theoretical value	
	Y_0	Y_1	r	R^2	Y_0	$Y_1 = R_p - R_f$
	−0.15	1.94	0.98	0.96	0.44	1.56
SE	0.10	0.12	–	–	–	0.12
t	−1.55	16.1	15.86	–	–	13.0

Source Compiled from Dhankar and Kumar (2007)

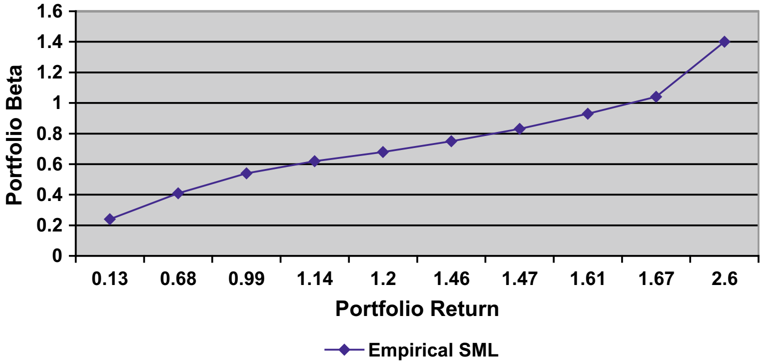

Fig. 5.1 Relationship between portfolio's beta and expected return. *Source* Compiled from Dhankar and Kumar (2007)

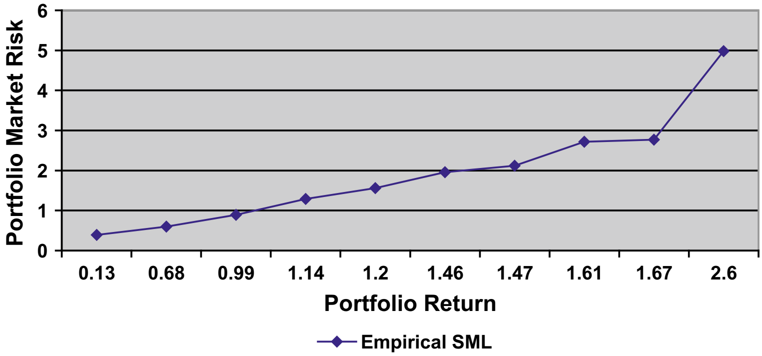

Fig. 5.2 Relationship between portfolio's market risk and expected return. *Source* Compiled from Dhankar and Kumar (2007)

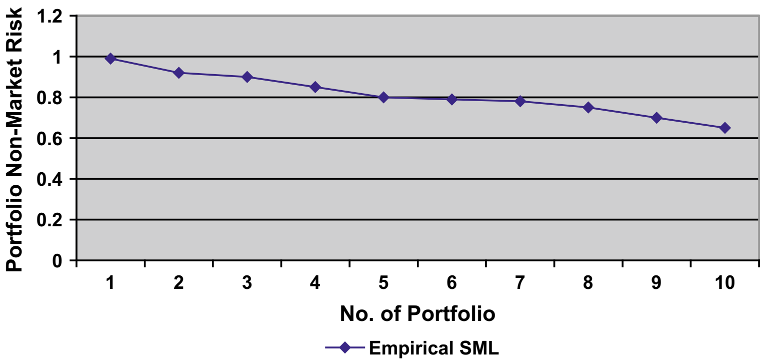

Fig. 5.3 Relationship between portfolio's non-market risk and diversification. *Source* Compiled from Dhankar and Kumar (2007)

Non-market Risk and Process of Diversification

According to CAPM, non-market risk of the portfolio will go on declining as diversification is carried out. Figure 5.3 presents the effect of diversification on the non-market risk of the portfolio. The negative sloping line which represents the various combinations of non-market risk and successive portfolio, asserts that as diversification is carried out, non-market risk successively declines.

Conclusion

The paper examines the implication of CAPM in the Indian stock market in determining the required rate of return of risky securities. Efficient capital market which assumes normality of risk and return indicates that investors can get an extra return only by bearing extra risk. CAPM assumes efficient market in determining the return and risk of risky securities. The findings of the study provide a significant relationship between risk and return. Investors can integrate the performance of their portfolios to the market developments. The significant relationship between portfolios' market risk and expected return suggests that investors are getting an excess return for taking extra risk. Investors have realized higher return by opting for higher risky portfolios. As investors move from low risky portfolios to the higher risk portfolios, their exposure to non-market risk gets reduced. The statistical validity of CAPM coefficients signifies the implication of the CAPM in the Indian stock market in determining the required rate of return of risky securities. Investors can establish a trade-off between risk and return preference by applying the CAPM. The significant relationship between risk and return also validates efficient market hypothesis in the Indian stock market.

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Chapter 6
Variance Ratio Test, ARIMA Model and Stock Price Behaviour

The real measure of your wealth is how much you would be worth if you lost all your money.
Author unknown

Abstract This study investigates the stock price behaviour of Indian stock market using BSE Sensex as well as 30 individual underlying shares included in the Sensex. Variance Ratio test for the market index suggests dependency of the aggregate market series, which violates the assumption of Random Walk Hypothesis (RWH). However, the test results manifest mixed behaviour of return generating process for individual companies. The study has also developed one forecasting model for the market index using the ARIMA process. The AR (9) model has been found to be an appropriate model for forecasting future returns to the Sensex, the validity of which is of course, subject to real-world experiments.

Introduction

For many years, financial economists have been interested in developing and testing models of stock price behaviour. One important model that has evolved from this research is the theory of Random Walk. To test Random Walk Hypothesis (RWH), one can examine the patterns of short-term movements in return series and attempt to identify the process underlying those returns. Acceptance of this hypothesis implies that stock prices are independent and one is unable to identify a pattern. On the other hand, rejection of the hypothesis has serious implications for investors, as it is possible to establish a pattern where past data can be used to predict future market movements, and thereby, one can earn profits from forecasting future prices.

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A considerable body of finance literature has tested the efficient markets model by examining individual autocorrelations and applying runs test in security returns. The early tests surveyed by Fama (1970), found little evidence of patterns in security returns and is frequently adduced in support of the efficient markets hypothesis. Recent work by Shiller and Perron (1985) and Summers (1986) has shown that such tests have relatively little power against interesting alternative hypothesis of market efficiency, which led to the evolution of a new generation of tests.

Several recent studies using new tests for serial dependence have rejected the random walk model in the US market. Lo and MacKinlay (1988) found that stock returns do not follow random walks for the US markets using a variance ratio test. Poterba and Summers (1988) suggest that the values of variance ratios give evidence of negative autocorrelations (mean reversion) at long investment horizons and positive autocorrelations at short horizons.

For other markets, Frennberg and Hansson (1993) used variance ratio test on the Swedish market and found evidence of positive autocorrelated return for short investment horizons, 1–12 months, and for longer horizons, 2 years or more, they found indications of negative autocorrelation, in line with research on the US stock market.

Shastri and Shastri (1994) analysed stocks listed on the Tokyo Stock Exchange and found evidence of deviations from the random walk for small-sized stocks using the variance ratio test. They could not reject the RWH for medium-sized and larger stocks, though. Ayadi and Pyun (1994) show that for daily data the RWH could be rejected for the Korean Stock Exchange assuming that errors are homoscedastic. However, with heteroscedastic error terms, the RWH is rejected. Lee et al. (2000) examined the French derivatives market to assess whether financial contracts were efficient. They found evidence that the RWH cannot be rejected for these contracts.

While some findings suggest that stock market prices contain predictable components and there may be significant returns to active management, others suggest that markets may be efficient. Thus, results in the literature are mixed.

Few studies have also been made in the Indian context, mostly using traditional Serial Correlation Test and Runs Test, such as Ray (1976), Sharma and Kennedy (1977), Barua (1981), Gupta (1985), Chaudhury (1991), Dhankar (1991). Majority of the findings have supported the Random Walk Hypothesis. However, the traditional Serial Correlation Test and the Runs Test used in these studies suffer from some limitations. While the former assumes normality and homoscedasticity of return distribution, the latter is non-parametric in nature. The innovation in this paper lies in the use of the sophisticated Variance Ratio (VR) test as proposed by Lo and MacKinlay (1988), which unlike the traditional models adequately address the problem of non-normality and heteroscedasticity in financial time series.[1] This study is particularly relevant in view of the evidence that financial time series possess time-varying volatilities, and therefore, deviate from normality, Malliaris and Urrutia (1991) and Karmakar (2003). Of course, Madhusoodanan (1998) tested the behaviour of stock prices by applying the 'Variance Ratio' test to the weekly data on BSE Sensitive Index, BSE National Index and also to the data on 120 individual stocks traded on BSE for the period January 1987–December 1995. The results indicated that Random Walk Hypothesis could not be accepted in the Indian market. However, this paper is different in two respects: First, the data to be used is a higher frequency data, i.e. the daily market index and individual daily stock prices. Second, if the result is found to be inconsistent with Random Walk Hypothesis, the study further attempts to develop a predictive model using ARIMA approach. On the basis of the predictive model, one may forecast future price movements and accordingly build up future trading strategies. The implication of the study may hold relevance to both academics and practitioners, and the findings will provide additional evidence to the existing literature.

The remainder of the paper is organized as follows. Section "Data and Methodology" discusses the data and methodology. Empirical results are discussed in section "Variance Ratio Test". Section "Empirical Evidence" sums up the study with concluding remarks.

Data and Methodology

The data set in our study consists of two different sub-samples. One sub-sample consists of the daily closing prices of BSE Sensex constructed by the Stock Exchange, Mumbai, for the period 1 January 1991–December 2001. This data set includes 2500 observations. To avoid thin trading bias, individual companies' daily share prices are also considered and accordingly sub-sample 2 is comprised of daily-adjusted closing prices of 30 underlying individual companies included in the BSE Sensex. The time period of the study varies from company to company. The final date is the same for all companies, i.e. 31 December 2001. While the initial date is from 1 January 1991 for 22 companies, for the rest of 8 companies, the date varies from September 1992 to February 1994. The choice of these sub-sample periods has been guided by the ready availability of the price data with the authors.

The study uses the sophisticated variance ratio test to investigate whether the market moves randomly or not. It also uses the ARIMA approach to build up a predictive model for the index series.

Variance Ratio Test

The Variance Ratio Test exploits the fact that the variance of the increments in a random walk is linear in the sampling interval. That is, if a series follows a random walk process, the variance of its q-differences would be q times the variance of its first differences. Therefore, if we obtain nq + 1 observations (Y_0, Y_1, $Y_2 \ldots Y_{nq}$) of the log of stock prices at equally spaced intervals (q is an integer greater than one), the ratio of 1/q of the variance Y_t Y_{t-q} to the variance of Yt Y_{t-1} would be equal to one.

However, while the use of a point estimate of the variance ratio[2] is not uncommon, the variance ratio test statistic (a Z-statistic) developed in Lo and MacKinlay (1988) is unique for the following reasons. First, after deriving an asymptotic distribution of the variance ratio, the Z-statistic is developed by comparing the sample variance ratio with the asymptotic variance of this variance ratio, which hence provides an asymptotic standard normal test statistic for the variance ratio. Second, the refined Z^* statistic, which is heteroscedasticity-consistent and able to use overlapping data, allows a more efficient and powerful test. Actually, it is shown in the Monte Carlo experiment performed in Lo and MacKinlay (1989) that under a heteroscedasticity null, this variance ratio test is more reliable than the Box–Pierce Q test, which is often adopted in the literature for detecting serial correlations. Moreover, the variance ratio test is also shown to be as powerful as or more powerful than either the Box–Pierce or Dickey–Fuller test against several interesting alternative hypotheses, including an AR (1), an ARIMA (1,1,1) and an ARIMA (1,1,0).

In testing the Random Walk Hypothesis in this study, both the Z and Z^* statistics are calculated for various q. By using 1-day as our base observation interval, Z and Z^* statistics are calculated for each q by comparing the variance of the base interval with that of 2-day, 4-day, 8-day, 12-day, 16-day, 20-day and 30-day observation intervals. That is, the variance ratio VR(q), for each interval q will be calculated and used to generate the corresponding Z-statistics, Z(q), for each of the intervals q-2, 4, 8, 12, 16, 20 and 30. Similarly, the heteroscedasticity-consistent Z^* statistics, Z^* (q), will also be calculated for each of the intervals q = 2, 4, 8, 12, 16, 20 and 30. It may be noted here that since the Z and Z^* statistics are both asymptotic standard normal, the conventional critical value applies when they are adopted to test the Random Walk-Hypothesis. The formulae for the calculations are presented below.

The variance ratio, VR(q), is defined as

$$\mathrm{VR(q)} = \frac{\sigma^2(q)}{\sigma^2(1)} \tag{6.1}$$

where $\sigma^2(q)$ is 1/q the variance of the q-differences and $\sigma^2(1)$ is the variance of the first differences.

The following formulae for calculating $\sigma^2(q)$ and $\sigma^2(1)$ are taken from Lo and MacKinlay (1988):

$$\sigma^2(q) = \frac{1}{m}\sum_{t=q}^{nq}(Y_t - Y_{t-q} - q\hat{\mu})^2 \tag{6.2}$$

where

$$\mathrm{m} = \mathrm{q(nq{-}q + 1)}(1 - \frac{q}{nq})$$

and,

$$\sigma^2(1)\,\frac{1}{nq-1}\sum_{t=1}^{nq}(y_t - y_{t-1} - \hat{\mu})^2 \tag{6.3}$$

where

$$\hat{\mu} = \frac{1}{nq}\,(Y_{nq} - Y_0)$$

$Y_0\ and\ Y_{nq}$ are the first and last observations of the time series.

Lo and MacKinlay (1988) also derive asymptotic standard normal test statistics for their variance ratio. The modified test statistics presented below are from Liu and He (1991). The first statistic, z(q), is developed under the maintained hypothesis of homoscedasticity:

$$zq = \frac{VR(q) - 1}{[\phi(q)]^{1/2}} \sim N(0,1) \tag{6.4}$$

where

$$\emptyset(q) = \frac{2(2q-1)(q-1)}{3q(nq)}$$

The second test statistic, $z^*(q)$, is robust to heteroscedasticity:

$$z^*(q) = \frac{VR(q) - 1}{[\phi^*(q)]^{1/2}} \sim N(0,1) \tag{6.5}$$

where

$$\emptyset^*(q) = \sum_{j=1}^{q-1}\left[\frac{2(\mathbf{q}-\mathbf{j})}{\mathbf{q}}\right]^2 \hat{\delta}(\mathrm{j})$$

and

$$\hat{\delta}(j)\,\frac{\sum\limits_{t=j+1}^{nq}(y_t - y_{t-1} - \hat{\mu})^2(y_{t-j} - y_{t-j-1} - \hat{\mu})^2}{\sum\limits_{t=1}^{nq}\left[(y_t - y_{t-1} - \hat{\mu})^2\right]^2} \sim (0,1)$$

It is interesting to note that a variance ratio of less than one suggests that the shorter interval returns tend towards mean reversion within the duration of the longer interval.[3] In contrast, a variance ratio of more than one suggests that the shorter interval returns are inclined to trend within the duration of the longer interval.[4] These patterns will be observed in the present study in section "Variance Ratio Test".

ARIMA Model

The acronym ARIMA stands for 'Auto-Regressive-Integrated-Moving Average', which is a process for forecasting a time series that can be stationarized by transformation such as differencing.

The Box–Jenkins technique, which provides a general model, called ARMA (p, q) model shown as

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_p Y_{tp} + e_t - W_{1e_{t-1}} - W_{2e_{t-2}} - \cdots - W_p e_{t-q} \tag{6.6}$$

where Y_t = dependent variable

Y_{t-1}, Y_{t-2}, … y_{t-p} = lagged variables up to p which is number of autoregressive terms.

B_1, B_2, B_p = regression coefficients

W_1, W_2, W_p = weights

e_t is the residual or error term up to q which is the number of past error terms included in the model.

ARMA models use combinations of past values and past errors, and offer a potential for fitting models that could not be adequately fitted by using an AR or MA model separately. When the time series have to be differenced to make it stationary, the model is called ARIMA instead of ARMA.

If the results of Variance Ratio test reject the Random Walk Hypothesis, then we shall attempt to identify the underlying pattern in the historical price series of the index to forecast the future price. ARIMA model of forecasting uses an iterative approach to identify the underlying pattern. To know whether a time series follows a purely AR process (and if so, what is the value of p), or a purely MA process (and if so, what is the value of q) or an ARMA process (and if so, what are the values of p and q), one can follow the Box–Jenkins Methodology.[5] Having chosen a particular ARIMA model, and having estimated its parameters, we will see whether the chosen model fits the data reasonably well.

One simple test of the chosen model is to see if the residuals estimated from this model are white noise, i.e. whether all the serial correlations of the residuals for lags I through m, are simultaneously equal to zero. For this purpose, one can use the Ljung–Box (LB) statistic, developed by Ljung and Box (1978), which is defined as

$$LB = \mathrm{n}(\mathrm{n}+2)\sum_{k=1}^{m}\frac{r^2 k}{n-k} \sim x^2(m\,d.f)$$

where

n = sample size,
m = lag length

The LB statistic is approximately (i.e. in large samples) distributed as the Chi-square distribution with m d.f. In an application, if the computed LB exceeds the critical LB value from the Chi-square table at the chosen level of significance, one can reject the null hypothesis that all r_k are zero; at least some of them must be nonzero, implying rejection of white noise. If the residuals are white noise, we can accept the parameter fit; if not, we must start over. Thus, the methodology is an iterative process.

Empirical Evidence

In this section, we first investigate the Random Walk Hypothesis using Variance Ratio test. If the RWH is violated, we will try to predict the trend by fitting an appropriate ARIMA model.

Result of Variance Ratio Test

By using one trading day as our base interval, the Random Walk Hypothesis is tested by calculating the VR(q) and the Z (q) for each of the cases q = 2, 4, 8, 12, 16, 20 and 30. In addition, the heteroscedasticity-consistent variance ratio test is also performed by calculating VR (q) and Z^* (q) for each of the cases q = 2, 4, 8, 12, 16, 20 and 30. The results for the Sensex and the individual companies are presented in Table 6.1. It is shown in the table that under the maintained hypothesis of homoscedasticity, there is evidence rejecting the Random Walk Hypothesis for the BSE Sensex. For example, for the sensex, the Z-statistic associated with intervals q = 2, 4, 8, 12, 16, 20 and 30 are 3.19953, 3.27307, 2.75072, 3.14989, 3.23582, 3.38093 and 2.77412, respectively. Compared with the conventional critical value (which is 1.96 for the 5% level), all the Z's indicate that the variance ratios are significantly different from one at 5% level. The Random Walk Hypothesis, is therefore, rejected for the sensex.

Further, since the results obtained from these Z (q)'s are under the maintained hypothesis of homoscedasticity, the rejections of the random walk may either be due to heteroscedasticity or serial correlation. To investigate this issue, a heteroscedasticity-consistent variance ratio test (the Z^* test) is also implemented. The test results in Table 6.1 indicate that under the assumption of heteroscedasticity also, the variance ratios for the Sensex are significant for all values of q, except, q = 30. This implies that the variance ratio is different from one due to autocorrelation, rather than to heteroscedasticity.

Table 6.1 Estimates of Variance Ratio VR (q) and Variance Ratio Test Statistics Z(q) and $Z^{*}(q)$

BSE Sensex and 30 individual companies	Particulars	Q = 2	Q = 4	Q = 8	Q = 12	Q = 16	Q = 20	Q = 30
BSE Sensex	VR	1.06399	1.1224	1.1628	1.2363	1.2850	1.3360	1.3428
	Z	3.1995*	3.2730*	2.7507*	3.1498*	3.2358*	3.3809*	2.7741*
	Z*	2.0873*	2.1046*	1.8086	2.0525*	2.1042*	2.2037*	1.8198
1	VR	1.0510	1.0848	1.1731	1.2556	1.3170	1.3585	1.3199
	Z	2.5527	2.2648*	2.9240*	3.4071*	3.5989*	3.6101*	2.5890*
	Z*	1.8022	1.6155	2.1265*	2.5152*	2.6912*	2.7306*	1.9884*
2	VR	1.0686	1.1279	1.1656	1.1962	1.2089	1.2183	1.2331
	Z	3.4314*	3.4198*	2.7976*	2.6148*	2.3716	2.1969*	1.8868
	Z*	2.3473*	2.3516*	1.9389	1.8591	1.7115	1.5996	1.4087
3	VR	0.9146	0.85064	0.8731	0.8943	0.9050	0.9300	0.9359
	Z	−3.839*	−3.591*	−1.928	−1.2645	−0.968	−0.632	−0.4659
	Z^{b}	−2.231*	−2.206*	−1.255	−0.8473	−0.663	−0.441	−0.3349
4	VR	1.1062	1.1399	1.1026	1.0633	1.0564	1.0766	1.0373
	Z	5.3098*	3.7377*	1.7329	0.8436	0.6405	0.7681	0.3022
	Z*	2.736*	1.6135	0.8525	0.4450	0.3486	0.4260	0.1732
5	VR	1.0112	1.0503	1.0323	1.0310	1.0765	1.0881	1.1123
	Z	0.5607	1.3451	0.5468	0.4141	0.8693	0.8867	0.9089
	Z*	0.2553	0.6437	0.2812	0.2208	0.4714	0.4849	05027
6	Z VR	1.1261	1.1880	1.2566	1.2994	1.3477	1.4096	1.4644
	Z	6.2723*	4.9983*	4.3141*	3.9716*	3.9211*	4.0877*	3.7360*
	Z*	2.9568*	2.4735*	2.0921	2.0062*	2.0810*	2.2696*	2.2592*
7	VR	1.0212	1.0176	1.0457	1.0805	1.0875	1.0979	1.1190
	Z	1.0611	0.4709	0.7727	1.0732	0.9938	0.9852	0.9634
	Z*	0.5499	0.2718	0.4937	0.7085	0.6645	0.6642	0.6621

(continued)

Table 6.1 (continued)

BSE Sensex and 30 individual companies	Particulars	Q = 2	Q = 4	Q = 8	Q = 12	Q = 16	Q = 20	Q = 30
8	VR	1.0363	1.0969	1.1683	1.1798	1.1649	1.1591	1.1342
	Z	1.8153	2.5919*	2.8426*	2.3970*	1.8719	1.6011	1.0864
	Z*	1.0387	1.4997	1.7866	1.5908	1.2922	1.1384	0.8154
9	VR	1.0226	1.0208	0.9681	0.9710	0.9665	0.9986	1.0258
	Z	1.1339	0.5563	−0.5386	−0.3852	−0.379	−0.0132	0.2091
	Z*	0.6379	0.3352	−0.3508	−0.2555	−0.255	−0.0089	0.1448
10	VR	1.1149	1.2341	1.3415	1.3424	1.2780	1.2375	1.2524
	Z	5.7461*	6.2587*	5.7687*	4.5639*	3.1558*	2.3896*	2.0432*
	Z*	3.8513*	4.3272*	4.1078*	3.3121*	2.3176*	1.7714	1.5237
11	VR	1.0176	1.0260	1.0636	1.0733	1.0451	1.0593	1.0228
	Z	0.8810	0.6958	1.0757	0.9768	0.5119	0.5942	0.1845
	Z*	0.6046	0.4984	0.7994	0.7278	0.3829	0.4457	0.1409
12	VR	1.0868	1.1504	1.1878	1.2249	1.2277	1.2428	1.2669
	Z	4.3383*	4.0182*	3.1733*	2.9979*	2.5847*	2.4332*	2.1606*
	Z*	3.2326*	2.7711*	2.2002*	2.1195*	1.8490	1.7451	1.5740
13	VR	1.0683	1.0947	1.0071	0.9756	0.9430	0.9642	0.9918
	Z	3.4154*	2.5312*	0.1208	−0.3245	−0.6464	−0.3578	−0.0659
	Z*	1.8258	1.3897	0.0665	−0.1811	−0.3664	−0.2061	−0.0388
14	VR	0.9988	0.9980	0.9790	0.9874	1.0089	1.0051	0.9692
	Z	−0.052	−0.046	−0.3245	−0.152	0.0930	0.0474	−0.2283
	Z*	−0.035	−0.032	−0.2332	−0.111	0.0684	0.0351	−0.1709
15	VR	1.0268	1.0711	1.1080	1.1278	1.1709	1.2088	1.1942
	Z	1.3381	1.8939	1.8196	1.6998	1.9335	2.0930*	1.5622
	Z*	0.5600	0.8891	0.9952	1.0008	1.1844	1.3219	1.0265

(continued)

Table 6.1 (continued)

BSE Sensex and 30 individual companies	Particulars	Q = 2	Q = 4	Q = 8	Q = 12	Q = 16	Q = 20	Q = 30
16	VR	1.1458	1.2157	1.1763	1.1494	1.2098	1.2471	1.2931
	Z	6.5562*	5.1825*	2.6772*	1.7893	2.1403*	2.2352*	2.1312*
	Z*	4.5215*	3.7076*	1.9886*	1.3522	1.6352	1.7253	1.6844
17	VR	1.2645	1.3522	1.4153	1.1444	1.4522	1.4700	1.4832
	Z	13.225*	9.4137*	7.0147*	5.9211*	5.1330*	4.7287*	3.9107*
	Z*	7.3676*	5.1033*	3.9420*	3.3817*	2.9908*	2.7990*	2.3612*
18	VR	1.3592	1.4285	1.5055	1.5669	1.5591	1.5675	1.4738
	Z	17.960*	11.453*	8.5377	7.5553*	6.3467*	5.7093*	3.8346*
	Z*	8.9251*	5.9262*	4.6735*	4.1721*	3.5126*	3.1798*	2.1669*
19	VR	1.4682	1.5596	1.6016	1.6586	1.6657	1.7046	1.7114
	Z	23.414*	14.957*	10.161*	8.7771*	7.5566*	7.0887*	5.7569*
	Z*	13.828*	9.3771*	6.5610*	5.8430*	5.1282*	4.8542*	4.0129*
20	VR	1.0543	1.0807	1.1118	1.1048	1.0414	1.0069	0.9915
	Z	2.4453*	1.9434	1.7008	1.2594	0.4229	0.0629	−0.0616
	Z*	1.5082	1.2649	1.1457	0.8583	0.2938	0.0444	−0.0450
21	VR	1.0384	1.0193	0.9631	0.9489	0.9380	0.9376	0.9137
	Z	1.9200	0.5165	−0.6231	−0.679	−0.703	−0.6248	−0.6977
	Z*	1.3596	0.3588	−0.4497	−0.506	−0.534	−0.4815	−0.5431
22	VR	1.0721	1.1111	1.1494	1.2127	1.2969	1.3541	1.4299
	Z	3.2461*	2.6739*	2.2732*	2.5481*	3.0289*	3.2025*	3.1262*
	Z*	1.8832	1.6264	1.4593	1.6945	2.0752*	2.2451*	2.2686*
23	VR	1.0469	1.0963	1.0926	1.0946	1.1124	1.1334	1.2022
	Z	2.3403*	2.5691*	1.5619	1.2819	1.2718	1.3370	1.6363
	Z*	1.1842	1.4141	0.9479	0.8056	0.8150	0.8672	1.0951

(continued)

Table 6.1 (continued)

BSE Sensex and 30 individual companies	Particulars	Q = 2	Q = 4	Q = 8	Q = 12	Q = 16	Q = 20	Q = 30
24	VR	1.0541	1.0939	1.0933	1.1367	1.1258	1.1198	1.0901
	Z	2.7056*	2.5105*	1.5761	1.8226	1.4289	1.2059	0.6356
	Z*	1.9765	1.7968	1.1439	1.2905	0.9965	0.8343	0.5466
25	VR	1.0588	1.1154	1.0668	1.0480	1.0547	1.0602	0.9399
	Z	2.5651*	2.6893*	0.9834	0.5584	0.5401	0.5287	−0.4497
	Z*	1.8435	1.9872*	0.7596	0.4461	0.4411	0.4411	−0.3495
26	VR	0.9500	0.9247	0.9048	0.9057	0.9183	0.9195	1.0321
	Z	−2.317*	−1.8674	−1.492	−1.1643	−0.858	−0.7491	0.2600
	Z*	−1.3754	−1.1583	−1.001	−0.8204	−0.625	−0.5588	0.1796
27	VR	1.0359	1.1386	1.2887	1.4351	1.5475	1.6148	1.6581
	Z	1.7735	3.6538*	4.7782*	5.7140*	6.1345*	6.0863*	5.2617*
	Z*	0.4264	0.9493	1.4832	2.0033*	2.3254*	2.4423*	2.3081*
28	VR	1.0963	1.1658	1.2275	1.2605	1.2672	1.2949	1.3132
	Z	4.8172*	4.4314*	3.8440*	3.4724*	3.0333*	2.9669*	2.5350*
	Z*	3.4041	3.2319*	2.9064*	2.6931*	2.3976*	2.3785*	2.0829
29	VR	1.0390	1.0493	1.0691	1.1114	1.1635	1.2029	1.2098
	Z	1.9509	1.3186	1.1682	1.4850	1.8559	2.0414*	1.6982
	Z*	1.4931	0.9961	0.8972	1.1483	1.4432	1.6013	1.3596
30	VR	1.1789	1.3343	1.3445	1.4264	1.4836	1.5177	1.4938
	Z	7.8361*	7.8223*	5.0925*	4.9683*	4.7947*	4.5410*	3.4818*
	Z*	4.9464*	5.2543*	3.6015*	3.5966*	3.5358*	3.4042*	2.6789*

Source Compiled from Dhankar and Chakraborty (2015)
Note Name of companies against their respective serial number and time period are given in Appendix 1

In other words, the random walk is rejected for the index because of autocorrelations of daily increments in the stock price series. For the individual companies, the variance ratios and test statistics show mixed results. A look at Table 6.1 reveals that there are 9 companies, which have no significant variance ratio at any lag under homoscedastic assumption, and 14 companies under heteroscedastic assumption. This implies that for these 14 companies, the price movements are not autocorrelated, i.e. randomness prevails for these shares and hence trying to predict the share prices using any technique could not have produced good results. However, predictability is there for the rest of 16 companies. It is also interesting to note the pattern in the values of q being more or less than one. From Table 6.2, also summarizes the number of companies having variance ratios significantly different from one under both the conditions. It indicates that variance ratio was significantly different from one for 20 out of 30 companies at lag 2 under the assumption of homoscedasticity and 12 out of 30 companies under the condition of heteroscedasticity. For lags 4, 8, 12, 16, 20 and 30, the number of companies significantly different from one was 20, 14, 13, 15 and 11, respectively, under homoscedastic assumption and 12, 11, 10 and 9 companies, respectively, under heteroscedastic assumption.

Thus, the evidence produced by the Variance Ratio test in respect of individual stock prices manifest mixed behaviour of return generating process in India. The stock prices seem to be dependent at some lag or the other for 16 companies, suggesting therefore, that Random Walk Model is not valid at least for these companies. However, the result is not deviated from Random Walk for the rest of 14 companies.

Predictive Model of Market Return

The result of Variance Ratio Test has indicated the rejection of Random Walk Hypothesis for the market index and 16 individual companies. This implies the possibility of building predictive models for developing trading strategies. An

Table 6.2 No. of variance ratio greater and less than one and no different from one: (Individual companies)

q	VR > 1	VR < 1	Homoscedastic	Heteroscedastic
2	27	3	20	12
4	27	3	20	11
8	25	5	14	9
12	24	6	13	10
16	25	5	13	10
20	25	5	15	9
30	24	6	11	9

Source Compiled from Dhankar and Chakraborty (2015)

attempt has been made here to identify one ARIMA model for the market index. To identify a particular ARIMA model, one has to compare the autocorrelations and partial autocorrelations of the stationarized log price series with the corresponding distribution for the various ARMA models, as suggested by Box–Jenkins methodology. Tables 6.3 and 6.4, respectively, display autocorrelation and partial correlation of the stationary log price series. It appears from Table 6.3 that the autocorrelations are significant at lags k = 1, 6, 7, 9, 10, 16 and 19 and rest of them are statistically not different from zero.

Table 6.4 indicates that the partial autocorrelations at lags 1, 6, 7, 9, 16 and 19 are statistically significant but the rest are not. If the autocorrelation and partial autocorrelation coefficients were significant only at lag 1, we could have identified this as an MA (1) or AR (1) model, respectively. Let us, therefore, assume that the process that generated the (first differenced) log price is at the most an AR (19) or MA (19) process. We have tried ARIMA for different values of p and q models including AR (19) and MA (19) for the whole sample period and AR (9) was found to fit the data quite well. The diagnostic checking shows that the sum of the 20 squared autocorrelations, as shown by Ljung–Box statistic (LB = 29.092, p-value = 0.086) is not statistically significant. The estimated parameters of the model are shown in Table 6.5, which reveals that the regression coefficients B_1, B_6,

Table 6.3 Autocorrelation coefficients and Ljung–Box statistics at 20 lags for the first differenced log price series of BSE Sensex

Lag	Autocorrelation	SE	Ljung–Box	Prob.
1	0.065*	0.020	10.455	0.001
2	0.022	0.020	11.698	0.003
3	0.007	0.020	11.811	0.008
4	0.030	0.020	14.000	0.007
5	−0.020	0.020	14.893	0.011
6	−0.052*	0.020	21.653	0.001
7	0.058*	0.020	30.158	0.000
8	−0.019	0.020	31.054	0.000
9	0.098*	0.020	55.215	0.000
10	0.042*	0.020	59.551	0.000
11	−0.001	0.020	59.555	0.000
12	−0.024	0.020	60.990	0.000
13	−0.037	0.020	64.476	0.000
14	0.33	0.020	67.153	0.000
15	0.021	0.020	68.263	0.000
16	0.057*	0.020	76.324	0.000
17	−0.011	0.020	76.623	0.000
18	−0.007	0.020	76.739	0.000
19	−0.055*	0.020	84.341	0.000
20	−022	0.020	85.608	0.000

Source Compiled from Dhankar and Chakraborty (2015)

Table 6.4 Partial correlation coefficients at 20 lags for the first differenced log price series of BSE Sensex

Lag	Partial correlation	SE
1	0.065*	0.020
2	0.018	0.020
3	0.004	0.020
4	0.029	0.020
5	−0.023	0.020
6	−0.051*	0.020
7	0.066*	0.020
8	−0.026	0.020
9	0.101*	0.020
10	0.032	0.020
11	−0.016	0.020
12	−0.024	0.020
13	−0.036	0.020
14	0.034	0.020
15	0.035	0.020
16	0.046*	0.020
17	−0.018	0.020
18	−0.022	0.020
19	−0.065*	0.020
20	−0.10	0.020

Source Compiled from Dhankar and Chakraborty (2015)

Table 6.5 Estimated parameters of AR (9): 1–2500 observations

Variables	Coefficient	SE	Prob.
AR1	0.0703	0.0199	0.0004
AR2	0.0126	0.0199	0.5290
AR3	0.0061	0.0199	0.7567
AR4	0.0338	0.0199	0.0893
AR5	−0.0242	0.0199	0.2241
AR6	−0.0548	0.0199	0.0059
AR7	0.0662	0.0199	0.0008
AR 8	−0.0324	0.0199	0.1048
AR 9	0.1021	0.0199	0.0000
Constant	0.0434	0.0476	0.3619

Source Compiled from Dhankar and Chakraborty (2015)

B_7 and B_9 have significant values. Using these parameters, which are significantly different from zero, we obtain the following AR process, which may be the tentative forecasting model. Let P* denote logarithmic first differences of stock price, then,

$$P^{*}t = InPt - InP_{t-1} = 0.0703P^{*}_{t-1} - 0.548P^{*}_{t-6} + 0.0662p^{*}_{t-2} + 0.1021p^{*}_{t-9}$$
$$S.E. = (0.0199)(0.0199)(0.0199)(0.0199)$$
$$P = (0.0004)(0.0059)(0.0008)(0.0000)$$

On the basis of the above equation, one may try to predict the trend and develop trading strategies. But, since the coefficients in the equation are in a sense averages over the sample data, one would have to be pretty confident that these 'average effects' were to persist in the future. In order to beat the market using the above equation, one would have to undertake repeated investments sequentially. One may also try to predict the trend and estimate the fitted ARIMA process to develop a trading strategy for the 16 non-random walks individual companies, following the same procedure as used with the market index. However, the question of whether the fitted model is economically relevant, is subject to real-world experiments, taking into consideration all transaction costs, bid–ask spreads and managerial and dealers' time and efforts.

Concluding Remarks

The study uses Variance Ratio test to investigate Random Walk Hypothesis in Indian stock market using BSE Sensex as well as 30 individual underlying shares included in the Sensex. The VR test for the index suggests dependency of the aggregate market series, which violates the assumption of Random Walk Hypothesis. However, the test results manifest mixed behaviour of return generating process for individual companies. 16 companies have been found to show dependence while the rest of 14 companies could be described by the Random Walk Hypothesis. Of course, the Lo–MacKinlay variance ratio test used here suffers from the limitation that it ignores the joint nature of the variance ratio test statistics. Nevertheless, the rest is more appealing than any of the other traditional tests of random walk. The study has also developed one forecasting model for the market index using the ARIMA process. The AR (9) model has been found to be an appropriate model for forecasting future returns to the Sensex, the validity of which is of course, subject to real-world experiments.

It is thus, evident from the study that the Indian market cannot be described as perfectly random, or absolutely non-random. In fact, this situation is true for most markets of the world, as in reality, markets are neither accurately efficient nor completely inefficient. All markets are efficient to a certain extent, some more so than others. Rather than being an issue of black or white, market efficiency is more a matter of shades of grey. Investors as well as analysts will be well advised not to accept market efficiency or inefficiency as a straight-jacketed fact of economic life.

Notes

1. Other important merits of the variance ratio test are discussed in the section on methodology.
2. See, for example, Huizinga (1987), Fama and French (1988) and Cochrane (1988).
3. One variation of serial dependence is called mean reversion. With mean reversion, returns revert to an average value or asset prices revert to an equilibrium value. If an asset is priced above its equilibrium value, its price will not change randomly; it will be more inclined to decrease than to increase. Conversely, if an asset is priced below its equilibrium value, it will be more likely to increase than to depreciate further.
4. Another variation of serial dependence is known as trending. In a trending pattern, a positive return is more likely to be followed by another positive return than a reversal, and a negative return is likely to be succeeded by another negative return than a positive return.
5. The method consists of four steps: Step 1. Identification, Step 2. Estimation, Step 3. Diagnostic checking and Step 4. Forecasting (see Box & Jenkins, 1978). The first step in model identification is to determine whether the series is stationary. If the series is not stationary, it can generally be converted to stationary series by the method of differencing. Once a stationary series has been obtained, the analyst must identify the form of the model to be used. This step is accomplished by comparing the autocorrelation and partial autocorrelation coefficients of the data to be fitted with the corresponding distributions for the various ARMA models. In general, the analyst should identify the autocorrelations that drop off exponentially to zero. If the partial autocorrelations trail off, an MA process is indicated; if both trail off, a mixed ARMA process is indicated. By counting the number of autocorrelation and partial-autocorrelation coefficients that are significantly different from zero, the analyst can determine the order of the MA and/or AR process.

Appendix 1: Names of 30 Companies Used in the Study

Serial No.	Name	Time period
1	ACC	January 1, 1991–December 31, 2001
2	Bajaj Auto Ltd.	January 1, 1991–December 31, 2001
3	BHEL	October 12, 1992–December 31, 2001
4	BSES	January 1, 1991–December 31, 2001
5	Castrol	January 1, 1991–December 31, 2001
6	Cipla	January 1, 1991–December 31, 2001
7	Colgate	January 1, 1991–December 31, 2001
8	Dr. Reddy's Lab	January 1, 1991–December 31, 2001

(continued)

(continued)

Serial No.	Name	Time period
9	Glaxosmith Pharm	January 1, 1991–December 31, 2001
10	Grasim Inds.	January 1, 1991–December 31, 2001
11	Gujarat Ambuja Cem	January 1, 1991–December 31, 2001
12	HINDALCO	January 1, 1991–December 31, 2001
13	HILL	January 1, 1991–December 31, 2001
14	HPCL	September 11, 1992–December 31, 2001
15	ICICI Bank	January 1, 1991–December 31, 2001
16	Infosys Technologies	June 14, 1993–December 31, 2001
17	ITC	January 1, 1991–December 31, 2001
18	L&T	January 1, 1991–December 31, 2001
19	M&M	January 1, 1991–December 31, 2001
20	MTNL	April 13, 1993–December 31, 2001
21	Nestle	January 1, 1991–December 31, 2001
22	NIIT	May 24, 1993–December 31, 2001
23	Ranbaxy Laboratories	January 1, 1991–December 31, 2001
24	Reliance Industries	January 1, 1991–December 31, 2001
25	Reliance Petroleum	February 14, 1994–December 31, 2001
26	Satyam Computers	November 26, 1992–December 31, 2001
27	SBI	January 1, 1991–December 31, 2001
28	TELCO	January 1, 1991–December 31, 2001
29	TISCO	January 1, 1991–December 31, 2001
30	Zee Telefilms	November 25, 1993–December 31, 2001

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Chapter 7
Multifactors Model and Portfolio Management

The moral justification of capitalism lies in the fact that it is the only system consonant with man's rational nature, that it protects man's survival qua man, and that its ruling principle is: justice.
Ayn Rand, Capitalism: The Unknown Ideal

Abstract Emerging stock market returns have been extensively studied by academic community over the past two decades. However, there is still no consensus among the researchers and practitioners as to which asset pricing models should be used to explain returns in these markets. The basic objective of the study is to evaluate the power and performance of multifactor asset pricing models (three and four factor model) over the traditional one factor CAPM, using the data from one of the fastest growing emerging market: India. The study using a large sample data of 470 listed stocks over a period of 16 years stretching from January 1997 to March 2013, evaluate the relevance of Fama and French three factor model as well as liquidity augmented four factor model in explaining the stock return variations in the Indian stock market. The study employs time series regression approach to examine the impact of market risk, size risk, value risk and liquidity risk on stock returns. The overall results of the study provide support to the multi-dimensional nature of risk and suggest the use of multifactor asset pricing models for consideration in investment decisions. Both Fama and French three factor model and liquidity augmented four factor model were found to be superior than traditional one factor CAPM. Though, liquidity augmented four factor model was found to be slightly better in explaining Indian stock returns as compared to Fama and French three factor model.

This chapter draws from the author's previous published work (Maheshwari & Dhankar, 2016) co-authored with **Supriya Maheshwari,** Faculty of Management Studies, University of Delhi, Delhi, India., and originally published in *IIMS Journal of Management Science*, Vol. 7 No. 3.

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Introduction

Asset Pricing theory deals with the understanding of the prices or values of claims to uncertain cash flows. The Capital Asset Pricing Model (CAPM) attempts to account for differences in returns across risky assets on the basis of differences in systematic risk or beta. Thus it is termed as single factor model. But given the fact that the positive abnormal returns accruing to common stocks that have low price-earnings ratios, small corporate capitalization and less institutional ownership, a pricing model that incorporates such factors in addition to systematic risk may provide estimates of return superior to those derived from a conventional Capital Asset Pricing Model.

Till the 1980s, CAPM dominated the financial literature and was widely advocated owing to its simplicity in calculating expected returns of the underlying asset. However, in the more recent times, the empirical records of the model were found to be unsatisfactory. The model failed to explain various stock market anomalies that were identified by academicians such as size effect (Banz, 1981), value effect (Rosenberg, Reid, & Lanstein, 1985), price-earning effect (Basu, 1977), cash-flow-to-price effect, overreaction effect (DeBondt & Thaler, 1985) and momentum effect (Jegadeesh & Titman, 1993). Such stock market anomalies have suggested that the single market factor (or CAPM beta) is not found to be sufficient enough in explaining differences in stock returns. As results, the focus of academicians switched towards multifactor asset pricing models. However, the central empirical issue that remains unresolved is the choice of factors that best account for differences in the returns and can be used as potential sources of risk in asset pricing models.

This motivated (Fama & French, 1993) to propose a three-factor model that could explain various stock market anomalies. The rationale given by Fama and French in suggesting a multifactor model was the enduring need for the complicated asset pricing model that can explain stock market anomalies. Fama and French (1992, 1993) proposed a multifactor model that was based on the market risk as well as the risk based on size and value [measured by book-to-market (B/M) ratio] for better estimates of returns. Fama and French (1993)] argued that as empirical findings show higher returns on stocks with small size and high B/M ratio than those predicted by CAPM, both size and B/M ratios can be used as better proxies for exposure to sources of systematic risk that CAPM failed to capture. Fama and French (1993) proposed that the three-factor model captures much of the variations in the stock returns as well as size, value, cash-flow-to-price effect and long-term reversal effect that were missed by traditional one-factor CAPM. However, the proposition made by Fama and French remains controversial on the economically meaningful risks of the Fama–French factors (Black, 1993; Bodie et al., 2009; Hong & Stein, 1999). There is an ongoing debate on interpreting Fama–French three-factor model as a rational risk model (Black, 1993; Cooper et al., 2004; Griffin, 2002). Even though Fama and French three-factor model claims to capture most of the stock market anomalies such as size and value effect, it still fails to explain abnormal returns from momentum investing. Hence, even (Fama & French, 1993) three-factor model is not considered as perfect asset pricing model, and the same is even accepted by Fama and French (2012), who stated, 'the model's explanation of average returns is far from complete. Despite all the criticism, Fama and French (1993) is represented as a major asset pricing model that successfully explained 70% of the changes in the United States stock returns (Unlu, 2013).

The debate over a sound model of returns has motivated academicians to search for other potential sources of risks. Carhart (1997) augmented the three-factor model by adding momentum factor. Using US mutual fund data, Carhart (1997) advocates that by enlarging the three-factor model by momentum factor the explanatory power of model could be increased by 15%. More recently, Fama and French (2012) investigated the Carhart (1997) four-factor model in the international stock market. Even though four-factor model was found to perform better in analysing portfolio returns internationally, it failed to explain excess momentum profits. Similar results were reported by Cakici, Fabozzi, and Tan (2013) when they replicated the work of Fama and French (2012) on emerging markets. In addition to Carhart (1997) momentum augmented four-factor model, academicians also tried to study the implication of liquidity for asset pricing. The earlier evidence of the role of liquidity in asset pricing was shown by Amihud and Mendelson (1986), Datar, Naik, and Radcliffe (1998), Amihud (2002). More recently, Chan and Faff (2005) using the Australian data examined the role of liquidity factor in Fama and French framework by adding liquidity as an additional factor in the three-factor model and concluded that liquidity could be used as an important risk factor.Similar results were obtained by Rahim and Nor (2006) and Unlu (2013), who reported that in addition to the market risk, factors like firm size, B/M ratio and liquidity constitute an important part of risk factor models, as they too affect the stock returns. Pastor and Stambaugh (2003), on the other hand, augmented the Carhart (1997) four-factor model into a five-factor model by adding a liquidity factor.

Nevertheless, there is growing amount of evidence that suggests the importance of company-specific characteristics in explaining stock returns. Even though there are some international studies supporting the validity of these company-specific characteristics–based asset pricing models in the United States and other developed stock markets, not much have been done to investigate the same in emerging markets. Emerging stock markets are identified as markets with unusual characteristics that differ from developed markets (Antoniou et al., 2005; Barry et al., 1998; Cakici et al., 2013; Chan & Hameed 2006; Harvey 1995). Moreover, Griffin (2002) observed that multifactor asset pricing models have different explanatory power in different countries. Hence, it is difficult to comment on the general ability of these models to explain stock returns globally. Given these caveats, there is a clear need for additional studies that test the validity of multifactor asset pricing models in a wide variety of stock markets outside the United States. The current study contributes the literature on the same aspects.

The current study tests the power of multifactor asset pricing models, including three- and four-factor models that attracted the attention of global investment community, to explain asset pricing in the Indian stock market. Some prior studies have independently evaluated the size, value and liquidity premium in the Indian stock market. Hence, it would be further interesting to test the role of these factors in asset pricing for the Indian investors. The current study, apart from enriching the existing literature, contributes in several additional aspects. The study evaluates if multifactor model performs better than traditional CAPM in markets outside the United States and other developed economies. From the perspective of domestic investors, the study will help in evaluating a better asset pricing model for pricing Indian stocks and portfolios.

The rest of the paper is organised as follows: "Data and Methodology" provides a description of data and methodology employed including the procedure adopted to construct different portfolios and risk factors. "Empirical Findings" show the empirical findings of the study which are further discussed in "Discussion". "Conclusion" concludes the paper.

Data and Methodology

Data Structure and Definitions

The data comprises month-end adjusted closing prices of sample companies from January 1997 to March 2013. The initial sample consists of all the stocks listed on Bombay Stock Exchange (BSE). However, due to non-trading and data restrictions, only those companies were selected that have completed monthly price data for the sample period. As a result, a sample of 470 stocks was selected. Data on stock prices, index values, company fundamentals such as size, value and liquidity were collected from CMIE Prowess database. The BSE sensitive index was used as the proxy for the return on the market portfolio. The implicit yield at the cut-off price on 91-day Treasury bills has been used as a surrogate for the risk-free proxy, and the same was collected from the Reserve Bank of India website. The monthly prices of sample stocks were converted into arithmetic returns.

To form the portfolios, the study uses monthly market portfolio return, monthly size, monthly value and monthly liquidity for the sample period to compute market, size, value and liquidity factor. The firm size is measured by market capitalisation or market value of equity. It is calculated as total shares outstanding multiplied by the current share price. Following Fama and French (1993, 2006, 2012), the value of the stock is measured using B/M ratio. It is the ratio of book value of equity to current market value (or the price of equity). However, using (Tripathi, 2008) operational definition of B/M ratio, it is calculated as an inverse of price-to-book ratio. A similar methodology is adopted by Hou, Karolyi, and Kho (2011) in calculating the B/M ratio for global stock markets. The study uses stock turnover as the measure of trading volume. Trading volume (volume) is defined as the average monthly turnover in the percentage during the portfolio formation period, where monthly turnover is the ratio of the number of shares traded each month to the number of shares outstanding at the end of the month. As suggested by Chordia and Swaminathan (2000), the turnover measure disentangles the effect of firm size on trading volume. As raw trading volume data is unscaled; it is highly correlated with the size of the firm.

Calculation of Risk Factors and Regression Tests

Risk factors size [represented as small minus big (SMB)], value [represented as high minus low (HML)] and liquidity [represented as illiquid minus very liquid (IMV)] are computed using the ($2 \times 3 \times 3$) sort as described in Chan and Faff (2005). At the start of each year, all the sample stocks were ranked by size (market capitalisation) and were split into small (S) and big (B) groups, by a median. Next, both the subgroups were independently sorted into three groups: low (L), medium (M) and high (H), based on the B/M ratio. Such double sorting as reported by Chan and Faff (2005) produces six portfolios (S/L, S/M, S/H; B/L, B/M and B/H). These six portfolios were independently sorted into three groups: very liquid that is high turnover stocks (V), neutral liquid (N) and illiquid (I) that is having low turnover stocks. Based on this $2 \times 3 \times 3$ sort, 18 portfolios were constructed, namely S/L/V, S/L/N, S/L/I, S/M/V, S/M/N, S/M/I, S/H/V, S/H/N, S/M/I; B/H/V, B/L/N, B/L/I, B/M/V, B/M/N, B/M/I, B/H/V, B/H/N and B/H/I based on the intersection of two size, three B/M and three liquidity groups (Chan & Faff, 2005). The equal weight returns for each of the portfolio were calculated over the next 12 months. Portfolios were reformed at the start of each year using the above sorting method.

The SMB risk factor is calculated, using (Chan & Faff, 2005), as the difference between the simple average of the returns on the nine small stock portfolio (S/L/V, S/L/N, S/L/I, S/M/V, S/M/N, S/M/I, S/H/V, S/H/N and S/H/I) and the simple average returns of the stocks contained in the nine big portfolio (B/L/V, B/L/N, B/L/I, B/M/V, B/M/N, B/M/I, B/H/V, B/H/N and B/H/I). Similarly, the HML factor is calculated as the difference between the simple average of the return on the six high B/M portfolio (S/H/V, S/H/N, S/H/I, B/H/V, B/H/N and B/H/I) and the average of the return on the low B/M portfolio (S/L/V, S/L/N, S/L/I, B/L/V, B/L/N and B/L/I). The IMV risk factors is the difference between the simple average returns on the six illiquid stock portfolios (S/L/I, S/M,I, S/H/I, B/L/I, B/M/I and B/H/I) and the simple average returns on the six very liquid portfolios (S/L/V, S/M/V, S/H/V, B/L/V, B/M/V and B/H/V). According to Chan and Faff (2005), the advantage of forming such 18 portfolios is that all portfolios are orthogonalised with each other and, hence, are free from any reciprocal effect. This is critical concerning size, B/M as well as liquidity portfolios as there is a concern in the academic literature that IMV factor may act as a proxy for size or value effect.

$$\mathrm{SMB} = \frac{\mathrm{S/L/V + S/L/N + S/L/I + S/M/V + S/M/N + S/M/I + S/H/V + S/H/N + S/H/I}}{9} - \frac{\mathrm{B/L/V + B/L/N + B/L/I + B/M/V + B/M/N + B/M/I + B/H/V + B/H/N + B/H/I}}{9}$$

$$\mathrm{HML} = \frac{\mathrm{S/H/V + S/H/N + S/H/I + B/H/V + B/H/N + B/H/I}}{6} - \frac{\mathrm{S/L/V + S/L/N + S/L/I + B/L/V + B/L/N + B/L/I}}{6}$$

$$\mathrm{IMV} = \frac{\mathrm{S/L/I} + \mathrm{S/H/I} + \mathrm{B/L/I} + \mathrm{B/M/I} + \mathrm{B/H/I}}{6} - \frac{\mathrm{S/L/V} + \mathrm{S/M/V} + \mathrm{S/H/V} + \mathrm{B/L/V} + \mathrm{B/M/V} + \mathrm{B/H/V}}{6}$$

The returns of six portfolios (S/L, S/M, S/H; B/L, B/M and B/H) as well as of 18 portfolios (S/L/V, S/L/N, S/L/I, S/M/V, S/M/N, S/M/I, S/H/V, S/H/N, S/M/I; B/H/V, B/L/N, B/L/I, B/M/V, B/M/N, B/M/I, B/H/V, B/H/N and B/H/I) were used as dependent variables (R_p) in time series regression. The following regression models were tested to estimate the stock returns:

- Regression using only the market factor (R_{mt}–R_{ft}) as explanatory variable also known as CAPM (Single index model).

$$R_{\mathrm{Pt}} - R_{\mathrm{ft}} = \alpha_P + \beta_m (R_{\mathrm{mt}} - R_{\mathrm{ft}}) + \varepsilon_{\mathrm{t}}$$

- Regression using market factor (R_m–R_f), SMB and HML as explanatory variables also known as Fama and French three-factor model.

$$\mathrm{R_{pt}} - \mathrm{R_{ft}} = \alpha_{\mathrm{p}} + \beta_{\mathrm{M}}(\mathrm{R_{Mt}} - \mathrm{R_{ft}}) + \beta_{\mathrm{S}}\mathrm{SMB_t} + \beta_{\mathrm{h}}\mathrm{HML_t} + \varepsilon_{\mathrm{t}}$$

- Regression using market factor (R_m–R_f), SMB, HML and IMV as explanatory variables also known as Chan and Faff (2005) four-factor model.

$$\mathrm{R_{pt}} - \mathrm{R_{ft}} = \alpha_{\mathrm{p}} + \beta_{\mathrm{M}}(\mathrm{R_{Mt}} - \mathrm{R_{ft}}) + \beta_{\mathrm{S}}\mathrm{SMB_t} + \beta_{\mathrm{h}}\mathrm{HML_t} + \beta_{\mathrm{i}}\mathrm{IMV_t} + \varepsilon_{\mathrm{t}}$$

The beta coefficients in above equations represent sensitivity coefficient (or slope coefficients) of different risk factors. To investigate the validity of asset pricing model, the focus is given on the intercepts parameter (α) that are obtained by regressing the various portfolio returns over potential sources of risk. If the alpha value (α) is significantly different from zero, then, there is a pricing error in the model and there are other risk factors that are not explained by the model (Chan & Faff, 2005; Fama & French, 1993; Unlu, 2013). Hence, for an ideal asset pricing model, the regression intercepts must be zero for all test portfolios.

In addition, following the literature, study also utilises GRS [as suggested by Gibbons, Ross, and Shanken (Gibbons, Ross, & Shanken, 1989) test statistics to evaluate the performance of different models. GRS F test is used to jointly test the intercepts equal to zero. The GRS statistics is described as follows:

$$\mathrm{GRS} = \left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\widehat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}}\right] \sim F(N, T-N-L)$$

where T is the number of observations, N is the number of regressions, L is the number of explanatory facts in the regression. $\hat{\alpha}$ is a vector of regression intercepts, $\widehat{\Sigma}$ is the residual covariance matrix in the sample, $\bar{\mu}$ is the vector of the factors portfolios means and $\hat{\Omega}$ is an unbiased estimate of the factor portfolios covariance matrix. The null hypothesis of the test is that all α_i coefficients obtained from the model are equivalent to zero ($\alpha_i = 0\ \forall_i$).

Before running the regression, the stationarity of the variable was tested using Augmented Dickey–Fuller (ADF) test. Using ADF-test, all variables were found to be stationary. The subsequent tests were employed to test the multicollinearity among the explanatory variables. The variance inflation factor (VIF) was calculated between the variables to detect the multicollinearity among the explanatory variables. VIF among all the regressions for market, size and book-to-ratio and liquidity factor was found to be near to 1 and less than 4. Hence, there is no evidence of multicollinearity among the Fama–French three factors and Chan and Faff four factors. In addition, the standard errors from the regression were corrected for autocorrelation and heteroskedasticity using Newey–West standard errors.

Empirical Findings

Descriptive Statistics

Table 7.1 presents the descriptive statistics of the explanatory variables. It is clear from the table that only SMB is large both statistically as well as from the investment perspective in the Indian stock market. In agreement with Fama and French (1993, 1996) and Chan and Faff (2005), positive premiums are observed for all the remaining three risk factors: Market, HML and IMV. The positive returns from SMB, HML and IMV portfolios suggest that there is a negative relation between size (or liquidity) and average return and positive relation between value and average return of the stocks. However, the observed value and (il)liquidity premium are extremely small (and statistically non-significant) as compared with size premium in the Indian stock market.The low value premium and strong size premium in the Indian stock market was also reported by previous studies such as Sehgal (2005).

Table 7.1 Descriptive statistics and correlation coefficients

	Descriptive statistics			Correlation coefficients			
	Mean	*t*(Mean)	Std. Dev.	R_m-R_f	SMB	HML	IMV
R_m-R_f	0.0660	1.227	0.0762	1.0000	–0.020	0.034	–0.430
SMB	0.0111	2.858*	0.0544	–	1.000	0.260	0.309
HML	0.0048	1.766**	0.0380	–	–	1.000	0.048
IMV	0.0033	1.602	0.0293	–	–	–	1.00

Source Compiled from Maheshwari and Dhankar (2016)
*Significant at 5%
**Significant at 10%

Table 7.2 Single-factor CAPM regression of monthly excess returns on six portfolios

Portfolio	α	β_m	Adj.R^2	F statistics
S/L	0.0147 (0.022)*	1.0879 (0.000)*	0.471	173.99 (0.000)*
S/M	0.0143 (0.021)*	0.9680 (0.000)*	0.427	145.63 (0.000)*
S/H	0.0161 (0.029)*	1.0035 (0.000)*	0.356	108.53 (0.000)*
B/L	0.0052 (0.089)**	0.9827 (0.000)*	0.774	666.65 (0.000)*
B/M	0.0042 (0.272)	1.0270 (0.000)*	0.715	488.65 (0.000)*
B/H	0.0076 (0.112)	1.0964 (0.000)*	0.613	308.41 (0.000)*
GRS F test	3.806 (0.001)*			

Source Compiled from Maheshwari and Dhankar (2016)
The table represents coefficients of time series regression of excess stock returns on CAPM. Sample period consists of 195 monthly observations. The t-statistics has been corrected for the effects of heteroskedasticity and autocorrelation using the method of Newey and West
*Significant at 5%
**Significant at 10%

Further, the Pearson correlations among the four explanatory variables are observed to be low (lower than 0.6) as presented in Table 7.1. The correlation among the factors is low which is desirable in multifactor pricing framework.

Accuracy and Validation of Competing Asset Pricing Models

The regression results pertaining to one factor CAPM are given in Table 7.2. Initially, the validity of CAPM and other multifactor asset pricing models are tested using six size and value-based portfolios. The F values and probability values of all the models suggest that models are significant.

It is clear from Table 7.2 that market factor explains a lot of variations in stock returns for the six portfolios, and market beta is found to be highly significant for all the six regressions. The single-factor CAPM produces adj. R^2 ranges from 0.356 to 0.774 with an average model fit of 0.55 in the current sample. The R^2 values are relatively lower for small stocks portfolios (S/L, S/M and S/H) showing the failure of market factor in explaining size effect in the Indian stock market. Moreover, the single market factor model (CAPM) generated statistically significant (at 5% level) positive intercepts for three small stock portfolios, indicating the failure of CAPM to explain stocks returns of size- and value-based Indian portfolios. Further, GRS test statistics also suggests failure of null hypothesis as GRS p-value are less than 5 per cent, rejecting the CAPM. Overall, the results from the study challenge the acceptability of CAPM as an ideal asset pricing model for the Indian stock market.

Using the three- as well as four-factor asset pricing models (Table 7.3), the intercepts of all the six size- and value-based portfolios are observed to be statistically not different from zero (at 5% level). GRS p-values are also observed to be above 5% for both three- and four-factor models, hence null hypothesis is failed to be rejected. Such results provide support in favour of multifactor asset pricing models in the Indian stock market.

The average model fit (as suggested by adj. R^2 value) increased for multifactor asset pricing models (both three and four) as compared with single-factor CAPM. The adj.R^2 value ranges from 0.788 to 0.875 with an average model fit increases to 0.82 with Fama and French three-factor model. The same ranges from 0.795 to 0.878 with an average model fit of 0.836 using Chan and Faff four-factor model. The liquidity augmented four-factor model has improved the R^2 value, suggesting that (Chan & Faff, 2005) four factor model to some extent, can capture more common variations in stock returns in the Indian stock market.

Table 7.3 also suggests the pervasive and significant market factor (or risk) even in the presence of other risk factors. The SMB factor is highly significant for all six sizevalue–based portfolios, though the coefficient of size factor increases with decrease in size, providing additional support to size effect in the Indian stock market. The HML slope becomes steeper as one moves from low-to-high-value portfolios providing support to value premium. Even though, IMV factor explains variations in stock returns, it is priced significantly negative across all the six sizevalue–based portfolios that indicate positive liquidity premium among size-based portfolios.

Robustness Check

It has been argued in the literature (e.g. Lewellen, Nagel, & Shanken, 2010) that many multifactor asset pricing models (especially Fama and French three-factor model) perform better in explaining average returns of size-B/M-based portfolios but failed to explain excess returns of portfolios sorted on other ways. Hence, the capability of asset pricing model must not be judged only from their capability to explain excess returns for size-B/M portfolio. Considering this caveat, an additional test is performed on additional portfolios to test the validity of underlying asset pricing models. Specifically, for further robustness, the validity of multifactor asset pricing model is checked over 18 size–value–liquidity-based portfolios. The results for the same are presented in Tables 7.4 and 7.5.

The market factor loadings are again found to be statistically significant across all the 18 size–value–liquidity-based portfolios,though CAPM failed to explain excess returns from the portfolios where 8 portfolios generated statistically significant positive intercepts (Table 7.4). The Fama and French (1993) three-factor model is again found to be successful in capturing excess returns from all the portfolios, except one, suggesting supremacy of three-factor model over CAPM. Similar results are obtained for Chan and Faff (2005) four-factor model (Table 7.5).

The loadings on size factor are found to be statistically significant and monotonically increasing as one moves from big-to-small-size stocks. On the other hand, the HML factor loadings decrease from high-to-low-value stocks. Considering the liquidity augmented four-factor model, the IMV factor loadings increase monotonically when moving from the most liquid portfolio to the least liquid portfolio. The factor loadings are observed to be positive for the least liquid portfolios and

Table 7.3 Multifactor model regression of monthly excess returns on six portfolios

	Fama and french three-factor model						Chan and faff four-factor model						
Portfolio	α	β_m	β_s	β_h	Adj.R^2	F value	α	β_m	β_s	β_h	β_i	Adj.R^2	F value
S/L	–0.0004 (0.901)	1.1079 (0.000)*	1.3674 (0.000)*	–0.0447 (–0.321)	0.846	356.51 (0.000)*	0.0008 (0.809)	1.0295 (0.000)*	1.4576 (0.000)*	–0.0808 (0.522)	–0.4853 (0.000)*	0.855	288.14 (0.000)*
S/M	–0.0013 (0.684)	0.9783 (0.000)*	1.2234 (0.000)*	0.4142 (0.000)*	0.875	454.45 (0.000)*	–0.0005 (0.874)	0.9304 (0.000)*	1.2791 (0.000)*	0.3922 (0.000)a	–0.2967 (0.018)*	0.878	353.03 (0.000)*
S/H	–0.0222 (0.605)	1.0124 (0.000)*	1.3781 (0.000)*	0.6226 (0.000)*	0.839	339.11 (0.000)*	–0.0013 (0.751)	0.9592 (0.000)*	1.4394 (0.000)*	0.5981 (0.000)*	–0.3295 (0.004)*	0.842	262.03 (0.000)*
B/L	0.0024 (0.376)	0.9916 (0.000)*	0.3519 (0.000)*	–0.2366 (0.041)*	0.812	281.32 (0.000)*	0.0032 (0.256)	0.9457 (0.000)*	0.4048 (0.000)a	–0.2578 (0.011)*	–0.2844 (0.008)*	0.818	219.86 (0.000)*
B/M	–0.0008 (0.816)	1.0262 (0.000)a	0.3196 (0.000)*	0.3174 (0.009)*	0.788	242.54 (0.000)*	0.0000 (0.990)	0.9750 (0.000)*	0.3786 (0.000)*	0.2938 (0.000)*	–0.3171 (0.008)*	0.795	189.20 (0.000)*
B/H	–0.0007 (0.836)	1.0833 (0.000)*	0.3195 (0.000)*	1.0037 (0.000)*	0.821	298.84 (0.000)*	0.0005 (0.868)	1.0072 (0.000)*	0.4079 (0.000)*	0.9683 (0.000)*	–0.4751 (0.000)*	0.833	243.23 (0.000)*
GRS F test	1.894 (0.083)						1.837 (0.094)						

Source Compiled from Maheshwari and Dhankar (2016)

The table represents coefficients of time series regression of excess stock returns on multifactor asset pricing models (three and four factor). Sample period consists 195 monthly observations. The *t*-statistics has been corrected for the effects of heteroskedasticity and autocorrelation using the method of Newey and West

*Significant at 5%

**Significant at 10%

Table 7.4 Single-factor CAPM regression of monthly excess returns on 18 portfolios

Portfolio	α	β_m	Adj.R^2	F statistics
S/L/V	0.01266 (0.083)	1.2396 (0.000)*	0.482	182.07 (0.000)*
S/L/N	0.0117 (0.003)*	0.9748 (0.000)*	0.458	165.40 (0.000)*
S/L/I	0.0197 (0.009)*	1.0493 (0.000)*	0.361	110.75 (0.000)*
S/M/V	0.0089 (0.161)	1.0446 (0.000)*	0.458	165.14 (0.000)*
S/M/N	0.0131 (0.033)*	0.9933 (0.000)*	0.434	150.17 (0.000)*
S/M/I	0.0210 (0.002)*	0.8632 (0.000)*	0.312	89.16 (0.000)*
S/H/V	0.0183 (0.006)*	1.1223 (0.000)*	0.386	123.24 (0.000)*
S/H/N	0.0153 (0.021)*	0.9975 (0.000)*	0.378	119.21 (0.000)*
S/H/I	0.0318 (0.000)*	0.9041 (0.000)*	0.248	65.00 (0.000)*
B/L/V	0.0016 (0.584)	1.0591 (0.000)*	0.814	854.34 (0.000)*
B/L/N	0.0075 (0.062)	1.0090 (0.000)*	0.673	401.47 (0.000)*
B/L/I	0.066 (0.108)	0.8799 (0.000)*	0.632	335.22 (0.000)*
B/M/V	0.0053 (0.224)	1.0562 (0.000)*	0.655	370.00 (0.000)*
B/M/N	0.0059 (0.170)	1.0329 (0.000)*	0.690	434.03 (0.000)*
B/M/I	0.0014 (0.701)	0.9917 (0.000)*	0.705	466.62 (0.000)*
B/H/V	0.0108 (0.050)*	1.1635 (0.000)*	0.559	274.51 (0.000)*
B/H/N	0.0082 (0.094)	1.1183 (0.000)*	0.625	325.28 (0.000)*
B/H/I	0.0037 (0.398)	1.0074 (0.000)*	0.575	263.84 (0.000)*
GRS F test	4.944 (0.0000)*			

Source Compiled from Maheshwari and Dhankar (2016)
The table represents coefficients of time series regression of excess stock returns on CAPM. Sample period consists of 195 monthly observations. The t-statistics have been corrected for the effects of heteroskedasticity and autocorrelation using the method of Newey and West
*Significant at 5%
**Significant at 10%

negative for the most liquid portfolios. In addition, there is also some evidence that suggests higher IMV loadings for small size stocks as compared with big size stocks. This provides support to Amihud (2002) findings, who suggested that excess returns of small size stocks are in part a premium of illiquidity of these stocks.

Comparing the average model fit (adj.R^2), the multifactor asset pricing model again found to be superior as compared with CAPM in the Indian stock market. The average model fit for the 18 portfolio is observed to be 0.524 using one single-factor CAPM. This increases to 0.787 for Fama and French (1993) three-factor model and 0.802 for Chan and Faff (2005) liquidity augmented four-factor model. Overall, the results provide support in favour of multifactor asset pricing models in the Indian stock market. In addition, the results suggest that liquidity explains a portion of common variations in stock returns and, hence, constitute an important part of risk factor models. Moreover, comparing the adj. R^2 values, it is observed that adding a liquidity factor to the Fama and French (1993) three-factor model results in improvement of model's ability to explain stock returns in the Indian stock market.

Table 7.5 Multifactor model regression of monthly excess returns on 18 portfolios

	Fama and french three-factor model						Chan and faff four-factor model						
Portfolio	α	β_m	β_s	β_h	Adj.R^2	F value	α	β_m	β_s	β_h	β_i	Adj.R^2	F value
S/L/V	–0.0004 (0.918)	1.2645 (0.000)*	1.3299 (0.000)*	–0.3834 (0.114)	0.725	171.71 (0.000)*	0.0035 (0.431)	1.0235 (0.000)*	1.6079 (0.000)*	–0.4944 (0.006)*	–1.4960 (0.000)*	0.803	195.43 (0.000)*
S/L/N	–0.0015 (0.681)	0.9867 (0.000)*	1.0920 (0.000)*	0.2097 (0.1383)	0.796	253.66 (0.000)*	–0.0009 (0.807)	0.9535 (0.000)*	1.1302 (0.000)*	0.1944 (0.1837)	–0.2055 (0.200)	0.797	191.85 (0.000)*
S/L/I	0.0006 (0.869)	1.0722 (0.000)*	1.6760 (0.000)*	0.0436 (0.757)	0.845	3555.42 (0.000)*	–0.0000 (0.996)	1.1120 (0.000)*	1.6302 (0.000)*	0.0619 (0.660)	0.2464 (0.159)	0.847	269.63 (0.000)*
S/M/V	–0.0054 (0.197)	1.0569 (0.000)*	1.1295 (0.000)*	0.3395 (0.013)*	0.797	255.88 (0.000)*	–0.0037 (0.396)	0.9572 (0.000)*	1.2442 (0.000)*	0.2937 (0.011)*	–0.617 (0.001)*	0.813	213.16 (0.000)*
S/M/N	–0.0016 (0.646)	1.0009 (0.000)*	1.1129 (0.000)*	0.4822 (0.000)*	0.819	297.79 (0.000)*	–0.0006 (0.861)	0.9409 (0.000)*	1.1820 (0.000)*	0.4546 (0.000)*	–0.3718 (0.020)*	0.825	230.10 (0.000)*
S/M/I	0.0029 (0.386)	0.8763 (0.000)*	1.4295 (0.000)*	0.42207 (0.000)*	0.859	397.16 (0.000)*	0.0027 (0.447)	0.8929 (0.000)*	1.4104 (0.000)*	0.4297 (0.000)*	0.1028 (0.506)	0.859	297.50 (0.000)*
S/H/V	0.0003 (0.929)	1.1211 (0.000)*	1.1586 (0.000)*	1.0453 (0.000)*	0.806	270.62 (0.000)*	0.0037 (0.360)	0.9194 (0.000)*	1.3908 (0.000)*	0.9525 (0.000)*	–1.2494 (0.000)*	0.857	293.62 (0.000)*
S/H/N	–0.0020 (0.539)	1.0060 (0.000)*	1.2997 (0.000)*	0.5821 (0.000)*	0.838	336.99 (0.000)*	–0.0016 (0.639)	0.9806 (0.000)*	1.3290 (0.000)*	0.570 (0.000)*	–0.1576 (0.369)	0.838	253.33 (0.000)*
S/H/I	0.0098 (0.010)*	0.9199 (0.000)*	1.7378 (0.000)*	0.5206 (0.002)*	0.837	334.71 (0.000)*	0.0084 (0.033)*	1.0044 (0.000)*	1.6405 (0.000)*	0.5595 (0.001)*	0.5234 (0.005)*	0.845	267.35 (0.000)*
B/L/V	–0.0002 (0.944)	1.0680 (0.000)*	0.2866 (0.000)*	–0.2849 (0.019)*	0.838	337.85 (0.000)*	0.0015 (0.580)	0.9664 (0.000)*	0.4035 (0.000)*	–0.3316 (0.001)*	–0.6291 (0.000)*	0.869	323.46 (0.000)*
B/L/N	0.0045 (0.207)	1.0202 (0.000)*	0.3984 (0.000)*	–0.3270 (0.047)*	0.713	162.42 (0.000)*	0.0057 (0.113)	0.9536 (0.000)*	0.4751 (0.000)*	–0.3576 (0.022)*	–0.4172 (0.001)*	0.724	128.76 (0.000)*
B/L/I	0.0029 (0.430)	0.8868 (0.000)*	0.3702 (0.000)*	–0.0972 (0.381)	0.679	137.97 (0.000)*	0.0024 (0.523)	0.9172 (0.000)*	0.3352 (0.000)*	–0.0832 (0.462)	0.1885 (0.230)	0.680	104.42 (0.000)*
B/M/V	–0.0007 (0.833)	1.0522 (0.000)*	0.3289 (0.000)*	0.5094 (0.000)*	0.756	202.03 (0.000)*	0.0004 (0.894)	0.9776 (0.000)*	0.4148 (0.000)*	0.4750 (0.000)*	–0.4622 (0.003)*	0.768	162.42 (0.000)*

(continued)

Table 7.5 (continued)

	Fama and french three-factor model						Chan and faff four-factor model						
Portfolio	α	β_m	β_s	β_h	Adj.R^2	F value	α	β_m	β_s	β_h	β_i	Adj.R^2	F value
B/M/N	0.0003 (0.923)	1.0359 (0.000)*	0.4241 (0.000)*	0.1768 (0.179)	0.769	216.71 (0.000)*	0.0014 (0.712)	0.9676 (0.000)*	0.5028 (0.000)*	0.1456 (0.209)	–0.4233 (0.000)*	0.780	173.69 (0.000)*
B/M/I	–0.0020 (0.517)	0.9900 (0.000)*	0.2007 (0.004)*	0.2723 (0.033)*	0.744	189.47 (0.000)*	–0.0019 (0.621)	0.9801 (0.000)*	0.2121 (0.004)*	0.2677 (0.035)*	–0.0163 (0.680)	0.744	141.58 (0.000)*
B/H/V	0.0007 (0.843)	1.1492 (0.000)*	0.3971 (0.000)*	1.1829 (0.000)*	0.801	261.80 (0.000)*	0.0028 (0.470)	1.0241 (0.000)*	0.5411 (0.000)*	1.1254 (0.000)*	–0.7749 (0.000)*	0.827	232.25 (0.000)*
B/H/N	0.0081 (0.824)	1.1042 (0.000)*	0.2285 (0.000)*	1.0274 (0.000)*	0.809	274.90 (0.000)*	0.0019 (0.606)	1.0362 (0.000)*	0.3067 (0.000)*	0.9961 (0.000)*	–0.4207 (0.013)*	0.817	218.42 (0.000)*
B/H/I	–0.0037 (0.289)	0.9985 (0.000)*	0.3313 (0.000)*	0.8020 (0.000)*	0.746	191.56 (0.000)*	–0.0030 (0.401)	0.9615 (0.000)*	0.3738 (0.000)*	0.7850 (0.000)*	0.2290 (0.137)	0.748	145.37 (0.000)*
GRS F test	3.320 (0.002)*						2.950 (0.003)*						

Source Compiled from Maheshwari and Dhankar (2016)

The table represents coefficients of time series regression of excess stock returns on multifactor asset pricing models (three and four factor). Sample period consists 195 monthly observations. The t-statistics has been corrected for the effects of heteroskedasticity and autocorrelation using the method of Newey and West

*Significant at 5%

**Significant at 10%

These results provide support to the findings of Datar et al. (1998), Chan and Faff (2005), Rahim and Nor (2006), Unlu (2013) and others, who reported that liquidity plays an important role in explaining variations in stock returns even after controlling for size, B/M ratio and the firm beta.

However, it is important to mention here that according to the GRS statistics (Tables 7.4 and 7.5), all models –CAPM, three- and four-factor models are rejected for 18 portfolios sorted on size, value and liquidity. The GRS *p*-values are found to be less than 5% for all the three models suggesting the failure of null hypothesis. The rejections are weaker when using four-multifactor model (with higher *p*-value) relative to CAPM, suggesting better performance of multifactor models from econometric perspective. Similar results were obtained by Fama and French (1993, 2012) and Cakici et al. (2013) for three-factor model who also reported high GRS value (or low GRS *p*-values) for multifactor asset pricing models. However, Fama and French (1993, 2012) argued that despite the failure from GRS test, three-factor model performs better in explaining average stock returns and, hence, is suitable from the economic perspective. Based on similar argument, despite rejection from GRS statistics, the low intercepts and high R^2 provide support in favour of multifactor asset pricing models in the Indian stock market.

Discussion

There are several findings from the study that are worth reiterating. The study provides support for multifactor asset pricing models as compared with CAPM in the Indian stock market. The failure of CAPM in explaining excess returns from various size, value and liquidity-based portfolios suggest CAPM as a miss-specified model as it omits certain risk-factors. These results are consistent with the findings of Fama and French (1993) for the United States and Connor and Sehgal (2003) for the Indian stock market. However, both three-factor and liquidity-augmented four-factor model may not be absolute and ideal for application in the Indian stock market. It may not be so because of the resulted non-zero intercept for S/H/I portfolio. This point to the fact that even liquidity augmented four-factor model's explanation of average returns is far from complete. Some risk factors, other than market risk, size, value and liquidity risk, such as momentum (Carhart, 1997), investment factor (Chen & Zhang, 2010), profitability (Fama & French, 2015) as well as macroeconomic factors have been proposed in the literature. Also, a portion of the academic literature (concentrating to behavioural finance) emphasises the use of psychological and behavioural elements of price determination. Hence, it would be interesting to explore the effect of these variables on the asset pricing models in the Indian stock market. The same is left for the future research.

The study also provides support to Lewellen et al. (2010) and Artmann et al. (2012) findings that suggest that the Fama and French three-factor model validity is highly dependent on the underlying test assets. The Fama and French (1993) three-factor model works extremely well for size-B/M-based portfolios but were not entirely successful in explaining returns of liquidity-based portfolios in the Indian stock market.

The failure of CAPM, three-factor and liquidity-augmented four-factor model in capturing excess returns from S/H/I portfolio suggests profitable investment opportunity in the Indian stock market. S/H/I portfolio consists small, high-value and illiquid stocks. Hence, the positive and statistically significant intercept for the S/H/I portfolio suggests that small size, high-value and illiquid stocks portfolio are not easily beaten in the Indian stock market. Moreover, as size and value premium are already captured by multifactor asset pricing models, it can be argued that illiquidity premium cannot be captured by three or liquidity-augmented four-factor model in the Indian stock market.

Conclusion

The study conducted an empirical comparison of asset pricing models in the Indian stock market, including CAPM, Fama and French (1993) three-factor model and Chan and Faff (2005) liquidity-augmented four-factor model. In general, similar to developed stock markets, Indian stock market also supports multifactor asset pricing model over single-factor CAPM. The market factor even though has high predictability power for various size, value and liquidity-based portfolios, the incorporation of other risk factors (SMB, HML and IMV) suggests the superiority over the CAPM. Also, the results of the study provide support to the literature regarding the role of liquidity in asset pricing models. The liquidity-augmented four-factor model suggested its supremacy over Fama and French (1993) three-factor model in explaining variations in stock returns. However, even liquidity-augmented four-factor model's explanation of average returns is found to be far from complete suggesting some missing factor in the model. The findings also point towards the presence of size and value premium in the Indian stock market.

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Chapter 8
Market Efficiency and Stock Market

Invest in yourself; your career is the engine of your growth.
Paul Clitheroe

Abstract This study examines the concept of variable efficiency (time-varying levels of efficiency) and time-varying return predictability in the Indian stock market, which are the implications of Adaptive Markets Hypothesis (AMH). We apply linear tests to examine the time-varying dependence in two different indices of the Bombay Stock Exchange (BSE) in India, i.e. Sensex (benchmark) and BSE 500 (broad-based) Index. We utilize rolling window approach to analyse the impact of observation period, time horizon and data frequency, on the weak form level of market efficiency. The results suggest patterns that are consistent with the implications of Adaptive Markets Hypothesis for both the indices. The broad-based BSE 500 Index has been found to be more inefficient than the benchmark Sensex.

Introduction

In a modern society, especially a capitalistic one, there is some form of capital market to serve as a bridge between fund providers and fund users. Specifically in the corporate sector, either through direct financing or through indirect financing, collective funds are made available to business concerns, and, then, channelled into productive uses. Viewed from such perspective, the efficiency of capital market has always been a source of concern (Yen & Lee, 2007).

Efficient Market Hypothesis (EMH), which deals with the informational efficiency of the capital market, is one of the most thoroughly tested hypotheses in

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finance. Nonetheless, it remains an unresolved empirical issue as to whether the capital market satisfies the notion of market efficiency (Bergen, 2011).

An important debate among stock market investors is whether the market is efficient—that is, whether it reflects all the information made available to market participants at any given time. The efficient market hypothesis maintains that all stocks are perfectly priced according to their inherent investment properties, the knowledge of which all market participants possess equally.

The concept of informational efficiency of markets suggests that the prevailing asset prices reflect all available information and investors cannot make money in the market by taking positions based on the information they possess (Fama, 1970). Although the idea of random fluctuation of asset prices was discussed earlier as well (Samuelson, 1965), but (Fama, 1970) examined the same in terms of stock markets and posited three different levels[1] of informational efficiency: Weak form, Semi-strong form and Strong Form.

After its initial appeal and early acceptability, few cracks began to appear regarding the empirical validity of informational efficiency in the real-world financial markets. Several anomalies that challenged the concept of informational efficiency of stock markets were reported which include 'January effect' (Rozeff and Kinney, 1976), 'Value effect' (Basu, 1977), 'Weekend effect' (French, 1980), 'Size effect' (Banz, 1981) and 'Weather effect' (Saunders, 1993), among others.[2] Several studies have tested different levels of EMH in different financial markets, but a consensus has never been reached.

A central theme of EMH is investor rationality, which has been questioned by an opposing school of thought that advocates the existence of several psychological phenomena having an impact on asset prices as well as on informational efficiency of markets. This has led to a polarization among the defenders of EMH and the proponents of behavioural finance. Taking into consideration an evolutionary perspective of human behaviour that influences the informational efficiency of markets, Lo (2004) proposes the Adaptive Markets Hypothesis (AMH) as an attempt to reconcile the views of the two schools of thought. Utilizing the concepts of bounded rationality and satisfying (choices are merely satisfactory, not necessarily optimal), AMH is presented as a new version of EMH in which prices reflect as much information as dictated by the combination of economic conditions and the number and nature of distinct group of market participants[3] in the economy (Lo, 2004).

One of the primary implications of AMH is that market efficiency is not a steady state, and depends upon investor population (Lo, 2004, 2005), i.e. markets will be efficient when savvy investors are able to negate the effects of irrational behaviour

[1]Although some reclassifications were made in the levels of informational efficiency: Tests of return predictability, Event Studies and Tests for private information respectively (Fama, 1991); the initial categorizations are more widely recognized.

[2]For a description of various market anomalies please refer to Table 8.7 in the Appendix section.

[3]Each distinct group of market participant represents a group of investors that behave in a common manner. For example, pension funds, hedge funds, market makers and retail investors (Lo ,2004).

of noise traders. This implication signifies variable efficiency through time that leads to time-varying return predictability, without any convergence towards equilibrium (or higher level of efficiency) (Lo, 2005).

AMH has gained traction in the recent years as it provides a dynamic perspective to the concept of informational efficiency. A static view of market efficiency might lead to incorrect interpretations of informational content of prices (Shiller, 2003). Similar to EMH, most of the studies discussing time-varying efficiency have been tests of return predictability covered under the weak form level of efficiency, and have preceded the conceptualization of AMH. The weak form level of efficiency asserts that it is impossible to exploit any past market trading data to predict future price changes.

As factors like globalization, technological advances, adoption of electronic trading systems, implementation of price limit systems and changes in regulatory framework are expected to increase the efficiency of markets (Lim & Brooks, 2011), early studies testing time-varying efficiency focused on the concept of evolving efficiency. Most of the studies utilize newly developed tests to analyse the evolving efficiency of stock markets of emerging economies and find evidence of evolving efficiency (Abdmoulah, 2010; Jefferis & Smith, 2005; Li, 2003; Rockinger & Urga, 2000; Zalewska-Mitura & Hall, 1999) with some improvement in levels of efficiency during the sub-periods. Lim (2007) examines the time-varying efficiency of eleven emerging and two developed markets using rolling sample portmanteau bi-correlation test statistic. The author finds evidence of long periods of efficiency mixed with short periods of inefficiency. Ito and Sugiyama (2009) compute first-order autocorrelation in a sliding window approach to find varying degrees of efficiency through time in the U.S. stock markets without any discernable trend of convergence towards efficiency.

Todea, Ulici, and Silaghi (2009) were among the first ones to mention AMH while testing the profitability of moving average strategies. The authors find the profitability from these strategies to be episodic, thus providing evidence in favour of AMH. Few other studies have also found the U.S. stock markets to portray patterns consistent with the implications of AMH (Kim, Shamsuddin, & Lim, 2011; Lim, Luo, & Kim, 2013). AMH is still in its nascent stages and has received limited attention and testing in the Indian stock market. Hiremath and Kumari (2014) test AMH in the Indian stock markets. The authors utilize several linear as well as non-linear tests on non-overlapping sub-samples and find evidence in support of AMH. Dhankar and Shankar (2016) provide a comprehensive review of relevance and evolution of Adaptive Markets Hypothesis. They suggest that AMH provides a better paradigm than EMH to describe the behaviour of stock returns.

The present study extends the existing empirical research on AMH in the context of the Indian stock market by examining the time-varying efficiency through a rolling window methodology. We differ in our approach from Hiremath and Kumari (2014) as we utilize the notion of Popovic, Mugosa and Durovic (2013) regarding three factors that can impact weak form efficiency of markets: observation period represented by the sample period, time horizon represented by size of the rolling window and data aggregation level represented by data frequency. Under the rolling window approach, we consider rolling windows of 3, 5 and 10 years. We extend the approach of Popovic et al. (2013) to include monthly data frequency level in our analysis. This creates three different data frequency levels in our study: Daily, Weekly and Monthly. Shorter time windows and quarterly data frequency were not considered to avoid the problem of few data points while performing analysis on monthly data frequency and 3-year rolling window, respectively.

Instead of focusing on indices from two different stock exchanges in India, we focus our attention on two different indices of the Bombay Stock Exchange (BSE): Sensex and BSE 500 Index. Sensex is considered to be the barometer of Indian capital markets and comprises of 30 large-cap companies. This is also considered to be the benchmark index for Indian equities. BSE 500 Index is a broad-based index representing approximately 93% of the total market capitalization of BSE and comprises of 500 companies covering all 20 major industries of the economy. A comparison of efficiency between these two indices will be interesting from an asset pricing perspective. The asset pricing literature suggests a broad-based index to be considered as market proxy under the asset pricing models. Intuitively, a broad-based index is more likely to have a higher level of efficiency as there are more chances of the internal inefficiencies of stock level data to get cancelled out.

EMH only supports the notion of perpetual efficiency. Some of the literature discussed above also suggests a convergence towards efficiency, referred to as evolving efficiency, due to various factors having an impact on the market dynamics. Any other pattern suggesting a switch between efficiency and inefficiency will be covered under AMH. The remainder of the paper is structured as follows. The next section describes the data and methodology that is used to test time-varying linear dependence in Indian stock market. Section "Linear Tests" presents the empirical results and discusses the relevance of AMH in the Indian stock markets. Finally, section "Results and Discussion" summarizes the findings and concludes.

Data and Methodology

The data used in this study comprises of daily, weekly and monthly values of Sensex and BSE 500 Index from September 1999 to September 2015 extracted from Centre for Monitoring Indian Economy (CMIE) Prowess database. The data frequency level of daily, weekly and monthly observations has been considered as one of the factors affecting the informational efficiency of markets. Time-varying efficiency of the stock market indices has been examined through a rolling window approach to capture the impact of time horizon on the informational efficiency. Three different time horizons reflected by window sizes of 3, 5 and 10 years have been considered. This makes the analysis two-dimensional, with one dimension represented by the data frequency level and the other dimension represented by the rolling window approach. Shorter time windows and quarterly data frequency have not been considered to avoid the problem of few data points while performing analysis on monthly data frequency and 3-year rolling window, respectively.

Instead of focusing on indices from two different stock exchanges in India, analysis has been carried out on two different indices of the Bombay Stock

Exchange (BSE). Sensex is considered to be the barometer of Indian capital markets and comprises of thirty large-cap companies. This is also considered to be the benchmark index for Indian equities as it is mentioned most often to reflect the movements in the Indian stock market. BSE 500 Index is a broad-based index representing approximately 93% of the total market capitalization of BSE and comprises of 500 companies covering all 20 major industries of the economy. A comparison of efficiency between these two indices will be interesting from an asset pricing perspective as the asset pricing literature suggests a broad-based index to be considered as market proxy under the asset pricing models. Intuitively, a broad-based index is more likely to have a higher level of efficiency as there are more chances of the internal inefficiencies of stock level data to get cancelled out.

Under the rolling window approach, window sizes of 3, 5 and 10 years produce 14, 12 and 7 sub-samples, respectively. A description of sub-samples has been provided below.

Description of samples for testing AMH

Sample name	Window size—3 years	Window size—5 years	Window size—10 years
S1	September 1999–September 2002	September 1999–September 2004	September 1999–September 2009
S2	September 2000–September 2003	September 2000–September 2005	September 2000–September 2010
S3	September 2001–September 2004	September 2001–September 2006	September 2001–September 2011
S4	September 2002–September 2005	September 2002–September 2007	September 2002–September 2012
S5	September 2003–September 2006	September 2003–September 2008	September 2003–September 2013
S6	September 2004–September 2007	September 2004–September 2009	September 2004–September 2014
S7	September 2005–September 2008	September 2005–September 2010	September 2005–September 2015
S8	September 2006–September 2009	September 2006–September 2011	
S9	September 2007–September 2010	September 2007–September 2012	
S10	September 2008–September 2011	September 2008–September 2013	
S11	September 2009–September 2012	September 2009–September 2014	
S12	September 2010–September 2013	September 2010–September 2015	
S13	September 2011–September 2014		
S14	September 2012–September 2015		
FS	September 1999–September 2015	September 1999–September 2015	September 1999–September 2015

The study employs linear tests to investigate AMH in the Indian stock market. The following subsections provide a brief description of the two categories of tests. The relevant statistics pertaining to these tests have been computed for each sub-sample under the three different time horizons covering daily, weekly, monthly data frequency levels.

Linear Tests

Autocorrelation Test

The first-order autocorrelation investigates the independence of variables of the series at lag 1. If the autocorrelation coefficient is non-zero, then it means that the series exhibits autocorrelation. The Ljung–Box Q-statistic under its parametric test framework provides a more formal approach by testing for the null hypothesis that there is no autocorrelation up to order k.

Runs Test

Runs test is a simple and reliable non-parametric test, which investigates the randomness of a two-valued data sequence. It tests the mutual independence by a series by defining a run as a sequence of consecutive changes. If the calculated number of runs is close to the expected number of runs generated through a random process, then the series is random. The null hypothesis of runs test is that of independence of the series. If the p-value of the runs test is lower than level of significance, then the null hypothesis of randomness of series is rejected. In order to carry out runs test, the returns series has been transformed into a coded series, in which returns lower than zero are given one value and all other cases are given another value.

Variance Ratio Test

Variance ratio test is a popular approach under the parametric test framework by Lo and MacKinlay (1988) to assess the predictability of asset prices. In case of a random walk, the variance of a k-period difference should be k times the variance of one-period difference. The null hypothesis of variance ratio test is random walk, tested at different holding periods (k). The holding periods of 2, 4, 8 and 16 as suggested by Lo and MacKinlay (1988) have been considered for the analysis.

Multiple Variance Ratio Test

Chow and Denning (1993) suggest a modification to the variance ratio test wherein a set of multiple variance ratios over a number of holding periods are jointly tested to determine predictability of the series. The null hypothesis and holding periods remain the same as in the case of variance ratio test.

Results and Discussion

The first row of Fig. 8.1 represents the first-order autocorrelation coefficients of Sensex for 3-year time horizon. The first column representing daily data frequency reflects consistent positive autocorrelation. The second column representing weekly data frequency reflects a switch between high positive and low negative values of autocorrelation coefficients over different sub-samples. The third column representing monthly data frequency reflects a switch between high positive and high negative values of autocorrelation coefficients over different sub-samples. The second row of the figure represents 5-year time horizon with the pattern similar to 3-year time horizon results. The third row represents 10-year time horizon with consistent positive autocorrelation coefficients. Figure 8.2 presents the first-order

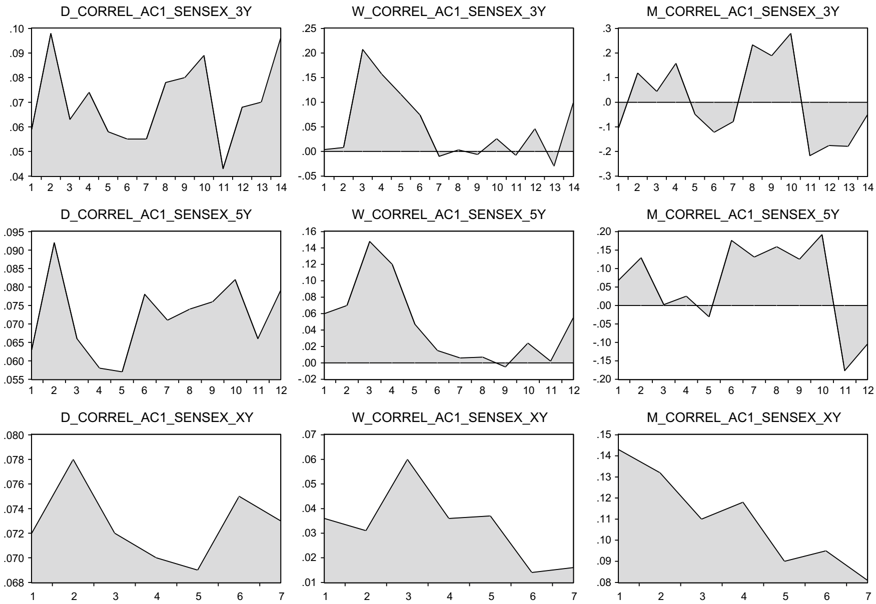

Fig. 8.1 First-order Autocorrelation coefficients for Sensex. *Source* Compiled from Dhankar and Shankar (2018)

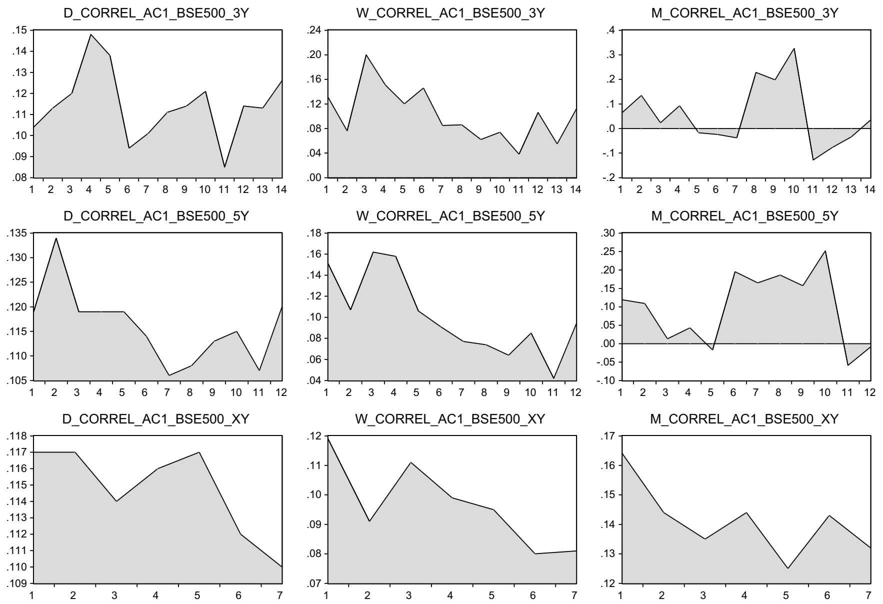

Fig. 8.2 First-order Autocorrelation coefficients for BSE 500 Index. *Source* Compiled from Dhankar and Shankar (2018)

autocorrelation coefficients of BSE 500 Index. While, the pattern is similar to that of Sensex over different time horizons and across data frequency levels, the values of autocorrelation coefficients for BSE 500 Index are higher in magnitude.

Figure 8.3 presents the p-values of Ljung–Box Q-statistic of Sensex and provides a more sophisticated way to analyse the autocorrelation. The rows represent different time horizons and the columns represent different data frequency levels in the graph panel, with dashed horizontal line representing 5% level of significance. The graphs indicate that the number of significant values over different sub-samples gets reduced across daily, weekly, and monthly data frequency levels, irrespective of the time horizon. The number of significant values over different sub-samples also gets reduced for BSE 500 Index across daily, weekly, and monthly time horizon for 3-year and 5-year time horizon (Fig. 8.4). In case of 10-year time horizon, the Q-statistic remains significant for all sub-samples across daily and weekly data frequency levels. Significant values of Ljung–Box Q-statistic indicate autocorrelation which reflects inefficiency.

Significant values over all sub-samples for a combination of time horizon and data frequency level suggests perpetual inefficiency. A move from significant values in older sub-samples to insignificant values in recent sub-samples suggests evolving efficiency. A move from insignificant values in older sub-samples to significant values in recent sub-samples suggests evolving inefficiency. A switch between significant and insignificant values more than once over the sub-samples

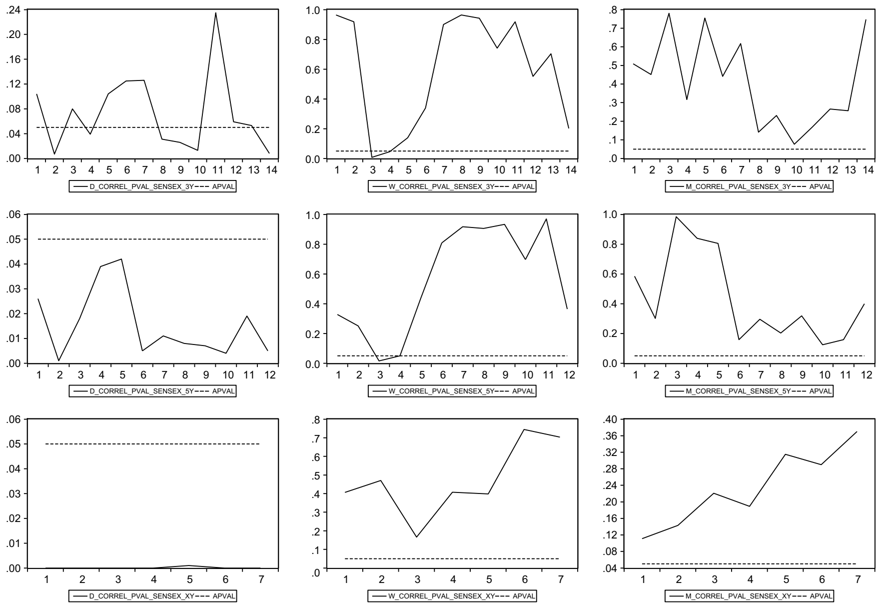

Fig. 8.3 P-values of Ljung–Box Q-statistic for Sensex. *Source* Compiled from Dhankar and Shankar (2018)

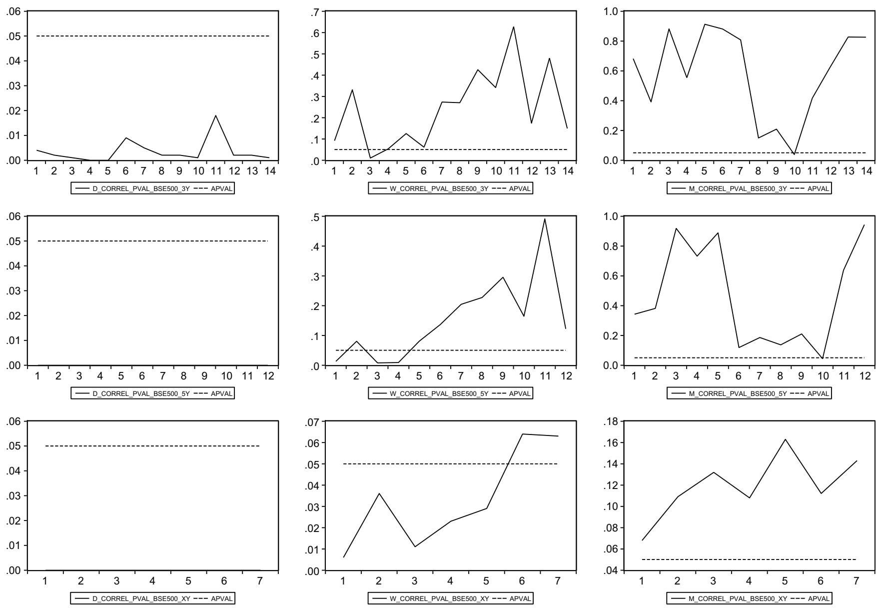

Fig. 8.4 P-values of Ljung–Box Q-statistic for BSE 500 Index. *Source* Compiled from Dhankar and Shankar (2018)

reflects time-varying levels of efficiency in line with the AMH framework. The case of perpetual efficiency reflects insignificant values over all sub-samples. The various definitions and interpretations of EMH only cover perpetual efficiency in a strict sense, with the addition of evolving efficiency in a relaxed framework. Perpetual inefficiency and evolving inefficiency combined with time-varying levels of efficiency are discussed under the AMH framework.

The graphs for Runs test present patterns similar to those suggested by Q-statistic. Sensex shows a mix of time-varying efficiency, perpetual inefficiency, evolving efficiency, and perpetual efficiency, with a decrease in number of significant values across data frequency level (Fig. 8.5). BSE 500 Index shows perpetual inefficiency for daily frequency level and perpetual efficiency for monthly data frequency level (Fig. 8.6). The full sample results are not a part of these graphs. Ljung–Box Q-statistics and Runs test values for both the indices over sub-samples and full sample have been presented in Table 8.1 through Table 8.6.

Variance Ratio test results for Sensex over 3-year time horizon in Table 8.1 at holding periods of 2, 4, 8 and 16 show that there is independence in most of sub-samples as the variance ratio statistic is not significant at 5% for daily, weekly, and monthly data frequency level. The number of sub-samples with significant variance ratios increases across daily to monthly data frequency level. The significant ratios are greater than 1, implying positive serial correlations or trend formation. Most of the significant ratios lead to a switch between efficiency and inefficiency more than once over sub-samples, implying AMH framework. Table 8.2 for BSE 500 Index over 3-year time horizon shows higher percentage of significant variance ratios for different

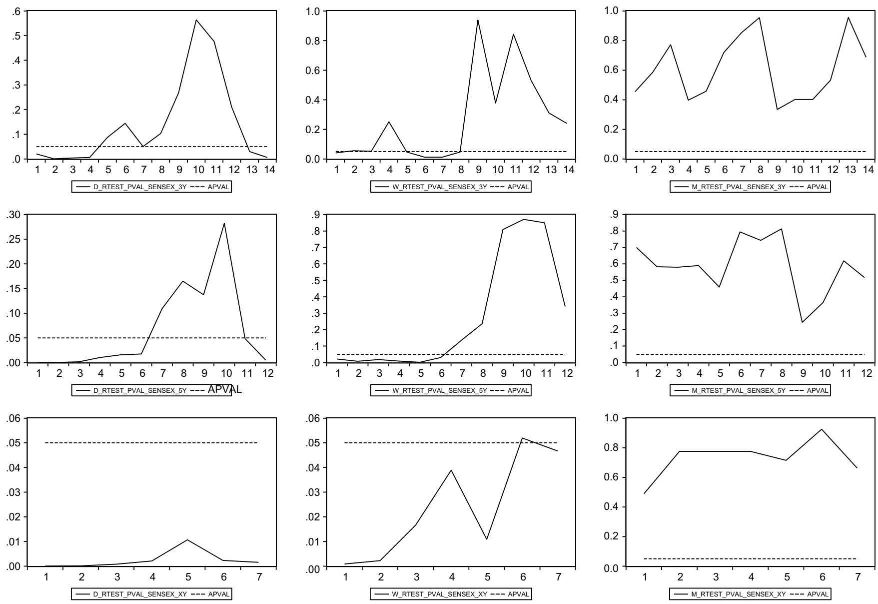

Fig. 8.5 P-values of Runs test for Sensex. *Source* Compiled from Dhankar and Shankar (2018)

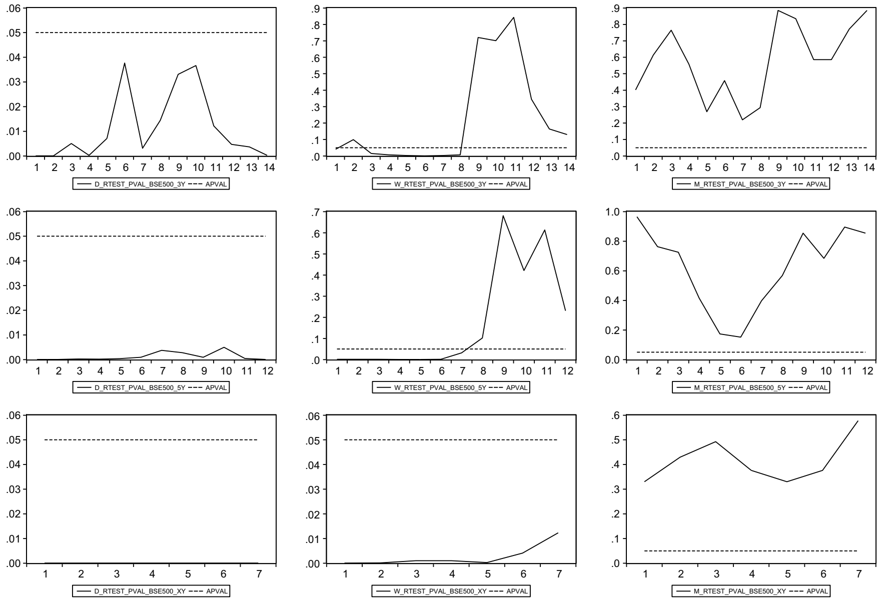

Fig. 8.6 P-values of Runs test for BSE 500 Index. *Source* Compiled from Dhankar and Shankar (2018)

holding periods than Sensex, implying considerable trend formation and dependence. Variance ratios of Sensex over 5-year time horizon shows less number of significant values, implying independence and perpetual efficiency for most of the holding periods. BSE 500 Index for 5-year time horizon (Table 8.4) with higher number of significant values implies greater trend formation than Sensex. The switch between significant and insignificant ratios more than once in BSE 500 Index provides evidence of AMH framework. Variance ratios over 10-year time horizon for Sensex (Table 8.5) and BSE 500 Index (Table 8.6) show a greater contrast with enhanced emphasis dependence in BSE 500 Index (Tables 8.3 and 8.8).

The percentage summary of significant results for 3-year, 5-year and 10-year time horizon provide an uncomplicated description of the linear tests executed to analyse the dependence in the stock indices (Table 8.7 through Table 8.9). Higher percentages reflect greater inefficiency. Sensex values provide higher instances of perpetual efficiency reflected by the number of 0% significant results in the percentage summary tables. Perpetual inefficiency is exhibited in cases having 100% significant results. The percentage summary suggests some disparity between results of variance ratio test at different holding periods and Q_statistics as well as Runs test. The Chow and Denning multiple variance ratio helps to overcome this disparity by providing a single statistic across different holding periods. These percentages help in distinguishing between the two extreme cases of perpetual efficiency and perpetual inefficiency (Table 8.11).

Table 8.1 Sensex results—3-year time horizon

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	FS
Sensex															
D_QSTAT	2.641	7.35*	3.075	4.282*	2.639	2.355	2.342	4.674*	4.944*	6.107*	1.412	3.558	3.743	6.986*	19.881*
D_RTEST_RUNS	349*	331*	344*	342*	355	353	353	356	365	374	376	369	353*	342*	1840*
D_VRAT_CD	1.185	1.857	1.114	0.748	0.697	0.975	1.153	1.759	1.765	1.766	1.306	1.845	1.978	2.562*	2.66*
D_VRAT_PVR2	1.06	1.102	1.065	1.077	1.06	1.056	1.056	1.079	1.082	1.092	1.046	1.067	1.074*	1.096*	1.071*
D_VRAT_PVR4	1.092	1.128	1.044	1.029	0.986	1.034	1.083	1.079	1.086	1.057	1.091	1.087	1.075	1.049	1.07
D_VRAT_PVR8	1.072	1.231	1.176	1.072	1.05	1.057	0.974	0.958	0.984	1.001	1.089	1.057	1.003	1.036	1.031
D_VRAT_PVR16	1.084	1.322	1.287	1.148	1.082	1.084	1.016	1.056	1.083	1.119	1.072	1.045	0.934	0.973	1.084
W_QSTAT	0.002	0.011	7.062*	4.027*	2.194	0.913	0.016	0.002	0.005	0.109	0.011	0.353	0.146	1.629	1.076
W_RTEST_RUNS	69*	69	67	68	61*	56*	62*	66*	78	85	82	78	75	74	366*
W_VRAT_CD	0.677	0.506	2.552*	3.25*	1.905	0.897	1.05	1.847	1.586	1.534	0.688	0.873	0.547	1.345	1.7
W_VRAT_PVR2	1.02	1.017	1.214*	1.163*	1.137	1.076	0.983	1.011	1.001	1.028	0.994	1.047	0.999	1.105	1.039
W_VRAT_PVR4	0.977	1.099	1.403*	1.391*	1.295	1.14	1.162	1.244	1.215	1.235	1.038	1.088	1.001	1.003	1.148
W_VRAT_PVR8	0.834	1.122	1.527	1.657*	1.31	0.961	1.211	1.5	1.439	1.441	0.916	0.863	0.914	0.78	1.19
W_VRAT_PVR16	0.794	1.149	1.926*	2.152*	1.515	0.858	1.255	1.762	1.65	1.7	0.744	0.668	0.784	0.714	1.265
M_QSTAT	0.436	0.567	0.078	1.003	0.097	0.594	0.248	2.167	1.436	3.153	1.89	1.239	1.289	0.104	1.548
M_RTEST_RUNS	21	21	18	15	13	13	16	19	22	22	22	21	19	20	95
M_VRAT_CD	0.496	0.965	3.149*	2.034	0.867	1.06	0.672	1.873	2.003	2.373	1.941	1.254	1.527	0.366	1.643
M_VRAT_PVR2	0.931	1.127	1.105	1.155	1.007	0.863	0.91	1.278	1.202	1.312	0.781	0.845	0.952	0.974	1.094
M_VRAT_PVR4	0.867	1.142	1.405	1.46*	1.163	0.769	1.048	1.579	1.445	1.576	0.587	0.648	0.871	0.909	1.194
M_VRAT_PVR8	1.172	0.948	1.8*	1.604	1.053	0.589	1.136	1.815	1.947*	2.15*	1.82	0.626	1.099	1.021	1.387
M_VRAT_PVR16	0.752	1.231	2.869*	2.107	0.495	0.829	1.328	1.894	1.86	2.089	2.254	0.732	2.053	0.959	1.386

Source Compiled from Dhankar and Shankar (2018)

*Represents values significant at 5%. Prefixes D, W, and M represent Daily, Weekly, and Monthly data frequency level, respectively. QSTAT represents Ljung Box Q_statistic. RTEST_RUNS represents Runs test. VRAT_CD represents Chow Denning multiple variance ratio. VRAT_PVARi represents variance ratios at different holding periods with i = 2, 4, 8 and 16

Table 8.2 BSE 500 Index results—3-year time horizon

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	FS
BSE 500															
D_QSTAT	8.32*	9.759*	11.141*	16.939*	14.808*	6.785*	7.791*	9.437*	9.964*	11.12*	5.588*	10.046*	9.809*	12.072*	52.334*
D_RTEST_RUNS	319*	323*	340*	324*	337*	339*	337*	342*	349*	352*	350*	347*	341*	326*	1730*
D_VRAT_CD	2.384	2.345	1.23	1.328	1.458	1.445	1.73	2.24	2.241	2.28	2.623*	3.103*	3.214*	3.424*	3.87*
D_VRAT_PVR2	1.106*	1.116	1.123	1.15	1.141	1.095	1.102	1.112*	1.117*	1.123*	1.087*	1.114*	1.117*	1.126*	1.115*
D_VRAT_PVR4	1.204*	1.172	1.093	1.097	1.093	1.116	1.177	1.186*	1.201*	1.176	1.188*	1.194*	1.187*	1.134	1.171*
D_VRAT_PVR8	1.277	1.342*	1.226	1.158	1.19	1.214	1.131	1.154	1.183	1.211	1.205	1.186	1.167	1.127	1.201*
D_VRAT_PVR16	1.512*	1.518*	1.316	1.206	1.201	1.269	1.224	1.355	1.372	1.425	1.212	1.234	1.194	1.13	1.348*
W_QSTAT	2.843	0.943	6.618*	3.754	2.357	3.517	1.202	1.219	0.636	0.908	0.235	1.852	0.498	2.083	10.354*
W_RTEST_RUNS	69*	71	64*	58*	55*	50*	60*	63*	78	83	82	76	73	72	352*
W_VRAT_CD	2.316	1.335	2.574*	2.643*	2.014	1.724	1.943	2.611*	2.307	2.198	0.686	1.347	1.145	1.383	3.812*
W_VRAT_PVR2	1.149	1.087	1.208*	1.151*	1.139*	1.149	1.082	1.094	1.072	1.079	1.039	1.108	1.087	1.118	1.115*
W_VRAT_PVR4	1.372*	1.258	1.386*	1.344*	1.29	1.25	1.313	1.414*	1.356	1.35	1.111	1.217	1.189	1.104	1.329*
W_VRAT_PVR8	1.428	1.354	1.516*	1.546*	1.305	1.127	1.428	1.745*	1.654*	1.643*	1.07	1.074	1.21	0.959	1.448*
W_VRAT_PVR16	1.515	1.441	1.908*	1.964*	1.4	0.979	1.426	2.052*	1.927*	2.001*	0.99	0.882	1.121	0.943	1.546*
M_QSTAT	0.168	0.733	0.022	0.35	0.012	0.022	0.059	2.08	1.578	4.291*	0.661	0.239	0.048	0.048	3.404
M_RTEST_RUNS	22	21	18	15	13	13	14	15	18	20	21	21	18	18	90
M_VRAT_CD	1.437	1.47	3.478*	1.663	0.781	1.337	0.302	1.808	2.139	2.67*	3.362*	0.879	1.407	0.526	1.876
M_VRAT_PVR2	1.134	1.146	1.087	1.115	1.059	0.963	0.959	1.276	1.218	1.358	0.879	0.948	1.087	1.053	1.144
M_VRAT_PVR4	1.232	1.223	1.357	1.364	1.091	0.838	1.065	1.549	1.465	1.644	0.719	0.749	1.042	1.059	1.242
M_VRAT_PVR8	1.691	1.526	1.913*	1.5	1.107	0.457	1.078	1.8	2.028*	2.335*	2.351*	0.688	1.185	1.222	1.455
M_VRAT_PVR16	1.021	1.902	3.04*	1.37	0.547	0.605	1.201	1.721	1.978	2.373	3.208*	0.974	1.938	1.329	1.318

Source Compiled from Dhankar and Shankar (2018)

*Represents values significant at 5%. Prefixes D, W, and M represent Daily, Weekly, and Monthly data frequency level, respectively. QSTAT represents Ljung Box Q_statistic. RTEST_RUNS represents Runs test. VRAT_CD represents Chow Denning multiple variance ratio. VRAT_PVARi represents variance ratios at different holding periods with i = 2, 4, 8 and 16

Table 8.3 Sensex results—5-year time horizon

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	FS
Sensex													
D_QSTAT	4.952*	10.679*	5.611*	4.257*	4.146*	7.735*	6.398*	6.974*	7.298*	8.5*	5.482*	7.907*	19.881*
D_RTEST_RUNS	568*	556*	572*	575*	585*	581*	595	605	605	612	598*	582*	1840*
D_VRAT_CD	1.224	1.537	1.188	0.934	1.134	1.994	1.844	1.917	1.942	1.913	2.282	2.754*	2.66*
D_VRAT_PVR2	1.063	1.094	1.068	1.059	1.058	1.079*	1.072	1.075	1.077	1.084	1.068*	1.079*	1.071*
D_VRAT_PVR4	1.073	1.079	1.038	1.019	1.053	1.072	1.066	1.076	1.086	1.058	1.084	1.08	1.07
D_VRAT_PVR8	1.082	1.169	1.147	1.054	0.988	0.99	0.988	0.973	0.992	1.001	1.067	1.058	1.031
D_VRAT_PVR16	1.135	1.235	1.237	1.108	1.013	1.082	1.078	1.049	1.063	1.091	1.035	1.014	1.084
W_QSTAT	0.959	1.316	5.882*	3.849	0.6	0.059	0.011	0.014	0.007	0.151	0.001	0.826	1.076
W_RTEST_RUNS	114*	108*	106*	101*	100*	107*	113	120	130	131	131	126	366*
W_VRAT_CD	1.048	1.782	2.151	2.387	1.752	1.633	1.48	1.555	1.339	1.125	0.859	0.906	1.7
W_VRAT_PVR2	1.07	1.077	1.152	1.121*	1.049	1.019	1.01	1.009	1	1.026	1.002	1.057	1.039
W_VRAT_PVR4	1.135	1.183	1.309*	1.292*	1.218	1.218	1.209	1.205	1.178	1.198	1.018	1.034	1.148
W_VRAT_PVR8	1.131	1.278	1.36	1.315	1.291	1.39	1.356	1.383	1.325	1.297	0.871	0.871	1.19
W_VRAT_PVR16	1.252	1.526	1.553	1.476	1.463	1.563	1.503	1.527	1.414	1.437	0.745	0.732	1.265
M_QSTAT	0.3	1.071	0	0.041	0.061	1.989	1.096	1.618	0.998	2.36	1.996	0.713	1.548
M_RTEST_RUNS	30	29	26	23	24	27	29	32	36	35	33	34	95
M_VRAT_CD	1.602	2.101	2.518*	0.696	0.838	1.549	1.631	1.598	1.399	1.761	1.425	1.079	1.643
M_VRAT_PVR2	1.08	1.124	1.049	1.014	0.977	1.189	1.141	1.196	1.134	1.207	0.833	0.909	1.094
M_VRAT_PVR4	1.207	1.341	1.218	1.128	1.173	1.399	1.327	1.38	1.256	1.358	0.686	0.756	1.194
M_VRAT_PVR8	1.511	1.578	1.424	1.066	1.165	1.583	1.654	1.662	1.56	1.742	1.466	0.823	1.387
M_VRAT_PVR16	1.836	2.06*	2.206*	1.186	0.744	1.571	1.607	1.611	1.306	1.487	1.407	0.899	1.386

Source Compiled from Dhankar and Shankar (2018)

*Represents values significant at 5%. Prefixes D, W, and M represent Daily, Weekly, and Monthly data frequency level, respectively. QSTAT represents Ljung Box Q_statistic. RTEST_RUNS represents Runs test. VRAT_CD represents Chow Denning multiple variance ratio. VRAT_PVARi represents variance ratios at different holding periods with i = 2, 4, 8 and 16

Table 8.4 BSE 500 results—5-year time horizon

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	FS
BSE 500													
D_QSTAT	17.981*	22.927*	18.175*	18.113*	17.954*	16.407*	14.295*	14.77*	16.187*	16.779*	14.544*	18.264*	52.334*
D_RTEST_RUNS	528*	538*	554*	545*	559*	559*	567*	573*	571*	580*	568*	544*	1730*
D_VRAT_CD	2.363	2.01	1.675	1.651	1.997	2.603*	2.465	2.507*	2.59*	2.604*	3.605*	4.183*	3.87*
D_VRAT_PVR2	1.12*	1.136*	1.121	1.12	1.12*	1.115*	1.108*	1.109*	1.115*	1.117*	1.109*	1.12*	1.115*
D_VRAT_PVR4	1.171	1.135	1.106	1.097	1.146	1.178*	1.171*	1.181*	1.201*	1.176*	1.185*	1.174*	1.171*
D_VRAT_PVR8	1.248	1.262	1.239	1.178	1.134	1.184	1.173	1.151	1.183	1.203	1.189*	1.168	1.201*
D_VRAT_PVR16	1.441*	1.365	1.314	1.234	1.184	1.355	1.333	1.312	1.339	1.382	1.207	1.186	1.348*
W_QSTAT	6.15*	3.06	7.101*	6.732*	3.045	2.219	1.61	1.462	1.098	1.934	0.475	2.394	10.354*
W_RTEST_RUNS	107*	104*	100*	89*	92*	100*	111*	118	130	127	129	124	352*
W_VRAT_CD	3.18*	1.973	2.374	2.805*	2.464	2.489	2.357	2.467	2.243	1.878	0.869	1.418	3.812*
W_VRAT_PVR2	1.162*	1.115	1.167*	1.16*	1.11	1.095	1.081	1.077	1.07	1.088	1.04	1.096	1.115*
W_VRAT_PVR4	1.41*	1.272	1.311*	1.336*	1.31*	1.358*	1.34*	1.348*	1.319*	1.328	1.112	1.149	1.329*
W_VRAT_PVR8	1.519*	1.376	1.371	1.372	1.404*	1.594*	1.558*	1.603*	1.54*	1.519	1.067	1.063	1.448*
W_VRAT_PVR16	1.685*	1.59*	1.515	1.47	1.519	1.782*	1.714*	1.801*	1.684*	1.731	1.027	0.972	1.546*
M_QSTAT	0.903	0.766	0.011	0.117	0.02	2.445	1.746	2.208	1.571	4.074*	0.223	0.005	3.404
M_RTEST_RUNS	31	29	26	23	22	23	25	28	32	33	31	32	90
M_VRAT_CD	1.865	2.613*	1.948	0.572	0.64	1.552	1.605	1.712	1.6	2.039	2.192	0.378	1.876
M_VRAT_PVR2	1.152	1.111	1.057	1.039	1	1.212	1.184	1.223	1.166	1.265	0.961	1.011	1.144
M_VRAT_PVR4	1.286	1.287	1.165	1.095	1.136	1.405	1.346	1.41	1.303	1.428	0.866	0.912	1.242
M_VRAT_PVR8	1.671	1.845*	1.363	0.956	1.186	1.553	1.665	1.732	1.661	1.879*	1.81*	0.991	1.455
M_VRAT_PVR16	1.764	2.247*	1.933	0.714	0.783	1.442	1.555	1.578	1.432	1.654	1.826	1.179	1.318

Source Compiled from Dhankar and Shankar (2018)

*Represents values significant at 5%. Prefixes D, W, and M represent Daily, Weekly, and Monthly data frequency level, respectively. QSTAT represents Ljung Box Q_statistic. RTEST_RUNS represents Runs test. VRAT_CD represents Chow Denning multiple variance ratio. VRAT_PVARi represents variance ratios at different holding periods with i = 2, 4, 8 and 16

Table 8.5 Sensex results—10-year time horizon

	S1	S2	S3	S4	S5	S6	S7	FS
Sensex								
D_QSTAT	12.976*	15.164*	13.216*	12.328*	12.061*	14.055*	13.216*	19.881*
D_RTEST_RUNS	1140*	1145*	1165*	1171*	1186*	1171*	1167*	1840*
D_VRAT_CD	2.287	2.361	2.153	2.067	2.044	2.419	2.364	2.66*
D_VRAT_PVR2	1.072*	1.079*	1.073*	1.071*	1.07*	1.075*	1.073*	1.071*
D_VRAT_PVR4	1.072	1.068	1.064	1.062	1.055	1.073	1.067	1.07
D_VRAT_PVR8	1.028	1.047	1.037	1.012	1.001	1.006	0.999	1.031
D_VRAT_PVR16	1.103	1.124	1.119	1.086	1.061	1.065	1.055	1.084
W_QSTAT	0.691	0.523	1.917	0.688	0.714	0.106	0.144	1.076
W_RTEST_RUNS	218*	217*	225*	229*	226*	233	236*	366*
W_VRAT_CD	1.819	1.963	2.068	2.024	1.847	1.375	1.35	1.7
W_VRAT_PVR2	1.041	1.035	1.06	1.039	1.042	1.016	1.018	1.039
W_VRAT_PVR4	1.18	1.195	1.236*	1.228*	1.214	1.165	1.162	1.148
W_VRAT_PVR8	1.275	1.312	1.358*	1.36*	1.309	1.246	1.227	1.19
W_VRAT_PVR16	1.415	1.47	1.504*	1.495	1.457	1.317	1.287	1.265
M_QSTAT	2.541	2.15	1.499	1.727	1.011	1.118	0.805	1.548
M_RTEST_RUNS	56	57	57	57	57	58	62	95
M_VRAT_CD	1.844	1.983	1.683	1.537	1.672	1.222	1.286	1.643
M_VRAT_PVR2	1.148	1.131	1.128	1.121	1.112	1.103	1.091	1.094
M_VRAT_PVR4	1.317	1.302	1.288	1.263	1.276	1.212	1.186	1.194
M_VRAT_PVR8	1.476	1.551*	1.477	1.447	1.503	1.392	1.414	1.387
M_VRAT_PVR16	1.539	1.583	1.43	1.312	1.34	1.313	1.327	1.386

Source Compiled from Dhankar and Shankar (2018)
*Represents values significant at 5%. Prefixes D, W, and M represent Daily, Weekly, and Monthly data frequency level, respectively. QSTAT represents Ljung Box Q_statistic. RTEST_RUNS represents Runs test. VRAT_CD represents Chow Denning multiple variance ratio. VRAT_PVARi represents variance ratios at different holding periods with i = 2, 4, 8 and 16

Summary of the behaviour of the two indices based on the different statistics for the two dimensions is provided in Table 8.10 through Table 8.12. Instead of just looking at the percentages of significant values, the trend followed over different sub-samples has been examined to categorize the behaviour of the index. Over the 3-year time horizon, Sensex follows AMH framework over daily and weekly data frequency level, while monthly data frequency is dominated by perpetual efficiency. In case of BSE 500 Index, perpetual inefficiency and AMH dominate the different data frequency levels. The same pattern of results is followed over 5-year and 10-year time horizon in which AMH seems to be a more appropriate framework, as evolving inefficiency and perpetual inefficiency are also covered under the framework of AMH.

Table 8.6 BSE 500 Index returns—10-year time horizon

	S1	S2	S3	S4	S5	S6	S7	FS
BSE 500								
D_QSTAT	34.152*	34.17*	32.673*	33.906*	34.347*	31.461*	30.043*	52.334*
D_RTEST_RUNS	1074*	1099*	1117*	1107*	1128*	1119*	1103*	1730*
D_VRAT_CD	3.358*	3.121*	2.952*	2.973*	3.004*	3.256*	3.219*	3.87*
D_VRAT_PVR2	1.117*	1.118*	1.115*	1.117*	1.118*	1.112*	1.11*	1.115*
D_VRAT_PVR4	1.174*	1.156*	1.154*	1.16*	1.158*	1.178*	1.17*	1.171*
D_VRAT_PVR8	1.211*	1.206*	1.19	1.178	1.17	1.183	1.168	1.201*
D_VRAT_PVR16	1.389*	1.34*	1.318*	1.304*	1.281	1.313*	1.292*	1.348*
W_QSTAT	7.561*	4.386*	6.513*	5.153*	4.779*	3.426	3.466	10.354*
W_RTEST_RUNS	205*	211*	217*	217*	216*	225*	232*	352*
W_VRAT_CD	3.731*	2.863*	2.97*	3.02*	2.888*	2.472	2.442	3.812*
W_VRAT_PVR2	1.124*	1.096	1.112*	1.101	1.1	1.082	1.083	1.115*
W_VRAT_PVR4	1.376*	1.31*	1.328*	1.336*	1.323*	1.294*	1.291*	1.329*
W_VRAT_PVR8	1.543*	1.466*	1.499*	1.519*	1.475*	1.45*	1.429*	1.448*
W_VRAT_PVR16	1.694*	1.615*	1.662*	1.669*	1.628*	1.547*	1.504	1.546*
M_QSTAT	3.336	2.562	2.268	2.579	1.95	2.532	2.149	3.404
M_RTEST_RUNS	53	53	53	53	53	53	56	90
M_VRAT_CD	1.863	2.228	1.78	1.588	1.828	1.32	1.356	1.876
M_VRAT_PVR2	1.179	1.145	1.152	1.149	1.152	1.153	1.145	1.144
M_VRAT_PVR4	1.322	1.286	1.3	1.279	1.287	1.263	1.235	1.242
M_VRAT_PVR8	1.499	1.63*	1.527	1.477	1.566	1.438	1.455	1.455
M_VRAT_PVR16	1.376	1.558	1.383	1.291	1.405	1.306	1.323	1.318

Source Compiled from Dhankar and Shankar (2018)
*Represents values significant at 5%. Prefixes D, W, and M represent Daily, Weekly, and Monthly data frequency level, respectively. QSTAT represents Ljung Box Q_statistic. RTEST_RUNS represents Runs test. VRAT_CD represents Chow Denning multiple variance ratio. VRAT_PVARi represents variance ratios at different holding periods with i = 2, 4, 8 and 16

Table 8.7 Summary of significant results (in percentage)—3-year time horizon

	Daily		Weekly		Monthly	
	Sensex (%)	BSE 500 (%)	Sensex (%)	BSE 500 (%)	Sensex (%)	BSE 500 (%)
CORREL_QSTAT_3Y	42.86	100.00	14.29	7.14	0.00	7.14
RTEST_RUNS_3Y	42.86	100.00	35.71	50.00	0.00	0.00
VRAT_C3Y	7.14	28.57	14.29	21.43	7.14	21.43
VRAT_PVR2_3Y	14.29	57.14	14.29	21.43	0.00	0.00
VRAT_PVR4_3Y	0.00	42.86	14.29	28.57	7.14	0.00
VRAT_PVR8_3Y	0.00	7.14	7.14	35.71	21.43	28.57
VRAT_PVR16_3Y	0.00	14.29	14.29	35.71	7.14	14.29

Source Compiled from Dhankar and Shankar (2018)
The table presents percentage of significant values out of fourteen sub-samples

Table 8.8 Summary of significant results (in percentage)—5-year time horizon

	Daily		Weekly		Monthly	
	Sensex (%)	BSE 500 (%)	Sensex (%)	BSE 500 (%)	Sensex (%)	BSE 500 (%)
CORREL_QSTAT_5Y	100.00	100.00	8.33	25.00	0.00	8.33
RTEST_RUNS_5Y	66.67	100.00	50.00	58.33	0.00	0.00
VRAT_C3Y	8.33	50.00	0.00	16.67	8.33	8.33
VRAT_PVR2_5Y	25.00	83.33	8.33	25.00	0.00	0.00
VRAT_PVR4_5Y	0.00	58.33	16.67	66.67	0.00	0.00
VRAT_PVR8_5Y	0.00	8.33	0.00	50.00	0.00	25.00
VRAT_PVR16_5Y	0.00	8.33	0.00	50.00	16.67	8.33

Source Compiled from Dhankar and Shankar (2018)
The table presents percentage of significant values out of twelve sub-samples

Table 8.9 Summary of significant results (in percentage)—10-year time horizon

	Daily		Weekly		Monthly	
	sensex (%)	BSE 500 (%)	Sensex (%)	BSE 500 (%)	Sensex (%)	BSE 500 (%)
CORREL_QSTAT_XY	100.00	100.00	0.00	71.43	0.00	0.00
RTEST_RUNS_XY	100.00	100.00	85.71	100.00	0.00	0.00
VRAT_C3Y	0.00	100.00	0.00	71.43	0.00	0.00
VRAT_PVR2_XY	100.00	100.00	0.00	28.57	0.00	0.00
VRAT_PVR4_XY	0.00	100.00	28.57	100.00	0.00	0.00
VRAT_PVR8_XY	0.00	28.57	28.57	100.00	14.29	14.29
VRAT_PVR16_XY	0.00	85.71	14.29	85.71	0.00	0.00

Source Compiled from Dhankar and Shankar (2018)
The table presents percentage of significant values out of seven sub-samples

Table 8.10 Summary of behaviour based on significant results—3-year time horizon

	Daily		Weekly		Monthly	
	Sensex	BSE 500	Sensex	BSE 500	Sensex	BSE 500
CORREL_QSTAT_3Y	AMH	PI	AMH	AMH	PE	AMH
RTEST_RUNS_3Y	AMH	PI	AMH	AMH	PE	PE
VRAT_CD_3Y	EI	EI	AMH	AMH	AMH	AMH
VRAT_PVR2_3Y	EI	AMH	AMH	AMH	PE	PE
VRAT_PVR4_3Y	PE	AMH	AMH	AMH	AMH	PE
VRAT_PVR8_3Y	PE	AMH	AMH	AMH	AMH	AMH
VRAT_PVR16_3Y	PE	AMH	AMH	AMH	AMH	AMH

Source Compiled from Dhankar and Shankar (2018)
PE represents Perpetual Efficiency with 0% significant values. EE represents Evolving Efficiency with a single switch from significant values to insignificant values over sub-samples. AMH represents Adaptive Market Hypothesis framework with a switch from insignificant to significant values or vice versa more than once over the sub-samples. EI represents Evolving Inefficiency with a single switch from insignificant values to significant values over sub-samples. PI represents Perpetual Inefficiency with 100% significant values

Table 8.11 Summary of behaviour based on significant results—5-year time horizon

	Daily		Weekly		Monthly	
	Sensex	BSE 500	Sensex	BSE 500	Sensex	BSE 500
CORREL_QSTAT_5Y	PI	PI	AMH	AMH	PE	AMH
RTEST_RUNS_5Y	AMH	PI	EE	EE	PE	PE
VRAT_CD_5Y	EI	AMH	PE	AMH	AMH	AMH
VRAT_PVR2_5Y	AMH	AMH	AMH	AMH	PE	PE
VRAT_PVR4_5Y	PE	EI	AMH	AMH	PE	PE
VRAT_PVR8_5Y	PE	AMH	PE	AMH	PE	AMH
VRAT_PVR16_5Y	PE	EE	PE	AMH	AMH	AMH

Source Compiled from Dhankar and Shankar (2018)

Table 8.12 Summary of behaviour based on significant results—10-year time horizon

	Daily		Weekly		Monthly	
	Sensex	BSE 500	Sensex	BSE 500	Sensex	BSE 500
CORREL_QSTAT_XY	PI	PI	PE	EE	PE	PE
RTEST_RUNS_XY	PI	PI	AMH	PI	PE	PE
VRAT_CD_XY	PE	PI	PE	EE	PE	PE
VRAT_PVR2_XY	PI	PI	PE	AMH	PE	PE
VRAT_PVR4_XY	PE	PI	AMH	PI	PE	PE
VRAT_PVR8_XY	PE	EE	AMH	PI	AMH	AMH
VRAT_PVR16_XY	PE	AMH	AMH	EE	PE	PE

Source Compiled from Dhankar and Shankar (2018)

Conclusion

As is evident from the results and analysis, observation period and time horizon represented by different rolling window sizes as well as data frequency level seem to have an impact on the informational efficiency of the market. First-order auto-correlation coefficients provide evidence against any efficiency in any of the windows or at any data frequency level for both the indices under consideration. Runs test provides evidence of time-varying efficiency with lower instances of inefficiency at lower (monthly) data frequency levels and lower levels of inefficiency at smaller (3-year) time windows for both the indices. The results of the Multiple Variance Ratio test do not show a discernable pattern as we change the data frequency level or rolling window size, but signal time-varying efficiency for both the indices do show. This can be due to the parametric nature of the Multiple Variance Ratio test, while Runs test is a non-parametric test. These results collectively support variable efficiency in Indian stock markets which is affected by the choice of window size and data frequency level.

Contrary to our expectations, BSE 500 Index has been found to possess higher levels of time-varying linear dependence than Sensex. These results can have implications on the choice of index being used for performance evaluation, forecasting, and analysis. This time-varying-linear dependence can provide investors with the ability to predict returns in a time-varying manner. Although this study only focuses on the linear dependence in stock market returns, there might be certain non-linear dependencies which can be tested and explored by using several non-linear tests.

AMH, being a much more dynamic perspective on the informational efficiency of markets than EMH, represents a much more acceptable view of stock market behaviour. A focus on AMH could very well explain and help us understand the constant booms and busts that take place in the financial markets, by providing a better financial paradigm to describe stock returns.

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Chapter 9
Risk-Return Analysis and Stock Markets

When money realizes that it is in good hands, it wants to stay and multiply in those hands.
Idowu Koyenikan

Abstract Efficient capital market theory postulates the random walk behaviour of stock market, i.e. risk and return are normally distributed. Capital asset pricing models, which assume the normality in risk and return, deal with how risky securities are valued in an efficient capital market. The present study applies a set of parametric and non-parametric tests to examine the normality of return and risk of daily, weekly, monthly and annual returns in the Indian stock market. The study examines the prices of the Bombay Stock Exchange (BSE)-listed indices: Sensex, BSE 100 and BSE 500 for the period 1996–2006, and three sub-periods (January 1996–December 1999, January 2000–December 2002, January 2003–December 2006) and reports the significant findings. The returns are negatively skewed for all the indices over the period. Asymmetry is found in risk and return in case of daily and weekly returns. Monthly and annual returns, however, are found normally distributed for all three indices over the period of time. These findings bring out the importance of time horizon in investment strategy for the Indian stock market.

Introduction

Any investment has two aspects: risk and return. Investors look for the lowest possible risk for highest possible return. The normal distribution quantifies these two aspects by the mean for returns and standard deviation for risk. Modern portfolio theory offers a systematic mathematical approach which aims to maximize a portfolio's expected return for a given amount of portfolio risk by selecting the

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proportions of various assets. Alternatively, it also offers to maximize risk for a given level of expected return.

Today, it is a well-known empirical fact that the distribution of stock market returns are usually not normal but leptokurtic, i.e. the empirical distribution has fat tails and a high degree of peakedness as compared to the normal distribution.

Stock market efficiency is a matter of interest for investors for formulating short- and long-term investment strategy. An efficient stock market is said to fully reflect all the publicly available information. It provides unbiased estimates of risky securities, which results in eliminating the possibilities of earning abnormal return under the condition of certainty. Under such situation, investors value risky securities on the basis of risk and return expectations (Kumar & Dhankar, 2009). Fama (1991) describes stock market efficiency in terms of investors' preferences for stock return subject to risk. An efficient capital market makes investors earn extra return with respect to bearing extra risk. The modern portfolio theory provides how risky securities are valued in the competitive and efficient capital market. In a competitive capital market, investors have homogenous expectations pertinent to stocks performance and earnings. Being risk averse, they tend to choose stocks with high expected return, when two or more stocks will have same risk level. They will tend to choose risky portfolios with the expectation of extra return from them. However, a number of studies have demonstrated market inefficiencies by identifying systematic variations in stocks return with respect to time-varying forces. These variations are subject to calendar anomalies and company size effect. The most common are days of the week effect (Aggarwal & Rivoli, 1989; Berument & Kiymaz, 2001), monthly effect (Ariel, 1987; Boudreaux, 1995) and company size effect (Keim, 1993; Muneesh & Seghal, 2004; Seghal & Tripathi, 2006). These studies report that stocks return on respective day or month is significantly different from the rest of days or months. The existence of such phenomenon in stock market suggests market inefficiencies which results, earning of abnormal return by utilizing such situation. It can also evolve the possibilities of market manipulation and thereby investors earn abnormal return in commensurate with the degree of risk. If efficient capital market holds true, it documents the random walk behaviour of stock prices, i.e. stocks return are normally distributed. The present study examines the hypotheses of normality of risk and return of Indian stock market over the time period.

Review of Literature

Lee (1990) brings out the importance of time horizon in formulating the investment strategy. The study considers 60 stocks during the period 1926–1985. It maintains that when risk is defined as variability in annualized returns, diversification over time reduces risk, yet when risk is defined as variability in holding period returns, lengthening the investment horizon increases risk. The proposition of the optimal mean–variance efficient portfolio invested in stocks increases as investment horizons are increased. Poshakwale (1996) examines BSE 100 companies' daily prices for the period from 1987 through 1994. The study involves the use of Kolmogorov–Smironv test to examine the normality of returns of Indian Stock Market. The study reports that the frequency distribution does not fit either normal or uniform distribution. It also reports day of the week effect, i.e. return of Monday and Friday are significantly different from the rest of days' return. Hameed (1997) study shows that the lead–lag pattern between large and small market value portfolio returns is consistent with differential variations in their expected return components. The results report large predictability of returns and small stocks portfolio tend to have higher exposure of these firms to persistent latent factors. Significant cross-autocorrelation exists between current returns on large stocks and lagged returns on small stocks when trading volume is high. Cagnetti (2001) examines the implication of CAPM and APT in the Italian stock market. It examines the monthly return of thirty stocks for the period from January 1990 to June 2001. The study first tests the normality of the Italian stock market return. It reports that stocks return is normally distributed over the period of time. The study also involves two phases regression. The first phase regression estimates stocks return and beta values. The second phase regression is cross-sectional, wherein portfolios return is regressed to the portfolios beta. The study reports important findings. The relationship between stock return and beta is weak, and CAPM coefficients are also not statistically significant. These findings question the application of CAPM in determining the asset pricing, and in establishing trade-off between risk and return. The study also examines arbitrage pricing theory, wherein five explanatory factors are considered in determining the asset pricing. The beta values of all explanatory variables are statistically significant. It provides that the behaviour of stocks in the Italian stock market is complex and can not be fully explained by single explanatory variable (market return). A large number of systematic factors affect stocks' and portfolios' return. The study validates the APT, and questions the CAPM in determining stocks pricing. Marisetty and Alayur (2002) study examines BSE 500 companies and three other indices namely BSE Sensex, BSE 100 and BSE 200 for the period ranging from 1991 to 2001. The study reports high skewness and Kurtosis in stock returns and thereby holds the asymmetry in return and risk in the Indian stock market. Kiymaz and Berument (2003) study investigates the day of the week effect on the volatility of major stock market indexes for the period of 1988 through 2002 by using the conditional variance. The results report that the day of the week effect is present in both return and volatility pattern.

Kumar and Dhankar (2009) examine the cross-correlation in stock returns of South Asian stock markets, their regional integration and interdependence on global stock market. The findings report the autocorrelation in stock returns in all Asian stock markets. It rejects the relationship between stock returns and expected volatility; however, the relationship is significant with unexpected volatility. It brings out that investors adjust their risk premium for expected variations in stock prices, but they expect extra risk premium for unexpected variations. Further, Kumar and Dhankar (2010) applies GARCH (1, 1) and T-GARCH (1, 1) to investigates the conditional heteroscedasticity in time series of the US stock market returns, and the asymmetric effect of good and bad news on volatility. The study also analyses the relationship between stock returns and conditional volatility, and standard residuals. It uses S&P 500 and NASDAQ 100 for the period from January 1990 to December 2007. The results suggest the presence of the heteroscedasticity effect and the asymmetric nature of stock returns. It also reports a negative significant relationship between stock returns and conditional volatility. However, the relationship between stock returns and standardized residuals is found to be significant.

Kumar and Dhankar (2011a, 2011b) investigates the asymmetric nature of the US stock market returns, heteroscedasticity effect on stock return volatility and the relationship between stock returns and conditional volatility, and standard residuals. The study uses S&P 500 for the period from January 1950 to December 2007. The results suggest the presence of non-linearity, heteroscedasticity effect and asymmetric nature of stock returns. It also finds no correlation between stock returns and conditional volatility, however, the relationship between stock returns and standardized residuals is found positively significant. These findings bring out the essential elements of the modern investment theory that investors adjust their investment decisions with respect to expected volatility, however, they tend to earn extra risk premium for unexpected volatility.

Data and Research Methodology

The data set consist daily, weekly, monthly and annually data of three Bombay stock exchange-listed indices, BSE Sensex, BSE 100 and BSE 500 for the period from January 1996 through December 2006. BSE Sensex consists of 30 large-cap stocks representing all the industries. In the same line, BSE 100 consists of 100 large- and mid-cap stocks. On the other hand, BSE 500 is based on the collective performance of 500 large-, mid- and small-cap stocks. The sample period exhibits a mixed set of economic environment in Indian economy. The early period (June 1996–December 1999) of the study can be categorized as decline phase with 6.3% average low growth rate. However, the later period (January 2003–December 2006) was growth oriented, when the economy started to register an impressive 7.7% average growth rate. These prices are adjusted with the bonus issue, right issue and other corporate actions. The data has been taken from Prowess, a database maintained by Centre for Monitoring Indian Economy. All the indices which cover all industry categories stocks are value weighted. They assign weights to all constituent stocks in proportion to market capilitazation as well as trading volume. The natural logarithmic mode is used to measure the return of stocks. The logarithmic difference between the movements of prices is symmetric, and is expressed in percentage terms for ease of comparability. Symbolically, it can be written as

$$R_t = [Log_e(P_t)/Log_e(P_{t-1})] * 100 \quad (9.1)$$

where R_{it} is realized return on index in time period t, Log_e is natural logarithm, Let P_t is the price of index in time period t, P_{t-1} is the price of index in preceding time period $t-1$. This measure of return takes into account only appreciation/depreciation of stock and neglect the dividend yield.

To test the statistical reliabilities of descriptive statistics, F-test and Kolmogrov–Smirnov (K-S) test are used. The K-S test determines how well a random sample data fits a particular distribution (uniform, normal or Poisson). It is based on comparison of the sample cumulative distribution against the standard cumulative function for each distribution. K-S tests the goodness of fit, which shows 0.000 probabilities for the 'Z' value at 5% level of significance for both normal and abnormal distribution. The F-test examines whether all the samples have emerged from same population or not.

Empirical Findings

Distribution of Risk and Return: Daily Return

Table 9.1 outlines the summary of descriptive statistics of daily return for the period 1996–2006 of three indices. The negative skewness of all three indices exhibits that daily returns are negatively skewed. The statistical significant of K-S test values signifies the non-normality of daily return of three indices. It outlines that daily return is not normally distributed. Widely documented day of the weak effect holds true in the Indian stock market. Return of particular day/s is significantly different from the returns of the rest of week. BSE 500 has given maximum return to the investors on a daily basis compared to other indices.

Table 9.2 provides the statistical summary in three sub-non-overlapping periods, i.e. January 1996–December 1999, January 2000–December 2002, January 2003–December 2006. In sub-period, daily returns of three indices are negatively skewed. The F-value of Sensex and BSE 100 indicate that risk for three sub-periods is not

Table 9.1 Daily return for the period January 1996–December 2006

Index	Average return	Standard deviation	Skewness	Kurtosis	K-S
Sensex	0.06	1.61	−0.04	3.43	2.45*
BSE 100	0.06	1.68	−0.42	5.15	3.22*
BSE 500	0.08	1.63	−0.76	4.53	3.49*

Source Compiled from Kumar and Dhankar (2011a, 2011b)
Note *Significant at 5% level of significance

Table 9.2 Statistics summary—daily return

Index	Period	Av. ret.	St. dev.	Skewness	Kurtosis	K-S	F
Sensex	1996–99	0.05	1.72	0.29	2.00	1.33*	0.68**
	2000–02	0.02	1.62	−0.39	2.42	1.89*	
	2003–06	0.11	1.46	−0.98	8.63	2.37*	
BSE 100	1996–99	0.07	1.74	−0.02	6.27	1.80*	0.52**
	2000–02	0.02	1.75	−0.05	2.41	2.34*	
	2003–06	0.10	1.49	−1.08	8.77	2.63*	
BSE 500	1996–99	0.27	1.80	−0.24	1.36	0.67*	5.70*
	2000–02	0.02	1.61	−0.53	2.33	1.89*	
	2003–06	0.11	1.53	−1.39	10.22	2.92*	

Source Compiled from Kumar and Dhankar (2011a, 2011b)
Note *Significant at 5% level of significance
**Not significant at 5% level of significance

significantly different from each others, i.e. all the three samples have emerged from the same population. However, in case of BSE 500, risk during three periods is significant from each other. The K-S values of all indices during the sub-periods are significant. It signifies that returns are not normally distributed over the periods of time. In sub–periods, BSE 500 comparatively has provided higher returns to the investors.

Distribution of Risk and Return: Weekly Return

Table 9.3 provides the statistically summary of weekly return of all indices for the period 1996–2006. The K-S value of three indices are significant at 5% level of significance, provides return of three indices are not normally distributed. On weekly basis, BSE 500 has offered maximum return compared to other indices. Table 9.4 provides the statistical summary of three indices for three sub-periods. The F-value of Sensex and BSE 500 for all three sub-periods is significant at 5% level of significance. It outlines that risk is not normally distributed, i.e. level of risk for three sub-periods is significantly different from each other. However, the F-value of BSE 100 is not significant, provides that risk is normally distributed. The

Table 9.3 Weekly return for the period January 1996–December 2006

Index	Av. ret.	St. dev.	Skewness	Kurtosis	K-S
Sensex	0.26	3.48	−0.25	1.70	1.11*
BSE 100	0.28	5.11	−0.92	2.00	2.74*
BSE 500	0.41	3.61	−0.83	2.27	1.42*

Source Compiled from Kumar and Dhankar (2011a, 2011b)
Note *Significant at 5% level of significance

Table 9.4 Statistics summary—weekly return

Index	Period	Av. ret.	St. dev.	Skewness	Kurtosis	K-S	F
Sensex	1996–99	0.23	3.77	0.43	0.38	0.57**	3.07*
	2000–02	−0.23	3.91	−0.49	2.17	1.09**	
	2003–06	0.67	2.73	−1.00	2.60	1.29*	
BSE 100	1996–99	0.28	7.01	−0.81	1.20	2.48*	1.70**
	2000–02	−0.30	4.35	−0.44	1.55	1.07**	
	2003–06	0.69	2.93	−1.07	3.02	1.41*	
BSE 500	1996–99	1.24	3.90	−0.56	1.26	0.72**	7.47*
	2000–02	−0.25	4.15	−0.47	1.27	1.05**	
	2003–06	0.72	3.01	−1.36	3.02	1.36*	

Source Compiled from Kumar and Dhankar (2011a, 2011b)
Note *Significant at 5% level of significance
**Not significant at 5% level of significance

K-S value of three indices during decline and recession periods are not statistically significant, shows that returns are normally distributed during these periods. However, the K-S values of three indices during the growth period are significant. It shows that weekly returns of three indices during growth period are not normally distributed.

Distribution of Risk and Return: Monthly Return

Table 9.5 outlines the statistical summary of monthly return. It provides that K-S value is not statistical significant at 5% level of significance, i.e. return is normally distributed. On monthly basis, BSE 500 has offered maximum return to the investors. Table 9.6 outlines statistical summary of three indices for three sub-periods. The K-S value of three indices is not statistically significant, i.e. returns are normally distributed. The F-values of three indicies for three sub-periods are statistically significant. It shows that risk levels of three sub-periods are significantly different.

Table 9.5 Monthly return for the period January 1996–December 2006

Index	Av. ret.	St. dev.	Skewness	Kurtosis	K-S
Sensex	1.18	7.38	−0.33	−0.52	0.82**
BSE 100	1.26	8.17	−0.50	−0.08	0.77**
BSE 500	1.75	8.34	-0.85	0.66	1.00**

Source Compiled from Kumar and Dhankar (2011a, 2011b)
Note **Not significant at 5% level of significance

Table 9.6 Statistics summary—monthly return

Index	Period	Av. ret.	St. dev.	Skewness	Kurtosis	K-S	F
Sensex	1996–99	1.13	8.17	−0.01	−1.02	0.75**	3.12*
	2000–02	−1.09	6.90	−0.26	−0.78	0.72**	
	2003–06	2.93	6.53	−1.00	1.47	0.69**	
BSE 100	1996–99	1.42	8.40	−0.09	−1.02	0.73**	2.84*
	2000–02	−1.26	9.00	−0.50	−0.27	0.56**	
	2003–06	2.98	6.86	−0.83	1.60	0.84**	
BSE 500	1996–99	5.67	9.17	−1.30	1.34	0.69**	6.71*
	2000–02	−1.16	8.84	−0.72	0.02	0.68**	
	2003–06	3.12	7.17	−0.95	2.01	0.70**	

Source Compiled from Kumar and Dhankar (2011a, 2011b)
Note *Significant at 5% level of significance
**Not significant at 5% level of significance

Distribution of Risk and Return: Annual Return

Table 9.7 provides the annual return of three indices during the pool period. The table shows that BSE 100 has offered maximum annual return to the investors subject to lower risk as compared to BSE 500. The negative skewness of all three indices signifies the negative skewedness of annual return. The K-S values of all indices are not statistical significant. It indicates that all three indices annual returns are normally distributed.

Conclusion and Summary

The present study attempts to examine the distribution of risk and return of Indian stock market. It brings out the time interval as significant factors in adjusting the stock prices with regards to market and non-market events. The findings report that daily and weekly returns are not normally distributed, i.e. significant negative asymmetry is found in stock market returns. However, monthly and annual returns

Table 9.7 Annual return for the period January 1996–December 2006

Index	Av. ret.	St. dev.	Skewness	Kurtosis	K-S
Sensex	15.00	29.00	−0.005	−1.55	0.54**
BSE 100	16.33	32.94	0.142	−1.04	0.42**
BSE 500	15.41	35.24	−0.030	−0.32	0.57**

Source Compiled from Kumar and Dhankar (2011a, 2011b)
Note **Not significant at 5% level of significance

are symmetric, i.e. return is normally distributed. These findings document the calendar anomalies like day of the week effect, week effect and month effect in Indian stock market. The study supports the findings of a number of studies on the Indian stock market, which examined the calendar anomalies and systematic variations in stock returns (Aggarwal & Tandan, 1994; Karmakar & Chakraborty, 2003; Jarrett & Kyper, 2005; Dhankar & Chakraborty, 2007). The study also supports Lee (1990), Jarrett and Kyper (2006) findings, which brings out the importance of time horizon in investment strategy. Indian stock market is not a safe venue for intraday investors. Risk and return relationship seems inconsistent in case of daily and weekly returns. Meaning thereby investors can not earn high return by investing in corresponding high risky portfolios.

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Part III
Risk-Return Analysis and Investment Decision

Chapter 10
Time Series of Return and Volatility

I would not pre-pay. I would invest instead and let the investments cover it.
Dave Ramsey

Abstract The study investigates the presence of conditional heteroskedasticity in time series of US stock market returns, and the asymmetric effect of good and bad news on volatility. Further, the study also analyses the relationship between stock returns and conditional volatility, and standard residuals. The daily opening and closing prices of the S&P 500 and NASDAQ 100 are used for the period January 1990–December 2007. The study applies GARCH (1, 1) and T-GARCH (1, 1) to examine the heteroskedasticity and the asymmetric nature of stock returns, respectively. The results of the study suggest the presence of the heteroskedasticity effect and the asymmetric nature of stock returns. Further, analysing the relationship, the study reports a negative significant relationship between stock returns and conditional volatility. However, the relationship between stock returns and standardized residuals is found to be significant. This study provides a robustness test of the conditional volatility and asymmetric impact of good and bad news. These findings bring out that investors adjust their investment decisions with regard to expected volatility, however, they expect extra risk premium for unexpected volatility.

Introduction

There have been substantial advances in the measurement, modelling and forecasting of volatility, which has centred around the realized volatility literature. Many econometric models underline the assumptions of the constant variance of

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residuals over the period of time. But a number of empirical studies question this assumption and hold the presence of autocorrelation in time series data (Morgan, 1976; Sentana & Wadhwani, 1992; Watanable, 2002; Karmakar, 2005; Faff & Mckenzie, 2007; Kumar & Dhankar, 2009). The presence of autocorrelation in time series data signifies the non-normality of error term so-called heteroskedasticity. The existence of such a phenomenon in financial time series such as stocks returns or exchange rates exhibit so-called volatility clustering. This suggests that large fluctuations in these series tend to be followed by large fluctuations and small fluctuations by small ones. This paper attempts to investigate the presence of heteroskedasticity and asymmetric effect of good or bad news on stock market returns. The presence of heteroskedasticity in stock returns signifies that the unexpected volatility in the last time period affects the investment decisions in the current time period. Under this situation, the use of variance to capture fluctuations in stock returns will provide only gross volatility. Researchers commonly use variance as the standard measures of risk (Schwert, 1990; Rakesh, 2007). In fact, the stock market crash of October 1987 and October 1992 led the researchers to give considerable attention to examine the sensitivity of stock returns to risk and uncertainty.

The modern investment theory educates the investors to make investment decisions under the risk and uncertainty. Investors and policymakers may be interested to see the value of their portfolio in some future point of time with respect to risk if such trend is persistent in stocks prices. In modelling this market phenomenon, autoregressive conditional heteroskedasticity (ARCH) approach is used. The approach uses the conditional variance to be a function of the past error term and allows the variance of error term to vary over time (Engle, 1982). Bollerslev (1986), further extended the ARCH process by allowing the conditional variance to be a function of past error term as well as the lagged value of conditional variance. This is based on the idea that past error term which affects current investment decisions and volatility of last time period combined together has a significant impact over current investment decisions. Following the introduction of ARCH models by Engle (1982) and further generalization by Bollerslev (1986), these models have been extensively used in explaining and modelling the time series data of the stock market.

In this paper, attempts are made to estimate the conditional heteroskedasticity and asymmetric effect on volatility, and thereafter testing the relationship between stock returns with expected volatility, and unexpected volatility. The present study roots its investigation back to the study of French, Schwert and Stambaugh.(1987). Their study examined the monthly stock prices and segregates monthly volatility into its expected and unexpected components. Their study also estimated the relationship between realized monthly returns and two volatility components. They found a significant negative relationship between returns and unexpected changes in volatility as well as a significant positive relationship between returns and expected volatility under the GARCH-M process. Since then a large number of studies support the use of ARCH models in forecasting stock market volatility. Akgiray

(1989), Pagan and Schwert (1990), Brailsford and Faff (1996) and Brooks (1998) used U.S. stock market data and found that GARCH models provide better results in forecasting returns and volatility. Using the dataset from Japanese and Singaporean stock markets, however, Tse (1991) and Tse and Tung (1992) found that the exponentially weighted moving average models provide more accurate forecast than GARCH models. Corhay and Rad (1994) used European stock market data and found GARCH (1, 1) better predictors of volatility.

Due to fact that, GARCH models fail to take into account the asymmetric effect of positive and negative stock returns, the models such as Exponential or E-GARCH (Nelson, 1991) and Threshold Autoregressive or TAR-GARCH (Glosten, Jagannathan, & Runkle, 1993, Engle & Ng, 1993; Tsay, 1998) have been used in forecasting and estimating volatility. These models are used to capture the asymmetric effect of good and bad news on investment decisions. This line of research highlights the asymmetric effect of news by emphasizing that negative shock to returns will generate more volatility than a positive shock of equal magnitude. Aggarwal, Inclan and Leal (1999) examined the sudden change in volatility in emerging stock market and found that the high volatility was attributed to a sudden change in variance. The periods with high volatility were found to be associated with important events in each country rather than global events. Chiang and Doong (2001) further used T-GARCH to examine the volatility of seven Asian stock markets and found an asymmetric effect on the conditional volatility when daily return is used. However, study questions this phenomenon in the case of monthly return. Further extending the GARCH model, Mala and Reddy (2007) examined the volatility in Fiji stock market by using multivariate GARCH model for the period 2001–2005. The study reports that interest rate changes have a considerable impact on stock market volatility.

Modelling of Volatility

Fluctuations in stock return mark volatility in the stock market. Let P_t is the price of index in time period t, P_{t-1} is the price of index in preceding time period t-1. The rate of return R_{it} investors will realize in t time period as follows:

$$R_t = [\log_e(P_t) - \log_e(P_{t-1})] * 100 \tag{10.1}$$

In fact, realized return consists a set of two components—expected return $E(R_t)$ and unexpected return $\boldsymbol{\varepsilon}_t$. Expected return is attributed by stock and economic fundamentals, while unexpected return arises due to good or bad news pertaining to stocks. Symbolically, it can be written as follows:

$$R_t = E(R_t) + \varepsilon_t \tag{10.2}$$

An upswing in ε_t(unexpected rise in return) suggests the arrival of good news, on the contrary, a downswing in ε_t(unexpected decline in return) is a mark of bad news. Volatility in stock market resultant to expected return is marked expected volatility, while volatility resultant to unexpected return is marked unexpected volatility (French et al., 1987). Engle (1982) suggests that the conditional variance (σ^2) is a function of the lagged $\varepsilon's$. It implies that volatility can be forecasted by the inclusion of the past news as a function of conditional variance. This process is called autoregressive conditional heteroscedasticity which can be written as follows:

$$\sigma_c^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots\ldots\ldots\ldots\ldots\ldots \alpha_p \varepsilon_{t-q}^2 \tag{10.3}$$

where $\alpha_0 > 0, \alpha_1, \alpha_2 \ldots\ldots\ldots \alpha_p \geq 0$. All things being equal, α_i carries more intense influence as compared to α_j. That is, older news bears less impact on current investment decisions which results in volatility, than the current news. Bollerslev (1986) generalized the ARCH (q) model to the GARCH (p,q) in which conditional variance depends upon both the squared residuals and its own lagged value (Eq. 10.4).

$$\sigma^2 = \left[\alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{t-p}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2\right] + \omega_t \tag{10.4}$$

where ω_t is white noise which represents unexpected volatility, whereas the first part exhibits the expected volatility. A large number of studies advocate the use of GARCH (1, 1) and holds it enough to capture volatility in time series data (Bollerslev et al 1992; Aggarwal et al., 1999; Dhankar and Chakraborty 2007; Mala and Reddy 2007; Kumar and Dhankar 2009). The present study also uses GARCH (1, 1) in estimating heteroskedasticity effect on U.S. stock market volatility. It can be written as follows:

$$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{10.5}$$

Data and Sample Period

The sample data used in the study consists the daily opening and closing prices of New York Stock Exchange (NYSE) listed index S & P 500 and NASDAQ listed index NASDAQ 100. The data period ranges from January 1990 to December 2007. The S & P 500 is value-weighted index and consists of 500 large-cap stocks, most of which are American. This index forms the part of broader S & P 1500[1] and

[1]The S & P 1500 is commonly known S & P 1500 Composite Index, is a stock market index of U. S. stocks made by Standard & Poor's. It includes all stocks of three indices—S & P 500, S & P 400 and S & P 600.

S & P Global 1200[2] stock market indices. All constituent stocks in the index are of largely publicly held companies and trade on the two largest U.S. stock markets-NYSE and NASDAQ. It represents nearly 75% of the U.S. equities market which coves 75% market capitalization. The NASDAQ-100, on the other hand, is based on the 100 largest domestic and international non-financial companies listed on the NASDAQ stock exchange.

Empirical Findings

Preliminary Results

To provide the general understanding of the U.S. stock market, Table 10.1 outlines the basic statistics of NYSE and NASDAQ stock markets. The average return of both indices are positive, which highlights the fact that stock indices have increased over the period. The negative skewness of S & P 500 exhibits that return is negatively skewed. The negative skewness provides that the returns distributions of the market have a higher probability of providing a negative return. The skewness, however, of NASDAQ 100 is positive, highlights the positive distribution of returns in the NASDAQ stock market. The high values of kurtosis as compared to 3, exhibits that indices return have a heavier tail than the standard normal distribution. The Jarque–Bera test which examines the normality of return is significant at 5% level of significance for both the indices. It outlines that returns are not normally distributed in the U.S. stock market. Figures 10.1 and 10.2 highlight the non-normality of stock returns in NYSE and NASDAQ stock market. Table 10.1 also outlines the unit root test. The Augmented Dickey–Fuller test is used to measure the stationarity property of U.S. stock market return series. The test rejects the null hypothesis of unit root, i.e. non-stationarity and holds stationarity presence in time series. The stationarity presence highlights that current stock returns are significantly affected by previous stock returns.

To examine the volatility clustering, i.e. autocorrelations in stock returns, here study employs the Ljung-Box (Q) statistics. Autocorrelation plots are one common method to test for randomness and, L-B statistics to test the significance level of autocorrelation at different lags. However, instead of testing randomness at each distinct lag, it tests the overall randomness based on a number of lags. If the stock returns are turned out to be uncorrelated, then efficient market hypothesis (EMH) is

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[2]The S &P Global 1200 index is a real time, free-float weighted stock market index of global stocks from Standard & Poor's. The index covers 31 countries and approximately 70% of global market capitalization. It is comprised of six regional indices—S&P 500 Index; S&P TSX 60 Index (Canada); S&P Latin America 40 Index (Mexico, Brazil, Argentina, Chile); S&P TOPIX 150 Index (Japan); S&P Asia 50 Index (Hong Kong, Korea, Singapore, Taiwan); S&P ASX 50 Index (Australia); S&P Europe 350 Index.

Table 10.1 Descriptive statistics of NASDAQ and NYSE

Statistics	NASDAQ 100	S & P 500
Mean	0.033	0.031
Median	0.105	0.046
Maximum	19.169	5.573
Minimum	−10.377	−7.112
Std. Dev.	1.745	0.993
Skewness	0.139	−0.121
Kurtosis	9.175	6.793
Jarque–Bera	7226.751* (0.000)	27.32* (0.000)
Unit root test (ADF Test)		
Constant, no trend	−31.73*	−32.00*
Constant, trend	−31.78*	−32.00*
Test of autocorrelations in stock returns		
Q (5)	1097.70* (0.000)	1108.30* (0.000)
Q (10)	1103.90* (0.000)	1116.30* (0.000)
Q (15)	1130.0* (0.000)	1135.40* (0.000)
Q (20)	1152.40* (0.000)	1136.50* (0.000)
Q (25)	1188.40* (0.000)	1142.60* (0.000)

Source Compiled from Kumar and Dhankar (2010)
Note *Significant at 5% level of significance
P value in parentheses

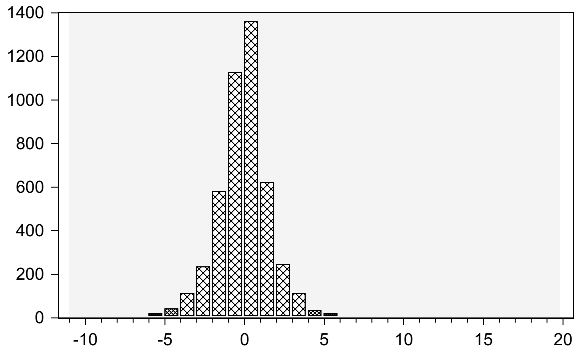

Fig. 10.1 Distribution of return of NASDAQ 100. *Source* Compiled from Kumar and Dhankar (2010)

accepted thereby rejecting the null hypothesis of autocorrelation in stock returns, and the stock markets in question are deemed informationally efficient. The holding of such situations highlights the fact that stocks prices are reflecting all inherent

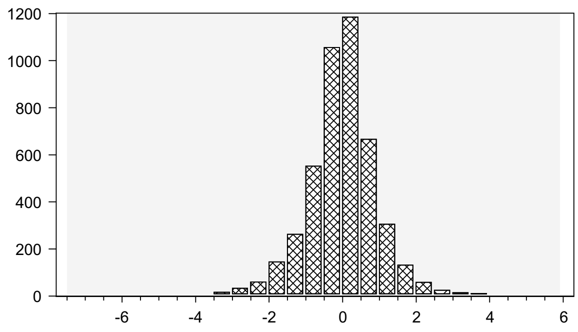

Fig. 10.2 Distribution of Return of S & P 500. *Source* Compiled from Kumar and Dhankar (2010)

information and investors primarily giving weightage to current information in stocks selection. As against it, if stock returns are found serially correlated, it will report volatility clustering in stock returns. That is, high volatility tends to be followed by high volatility and low volatility tends to be followed by low volatility. Such phenomenon involves the rejection of EMH and holds that current stock returns are significantly affected by returns being offered in the past. As indicated by Table 10.1, L-B statistics of 1–25 lags are significant, suggesting the presence of autocorrelation is stock returns in both the stock markets.

Measuring the Conditional Volatility in Stock Market Returns and Diagnosis Testing

Figures 10.3 and 10.4 measure the volatility of daily returns of NASDAQ 100 and S & P 500, respectively. A careful examination of the index movements highlights the volatility clustering. Once volatility clustering is traced, the study uses the vanilla GARCH (1, 1) model in the return series for both the stock markets. While running the GARCH (1, 1) process the following equations are estimated for forecasting the conditional volatility in both stock markets.

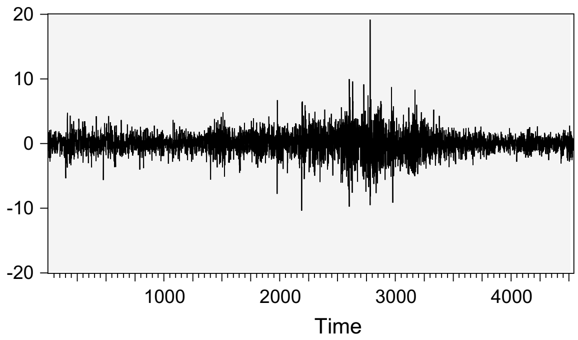

Fig. 10.3 Volatility of NASDAQ 100. *Source* Compiled from Kumar and Dhankar (2010)

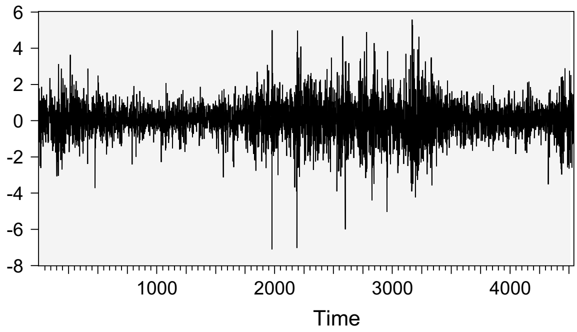

Fig. 10.4 Volatility of S & P 500. *Source* Compiled from Kumar and Dhankar (2010)

Table 10.2 Fitting of GARCH (1, 1) model in Nasdaq 100 and S & P 500

Stock market	Constant α_0	ARCH (1) α_1	GARCH (1) α_2
NASDAQ 100	0.008* (3.41)	0.045* (12.41)	0.951* (223.18)
S & P 500	0.006* (6.36)	0.054* (13.07)	0.939* (200.51)

Source Compiled from Kumar & Dhankar (2010)
Note *Significant at 5% level of significance
Z statistic in parentheses

$$\sigma^2_{NASDAQ} = 0.008 + 0.045\varepsilon^2_{t-1} + 0.951\sigma^2_{t-1} \tag{10.6}$$

$$\sigma^2_{NYSE} = 0.006 + 0.054\varepsilon^2_{t-1} + 0.939\sigma^2_{t-1} \tag{10.7}$$

Table 10.2 outlines the estimated coefficients of the model with their standard error and 'z' statistics. It reports that ARCH (1) coefficients α_1 for both indices are significant at 5% level of significance. It brings out that good or bad news which is measured by lagged error term has a significant impact upon current volatility. In the same way, the significant GARCH (1) coefficients of both indices α_2 also report that volatility in the preceding time period has a significant impact upon the volatility in the current time period. The observations can be made from the results that investment decisions are significantly affected by past good or bad news, and volatility in the preceding time period. Figures 10.5 and 10.6 show the time series plot for the estimated series of conditional variance for NASDAQ and NYSE stock markets, respectively. Conditional volatility as depicted in figures moves qualitatively like the apparent volatility variations in the returns as indicated in Figs. 10.3 and 10.4. From Figs. 10.5 and 10.6, the high volatile months can be traced with reasons why the market showed high conditional heteroscedasticity during those periods. After fitting the models, it is important to test the best fit of these models which can significantly explain the conditional volatility. The study again applied L-B test to examine the randomness of residual and squared residuals of stock returns for both stock markets in questions. If the fitted models significantly explain the conditional volatility, then the residuals at different lags should have zero mean

Fig. 10.5 Conditional volatility of NASDAQ 100. *Source* Compiled from Kumar and Dhankar (2010)

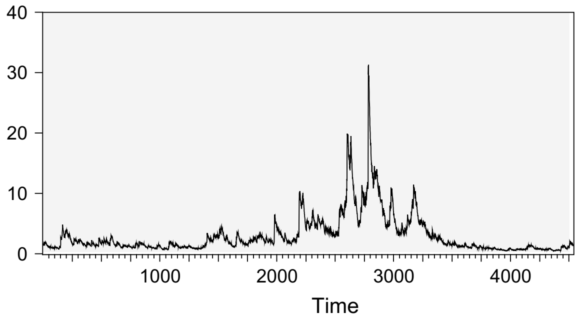

Fig. 10.6 Conditional volatility of S & P 500. *Source* Compiled from Kumar and Dhankar (2010)

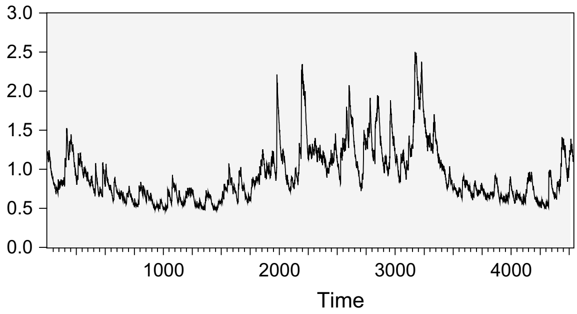

Table 10.3 Diagnosis testing of fitted models

L-B Statistics	S & P 500	NASDAQ 100
Q (5)	9.60** (0.086)	8.88** (0.114)
Q (10)	14.72** (0.143)	9.63** (0.473)
Q (15)	31.11* (0.008)	30.57* (0.010)
Q (20)	33.10* (0.033)	36.50* (0.013)
Q (25)	38.51* (0.041)	42.99* (0.014)

Source Compiled from Kumar and Dhankar (2010)
Note *Significant at 5% level of significance
**Not significant at 5% level of significance
P value in parentheses

and constant variance, i.e., residuals at different lags should serially be uncorrelated. Table 10.3 highlights that computed L-B statistics of residuals from 1 to 25 lags of null hypothesis has no autocorrelation. The 'Q' statistics suggest no correlation in residuals of both stock markets, holds the fitted models best fit in explaining the volatility.

Table 10.4 Fitting of T-GARCH (1, 1) model in the U.S. stock market

Stock Market	Constant α_0	ARCH (1) α_1	GARCH (1) α_2	TGARCH γ
NASDAQ 100	0.009* (3.89)	0.021* (4.19)	0.951* (202.79)	0.047* (7.85)
S & P 500	0.011* (9.66)	0.002 (0.61)	0.931* (185.61)	0.109* (14.79)

Source Compiled from Kumar and Dhankar (2010)
Note *Significant at 5% level of significance
Z statistic in parentheses

Measuring of Asymmetric Effect on Volatility

Recent empirical studies indicate that the impact of good or bad news is asymmetric on volatility (Pagan and Schwert 1990; Nelson 1991; Chiang and Doong 2001). That is, good and bad news carry a different magnitude of impact on investment decisions. This asymmetric impact on volatility is captured by using the T-GARCH (1, 1) procedure which can be written as follows:

$$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} \tag{10.8}$$

where $d_t = 1$ if $\varepsilon_t < 0$, and $d_t = 0$ otherwise.

In this model, the asymmetric volatility of index return is captured by the estimated coefficient γ. Good news ($\varepsilon_t < 0$), and bad news ($\varepsilon_t > 0$), have differential effects on the conditional variance—good news has an impact of α, while bad news has an impact of $\alpha + \gamma$. If $\gamma > 0$, we say that the leverage effect exists. If $\gamma \neq 0$, the news impact is asymmetric. Table 10.4 reports that coefficient γ is significant at 5% level of significance. It reports that impact of good and bad news is asymmetric on investment decisions in both stock markets.

Relationship Between Stock Returns and Conditional Volatility, and Standardized Residuals

There are conflicting empirical evidence with regard to the relationship between stock returns and conditional volatility, and standardized residuals. Studies such as French et al. (1987) and Campbell and Hentschel (1992) find the relation between stock return and conditional return to be positive, while studies such as Turner et al. (1989), Nelson (1991) and Glosten et al. (1993) find the relationship to be negative. The present study measures the relationship between stocks return and expected volatility by applying Eq. 10.9 and between stocks return and unexpected volatility (standard residuals) by using eq. 10.10.

Table 10.5 Relationship between return and conditional variance, and residuals

Correlation	ϕ_0	φ_1	R^2
S & P 500 and expected volatility	0.532* (40.28)	−0.521* (−64.18)	0.47*
NASDAQ 100 and expected volatility	0.428* (12.95)	−0.130* (−18.19)	0.06
	δ_0	δ_1	R^2
S & P 500 and Standardized residual	−1.120 (−0.002)	0.930* (180.01)	0.87*
NASDAQ 100 and Standardized residual	−0.001* (−0.12)	1.582* (147.06)	0.99*

Source Compiled from Kumar and Dhankar (2010)
Note *Significant at 5% level of significance
t statistic in parentheses

$$R_t = \phi_0 + \phi_1 Exp.Vol. + \omega_t \tag{10.9}$$

$$R_t = \delta_0 + \delta_1 Un\exp.Vol. + \omega_t \tag{10.10}$$

Table 10.5 reports the findings. The relationship between stock returns and conditional volatility (expected volatility) as measured by $\boldsymbol{\phi}_1$ is negatively significant for both indices. It brings out that investors adjust their stock returns in response to expected volatility. These results bring out the important elements of investment strategy, investors adjust their risk premium in view of anticipated or expected variations in stock prices resultant to ups and downs in corporate and economic fundamentals. They tend to withdraw or postpone their investment decisions in view of expected volatility or fluctuations in stock returns. However, the coefficient $'\delta_1'$ is significant for indices, which suggests a positive relationship between stock returns and standard residuals (unexpected volatility).

Relationship Between NYSE and NASDAQ Trading

This section examines the relationship between the movements of S & P 500 and NASDAQ 100. Here, the study involves the use of Granger casualty test to track the relationship. The results accept the acceptance of null hypothesis and holds that trading movements of S & P 500 do not affect the trading movements of NASDAQ 100. However, null hypothesis II is rejected and it is established that trading movements of S & P 500 are affected by trading movements of NASDAQ 100 (Table 10.6). The observations can be made that stock trading of NYSE is affected by trading of NASDAQ stock market.

Table 10.6 Relationship between NASDAQ and NYSE

	Null Hypothesis	F-Statistic	Probability
H0: I	S & P 500 does not Granger cause NASDAQ 100	1.39**	0.24
H0: II	NASDAQ 100 does not Granger Cause S & P 500	4.02*	0.01

Source Compiled from Kumar and Dhankar (12010)
Note *Significant at 5% level of significance
**Not significant at 5% level of significance

Conclusion and Summary

This paper provides the evidence of the presence of conditional heteroskedasticity and asymmetric effect of good and bad news on volatility. The study uses two broad-based stock market indices-S & P 500 and NASDAQ 100. The GARCH and T-GARCH models provide good forecast of volatility which can be used by investors for a number of purposes including asset allocation, performance measurement, etc. Risk averter investors, for example, can forecast the volatility of their portfolio and relocate their funds to establish trade-off between their risk and return preferences. The findings hold that volatility significantly depends upon past error term which represents an unexpected rise or decline in returns and volatility in the preceding time period. That is, unexpected rise or decline in stock return and volatility in the last time period combined together affect investors behaviour and thereby investment decisions. The study also reports the asymmetric effects of good and bad news on stock market volatility. That is investors perceive and react to good and bad news differently. The positive significant relationship between stock return and unexpected volatility highlights that investors expect risk premium during the unexpected rise or decline in stock return. The findings, however, report a negative significant relationship between stock returns and expected volatility. This phenomenon outlines that investors adjust their portfolios in advance with regard to expected volatility. Further research could be done by applying the multivariate GARCH model and more stock indices can be considered. The impact of monetary variables such as interest rate, exchange rate, inflation, etc. can be analysed on conditional volatility.

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Chapter 11
Correlation, Uncertainty and Investment Decisions

The key to making money in stocks is not to get scared out of them.
Peter Lynch

Abstract Capital market efficiency is a matter of great interest for policymakers and investors in designing investment strategy. If efficient market hypothesis (EMH) holds true, it will prevent the investors to realize extra return by utilizing the inherent information of stocks. They will realize extra returns only by incorporating the extra risky stocks in their portfolios. While empirical tests of EMH and risk–return relationship are plentiful for developed stock markets, the focus on emerging stock markets like India, Pakistan, Sri Lanka, etc., began with the liberalization of financial systems in these markets. With globalization and deregulation, the enormous opportunities of investment in South Asian stock markets have attracted the domestic and foreign institutional investors in general, and to reduce their portfolio risk by diversifying their funds across the markets in particular.

Introduction

Although uncertainty is more common in the decision-making process than risk, relatively little attention is paid to the phenomenon of uncertainty in empirical asset pricing literature. The empirical evidence to date in the finance literature suggests that there are two major style facts in stock return volatility. First, stock return volatility is time-varying and clustering. The change in volatility is serially correlated and persists for a long period of time. Second, the shocks to stock return volatility are negatively associated with unexpected stock returns.

This chapter draws from the author's previous publication (Kumar & Dhankar, 2009), co-authored with Rakesh Kumar, Assistant Professor in the Department of Business Studies, Deen Dayal Upadhyaya College (University of Delhi), New Delhi; originally published in *VIKALPA: The Journal for Decision Makers*, Vol. 34 No. 4.

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India Studies in Business and Economics,
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An efficient capital market fully reflects the available information pertaining to stocks resulting in investors having homogeneous expectations of the stocks' performance. Accordingly, investors value the stocks taking into account the risk and return prospects (Sharpe, 1964; Mossin, 1966). Such conditions prevent investors from realizing abnormal returns by utilizing the inherent information stock prices. If efficient capital market hypothesis holds true, it documents the random walk movements in stock prices, resulting in investors realize extra risk premium only by exposing their portfolios to unexpected variations in stock prices. Substantial empirical work supports the efficient market hypothesis in developed stock markets. This area has great potential for research in emerging stock markets like India as well. The underlying hypothesis is that the expected variations in stock prices (expected volatility) induce the investors to adjust their risk premium and remain invariable to these fluctuations. The study examines this hypothesis in the South Asian context by examining the relationship of stock returns with expected and unexpected volatility. Additionally, it investigates the regional integration among these markets and also with the global stock market. Existing research examines the integration of stock markets by tracing the co-movements in developed stock markets returns but hardly any work is done in the direction of measuring the interdependency among the South Asian stock markets. The present study makes an attempt to investigate the regional interdependency of South Asian stock markets in terms of stock returns and volatility by examining the cross-correlations in stocks returns and degree of correlation in conditional volatilities. This line of research provides the degree of regional sensitiveness of one stock market to the ups and downs of another stock market from the same region.

Many empirical works which investigate the seasonal patterns in stock returns in developed and developing stock exchanges question the efficient market hypothesis and suggest a seasonal pattern in these stock markets by identifying the autocorrelation in stock returns (Aggarwal & Rivoli, 1989; Lee, 1992; Ho & Cheung, 1994; Moorkejee & Yu, 1999; Pandey, 2002; Johnson & Soenen, 2002, 2003; Jarrett & Kyper, 2005, 2006). The presence of autocorrelation in time series data signifies the non-normality of the error term called heteroskedasticity. The existence of such a phenomenon in financial time series such as stock returns or exchange rates exhibits volatility clustering (Karmakar, 2005; Faff & Mckenzie, 2007; Dhankar & Charkraborty, 2007). This suggests that large fluctuations in these series tend to be followed by large fluctuations and small fluctuations by small ones. The presence of heteroskedasticity suggests that the past error term which represents non-market risk or unexpected volatility affects current investment decisions. Under this situation, variance captures aggregate fluctuations in stock returns and thereby provides only gross volatility (Schwert, 1990; Dhankar & Kumar, 2006; Kumar, 2007).

In modelling such phenomenon in stock returns, researchers commonly use autoregressive conditional heteroskedasticity approach. Akgiray (1989), Corhay and Rad (1994) and Brooks (1998) used the US and European stock market data and found GARCH (1, 1) as better predictors of volatility. Aggarwal, Inclan, and Leal (1999) examined the sudden change in volatility in the emerging stock markets and found that the high volatility was attributed to a sudden change in variance. The periods with high volatility were found to be associated with important events in each country rather than global events. In case there is no systematic pattern, stock returns may be time variant; however, the existence of systematic variations in the time series of stock returns suggests inefficient market, which results in earning of extra returns not in line with the degree of risk. It evolves the possibilities of market manipulation wherein investors tend to earn abnormal returns incommensurate with the degree of risk. The present study roots its investigation back to the study of French, Schwert, and Stambaugh (1987), wherein attempts were made to examine the relationship between stock returns and expected and unexpected volatility. Their study examined the monthly returns and segregated monthly volatility into its expected and unexpected components. It also estimated the relationship between realized monthly returns and two volatility components. They found a significant negative relationship between returns and unexpected changes in volatility as well as a significant positive relationship between returns and expected volatility under the GARCH-M process. King and Wadhwani (1990), Schwert (1990), King, Enrique, and Wadhwani (1994) reported time-varying relationship and held that stock market returns show high correlation during high volatility time.

Some empirical studies held monetary variables as dynamics of linkages between stock markets. Sasaki, Yamaguchi and Takamasa (1999) examined the dynamic relationship in accordance with the monetary policies and found significant evidence to suggest that monetary variables affected international interdependencies across stock markets. Several studies (Hamao, Masulisand, & Ng, 1990; Balaban, Bayar, & Kan, 2001; Kumar & Mukhopadyay, 2002) employed a two-stage GARCH model to study the dynamic relationship across the stock markets wherein daytime and overnight returns were used. They first extracted the unexpected shocks from the daytime returns of one market and used them as a proxy for volatility surprise while modelling the other markets' overnight returns in the second stage of modelling. Further, a number of studies (Cheung & Mak, 1992; Karolyi & Stulz, 1996; and Masih & Masih, 2001) employed co-integration and Granger causality tests and held that US stock market played a dominating role in the world stock market integration. Studies (McClure, Clayton, & Hofler, 1999; Hu, 2000; Frank & Frans, 2001) examining group stock markets held a strong interdependence across the stock markets. Ewing, Payne and Sowell (1999) examined how the North American Foreign Trade Agreement (NAFTA) affected the level of market integration in North America. They, however, found no evidence of integration in member markets even after NAFTA was embedded. The study of Darrat and Zhong (2001) produced opposite results while examining the markets of the US, Canada and Mexico. The results of their co-integration tests suggested that NAFTA enhanced the linkages across members stock markets. In conclusion, the majority of the studies found market integration to have increased significantly over the years. Yet a number of studies questioned this phenomenon and failed to report any dynamic relationship (Cheung & Lee, 1993; King, Enrique, & Wadhwani, 1994; McClure, Clayton, & Hofler, 1999; Ewing, Payne, & Sowell, 1999).

Data and Research Methodology

This study uses market indices as the proxy for stock markets. The dataset used in the study consists of a monthly process of four emerging South Asian markets; for ease of comparison with global stock market, a global index is also used. The study uses Bombay Stock Exchange listed index, BSE 100, for India, Colombo Stock Exchange listed Milanka Price Index for Sri Lanka, Karachi Stock Exchange listed KSE 100 for Pakistan, Dhaka Stock Exchange listed DSE-General Index for Bangladesh and S & P Global 1200 to represent the global market. Table 11.1 provides the details of sample indices, time period and data source. With the given data set, fluctuations in stock returns reflect volatility in the stock market. Suppose P_t is the price of index in time period *t*, P_{t-1} is the price of index in the preceding

Table 11.1 Sample and data source

Country	Index	Data period	Data source
India	BSE100[a]	January 1996–December 2007	Prowess, CMIE Ltd.
Sri Lanka	MPI[b]	January 1995–Dec 2005	www.cse.lk
Pakistan	KSE 100[c]	July 1997–December 2007	www.dsebd.org
Bangladesh	DSE-general index[d]	January 1995–December 2005	www.online.wsj.com
Global market	S & P Global 1200[e]	June 2001–December 2007	www.online.wsj.com

Source Compiled from Kumar and Dhankar (2009)

[a]BSE 100 is value-weighted index, which comprises 100 stocks listed with Bombay stock exchange. It represents approximately 75% market capitalization

[b]MPI is one of the most quoted indexes in Sri Lanka stock market, represents 25 stocks listed with Colombo stock exchange. It was introduced in January 1999, replacing a Sensitive Price Index (SPI)

[c]The KSE 100 index was introduced in 1991 and comprises 100 stocks selected on the basis of sector representation and highest market capitalization, which captures over 80% of the total market capitalization of the companies listed on Karachi Stock Exchange

[d]DSE-GI which has been calculated for A, B, G, and N categories of stocks is broad based and highly quoted index of Dhaka Stock Exchange

[e]The S & P Global 1200 Index is a real time, free-float weighted stock market index of global stocks compiled by Standard & Poor's. The index covers 31 countries and approximately 70% of global market capitalization. It is comprised of six regional indices—S&P 500 index; S &P TSX 60 index (Canada); S &P Latin America 40 Index (Mexico, Brazil, Argentina, Chile); S &P TOPIX 150 Index (Japan); S &P Asia 50 Index (Hong Kong, Korea, Singapore, Taiwan); S &P ASX 50 Index (Australia); and S &P Europe 350 index

time period *t-1*, the rate of return R_{it} investors will realize in 't' time period would be as follows:

$$\mathrm{R_t} = [\log_e(\mathrm{P_t}) - \log_e(\mathrm{P_{t-1}})] * 100 \tag{11.1}$$

In fact, the realized return consists of a set of two components—expected return $\mathrm{E(R_t)}$ and unexpected return 'εt'. While the expected return is attributed to the economic and stock fundamentals, unexpected return arises due to good or bad news pertaining to stocks. Symbolically, it can be written as follows:

$$\mathrm{R_t} = \mathrm{E(R_t)} + \varepsilon_\mathrm{t} \tag{11.2}$$

An upswing in ε_t (unexpected rise in return) suggests the arrival of good news; on the contrary, a downswing in εt (unexpected decline in return) is a mark of bad news. Volatility in the stock market as a result of expected variations in stock returns is termed as expected volatility, while volatility resultant to unexpected variations in stock returns is known as unexpected volatility (French et al., 1987). Investors and policymakers may be interested to see the value of their portfolio in risky situations in some future point of time. In modelling such situations, autoregressive conditional heteroskedasticity (ARCH) approach is applied wherein the conditional variance is used as a function of the past error term and allows the variance of error term to vary over time (Engle, 1982). It implies that volatility can be forecasted by the inclusion of the past news as a function of conditional variance. This process is called autoregressive conditional heteroskedasticity which can be written as follows:

$$\sigma_c^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots\ldots\alpha_p\varepsilon_{t-q}^2 \tag{11.3}$$

where $\alpha_0 > 0, \alpha_1, \alpha_2\ldots\ldots\alpha_p \geq 0$ All things being equal, α carries more intense influence as compared to α_j. That is, in comparison to current news, older news bears less impact on current investment decisions which results in volatility. Bollerslev, Chou, and Kroner (1992) further extended the ARCH process by allowing the conditional variance to be the function of past error term as well as lagged value of conditional variance. This is based on the idea that the past error term, which affects current investment decisions and volatility in the last time period combined together has a significant impact over the current investment decisions. Following the introduction of ARCH models by Engle (1982) and further generalization by Bollerslev et al., (1992), these models have been extensively used in explaining and modelling the time series data of stock market. A standard GARCH (1, 1) as developed by Bollerslev et al., (1992), can be symbolically written as

$$\sigma^2 = \alpha_0 + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{11.4}$$

The magnitude and persistence of volatility in the current time period directly depend upon the sizes of the coefficients α_i and β_i. A high 'β_i' suggests that if volatility was high yesterday, it will still be very high today. The shocks to conditional variance will take along time to die out. In the same fashion, the high value of 'α_i' suggests that unexpected ups and downs in stock returns react quite intensely to current market movements resulting in spike volatility. The closer 'αi' is to one, the more persistent is volatility following market shocks. However, recent empirical studies indicate that the impact of good or bad news is asymmetric on volatility (Nelson, 1991; Chiang & Doong, 2001). That is, good and bad news carries a different magnitude of impact on investment decisions (Bekaert & Wu, 2000). As the GARCH model fails to take into account the asymmetric effect between positive and negative stock returns, the models such as Exponential or E-GARCH (Nelson 1991) and Threshold Auto regressive or TAR-GARCH (Engle & Ng, 1993; Gloston, Jagannathan, & Runkle, 1993; Bae & Karoyli, 1994; Tsay, 1998) have been used in forecasting and estimation of volatility. These models are used to capture the asymmetric effect of good and bad news on investment decisions. This line of research highlights the asymmetric effect of news by emphasizing that negative shock to returns will generate more volatility than a positive shock of equal magnitude. T-GARCH (1, 1) model can be written as

$$\sigma^2 = \alpha_0 + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1}$$

where $d_t = 1$ if $\varepsilon_t < 0$, and $d_t = 0$ otherwise.

In this model, the asymmetric volatility of index return is captured by the estimated coefficient γ. The good news ($\varepsilon t < 0$) and bad news ($\varepsilon_t > 0$) have differential effects on the conditional variance—good news has an impact of α, while bad news has an impact of $\alpha + \gamma$. If $\gamma > 0$, we say that the leverage effect exists. If $\gamma \neq 0$, the news impact is symmetric. Chiang and Doong (2001) used T-GARCH to examine the volatility of seven Asian stock markets and found a symmetric effect on the conditional volatility when daily return is used. However, the study questions this phenomenon in the case of monthly return.

Empirical Findings

Preliminary Results

Some of the stochastic properties of the market returns of global and South Asian markets are presented in Table 11.2, which highlights the distribution of risk and returns in these markets for study time periods. The positive average return of all the markets highlights the fact that stock indices tend to increase over the period. The Indian stock market has offered the highest return next to Pakistan, subject to lower risk (8.05) compared to Pakistan (9.85). The negative skewness of India, Pakistan and global market suggests that the returns distribution of the markets have

Table 11.2 Descriptive statistics

	India	Sri Lanka	Pakistan	Bangladesh	Global
Mean	1.48	0.33	1.46	0.52	0.48
Median	2.49	0.74	1.77	0.28	1.07
Maximum	16.99	31.93	24.11	56.91	7.22
Minimum	−23.49	−24.26	−40.67	−38.92	−10.88
Std. Dev.	8.05	9.00	9.85	10.41	3.55
Skewness	−0.51	0.22	−0.67	0.87	−0.87
Kurtosis	2.94	4.41	5.25	10.56	3.97
Jarque–Bera test	6.30* (0.042)	12.04* (0.002)	38.40* (0.000)	330.66* (0.000)	13.15* (0.000)
Q(5)	39.12* (0.000)	32.90* (0.000)	37.85* (0.000)	37.43* (0.000)	22.98* (0.000)
Q(10)	52.23* (0.000)	41.80* (0.000)	43.79* (0.000)	47.93* (0.000)	24.49* (0.000)
Q(15)	55.35* (0.000)	53.35* (0.000)	46.09* (0.000)	50.16* (0.000)	26.36* (0.034)
Q(20)	61.63* (0.000)	55.32* (0.000)	57.26* (0.000)	56.67* (0.000)	28.29** (0.103)
Q(25)	64.75* (0.000)	59.36* (0.000)	59.28* (0.000)	62.02* (0.000)	33.40** (0.121)

Source Compiled from Kumar and Dhankar (2009)
Note *Significant at 5% level of significance
**Not significant at 5% level of significance

a higher probability of providing negative returns. The skewness of Sri Lanka and Bangladesh stock markets' returns are, however, positive implying that returns are positively distributed. The kurtosis of India is platykurtic which signifies the normal distribution of stock returns in Indian stock market; however, the high kurtosis of other markets exhibits heavier tail than the standard normal distribution implying that returns are concentrated on one level. The study uses Jarque–Bera test to examine the normal distribution characteristics of all stock markets. The fact that it is significant at 5% level of significance for all stock markets including the global market (as indicated by Table 11.2), questions the normal distribution of returns and thereby the random walk behaviour of the global and South Asian markets.

Test for Cross-Relation in Stock Returns

The linear regression econometric models underline the assumptions of the constant variance of residuals over the period of time. To examine the randomness, this study employs the Ljung–Box statistics to detect the autocorrelations in the returns of the stock markets under consideration. Autocorrelation plots are one common method used for testing randomness and L-B statistics for testing the significance level of autocorrelation at different lags. However, instead of testing randomness at each distinct lag, it tests the overall randomness based on the number of lags. If the stock returns turn out to be uncorrelated, then efficient market hypothesis (EMH) is accepted thereby rejecting the alternative hypothesis of autocorrelation in stock returns, and the stock market in question is deemed informationally efficient. Such situations highlight the fact that stock prices reflect all inherent information and investors primarily give weightage to current information in the selection of stocks. As against it, if stock returns are found serially correlated, it will report volatility clustering in stock returns, that is, high volatility tends to be followed by high volatility and low volatility tends to be followed by low volatility. Such phenomenon involves the rejection of EMH and holds that current stock returns are significantly affected by returns being offered in the past. As indicated by Table 11.2, L-B statistics of 1–25 lags are significant suggesting the presence of autocorrelation in stock returns in all the Asian markets. However, in the case of global market, autocorrelations are significant at 15 lags, after which they are insignificant, indicating that investors have already utilized inherent information of stocks.

Model Estimation, Forecasting of Conditional Volatility and Diagnosis Testing

The above tests report significant non-linear dependence in the stock returns of global and South Asian markets. The 'L-B' statistics which examines the autocorrelations in stock returns for lags 1–25, holds volatility clustering, i.e., serial correlation in stock returns. After tracing this phenomenon, the next task is to fit the best model in the global and South Asian markets' stock returns which can significantly explain the conditional volatility in these markets. Thus, an ARCH process or its generalized models may be the best fit in explaining the non-linear dependence as reported in stock returns of the stock markets under consideration. To fit in the best model, various criteria like Akaike information and Schwarz criterion are used.

Table 11.3 reports the estimated models with their coefficients and 'p' values for all stock markets. It reports that India's conditional volatility can be modelled with GARCH (2, 0) model, where ARCH terms up to 2 lags are significant, holding that unexpected fluctuations in stock prices make investors replan their investment strategy, whereas the volatility in the preceding time period has no impact upon investors' decisions, investors being invariable to expected fluctuations in stock prices. This is a clear indication that Indian stock market is moving towards

Table 11.3 Forecasting of volatility-model estimation

India	α_0	α_1	α_2	
GARCH (2, 0)	60.23* (0.000)	−0.17* (0.003)	0.16* (0.050)	
Sri Lanka	α_0	α_1	β_2	
GARCH (1, 1)	69.91* (0.000)	0.07* (0.000)	−0.57* (0.000)	
Pakistan	α_0	α_1	β_1	λ
T-GARCH (1, 1)	3.26* (0.000)	−0.11* (0.000)	1.03* (0.0000)	−0.11* (0.0000)
Bangladesh	α_0	α_1	β_1	
GARCH (1, 1)	14.71* (0.025)	0.29* (0.000)	0.53* (0.000)	
Global Market	α_0	α_1	β_1	λ
T-GARCH (1, 1)	1.15* (0.000)	−0.23* (0.019)	−0.98* (0.001)	−0.08* (0.000)

Source Compiled from Kumar and Dhankar (2009)
Note *Significant at 5% level of significance

efficiency. In the case of Sri Lanka and Bangladesh, GARCH (1, 1) model significantly explains the conditional volatility. Investors in these two South Asian markets significantly redesign their investment strategy in response to expected and unexpected changes in stock prices due to changes in corporate and economic factors, i.e. volatility in the preceding time period has a significant impact upon the volatility in the current time period. Observations can be made here from the results that investment decisions are significantly affected by past good or bad news and volatility in the preceding time period. The results report asymmetric volatility in Pakistan's and global stock market (Table 11.3). T-GARCH (1, 1) model significantly explains the volatility in the current time period as a function of unexpected and expected volatility in the preceding time period. It can be observed from the results that investment decisions are certainly being impacted by the good or bad news and the volatility in the preceding period. These results question the symmetric movements in stock returns and hold the rejection of efficient market hypothesis in stock markets in question. After fitting the models, it is important to test the best fit of these models which can significantly explain the conditional volatility in South Asian and global markets. The study again applied L-B test to examine the randomness of residual and squared residuals of stock returns for all the stock markets in questions. If the fitted models significantly explain the conditional volatility, then the residuals at different lags should have zero-mean and constant variance residuals at different lags should be serially uncorrelated.

Table 11.4 highlights the computed L-B statistics of residuals from 1 to 25 lags of null hypothesis of no autocorrelation. The 'L-B' statistics suggesting no correlation in residuals of all stock markets, holds that the fitted models best fit in explaining the volatility.

Table 11.4 Diagnostic testing of fitted models

LB statistic	India	Sri Lanka	Pakistan	Bangladesh	Global
Q(5)	2.50** (0.776)	1.76** (0.880)	1.08** (0.955)	6.98** (0.221)	5.73** (0.333)
Q(10)	9.28** (0.505)	7.26** (0.701)	5.92** (0.821)	8.21** (0.607)	8.38** (0.591)
Q(15)	11.05** (0.749)	13.46** (0.566)	7.64** (0.937)	11.44** (0.720)	12.71** (0.665)
Q(20)	14.54** (0.802)	14.97** (0.778)	12.25** (0.907)	18.35** (0.564)	13.90** (0.835)
Q(25)	20.54** (0.718)	16.30** (0.905)	14.93** (0.943)	23.51** (0.548)	16.41** (0.902)
Q^2 (5)	3.28** (0.656)	4.16** (0.528)	2.38** (0.794)	0.75** (0.980)	6.003** (0.305)
Q^2 (10)	4.06** (0.944)	7.45** (0.682)	5.57** (0.850)	3.68** (0.961)	11.02** (0.356)
Q^2 (15)	12.57** (0.635)	15.09** (0.445)	9.61** (0.843)	6.10** (0.978)	12.72** (0.623)
Q^2 (20)	22.02** (0.339)	18.73** (0.539)	16.04** (0.714)	9.99** (0.968)	13.87** (0.837)
Q^2 (25)	26.20** (0.397)	23.98** (0.520)	24.34** (0.499)	12.23** (0.985)	16.73** (0.891)

Source Compiled from Kumar and Dhankar (2009)
Note **Not significant at 5% level of significance

Relationship of Stock Returns with Expected and Unexpected Volatility

Conflicting empirical evidence is reported with regard to the relationship between stock returns and conditional volatility, and standardized residuals (unexpected volatility).

Studies (French et al., 1987; Campbell & Hentschel, 1992) found the relation between stock returns and conditional volatility positive, whereas a number of studies have held this relationship as negative (Nelson, 1991; Glosten, Jagannathan, & Runkle, 1993; Bekaert & Wu, 2000; Wu, 2001). The present study also examines the relationship of stock returns with that of expected volatility and unexpected volatility by estimating Eqs. 11.6 and 11.7, respectively.

$$\mathrm{R_t} = \phi_0 + \phi_1\, Exp.Vol + \omega_t \tag{11.6}$$

$$\mathrm{R_t} = \phi_0 + \phi_L\, Unexp._{Volt} + \omega t \tag{11.7}$$

Table 11.5 Relationship between stock returns and conditional volatility and residuals

	Relationship	φ_0	φ_1	R^2
India	Return and expected volatility	0.04** (0.984)	0.021** (0.370)	0.01
	Return and unexpected volatility	0.037** (0.770)	7.89* (0.000)	0.96
Sri Lanka	Return and expected volatility	−1.61** (0.556)	0.02** (0.459)	0.01
	Return and unexpected volatility	0.17** (0.148)	8.63* (0.000)	0.97
Pakistan	Return and expected volatility	2.86** (0.171)	−0.01** (0.459)	0.00
	Return and unexpected volatility	−0.18** (0.434)	9.479* (0.000)	0.93
Bangladesh	Return and expected volatility	1.54** (0.162)	−0.01** (0.106)	0.01
	Return and unexpected volatility	−0.42** (0.300)	9.34* (0.000)	0.80
Global Market	Return and expected volatility	1.68* (0.000)	−0.104* (0.017)	0.07
	Return and unexpected volatility	1.68* (0.009)	−0.104* (0.017)	0.07

Source Compiled from Kumar and Dhankar (2009)
Note *Significant at 5% level of significance
**Not significant at 5% level of significance

The findings reported in Table 11.5 suggest that the relationship between stock returns and expected volatility as measured by ϕ_1 is not significant in the case of all the South Asian stock markets thereby implying no correlation between the two. However, it is significant for the global stock market as it reports a positive relationship between stock returns and expected volatility. When measuring the relationship between stock returns and unexpected volatility, the coefficient ϕ_1 is significant and suggests a positive relationship between stock returns and unexpected volatility. These results bring out the important elements of investment strategy. Investors adjust their risk premium in advance in view of the anticipated or expected variations in stock prices as a result of the ups and downs in corporate and economic fundamentals. Observations can be made here that investors do not react spontaneously to expected variations in stock prices and they continue to hold the same portfolios. However, the significant positive relationship between stock returns and unexpected volatility brings out the fact that investors expect risk premium for exposing to unexpected variations in stock prices. If efficient market holds true, they will realize higher returns by bearing this risk.

Integration of South Asian Stock Markets with Global Stock Market

The liberalization of financial systems in the line of WTO norms, has led the growth of South Asian stock markets in terms of market capitalization and foreign institutional investments. The high earning prospects of these markets have attracted foreign capital on a large scale. It is evident from Table 11.2 that South Asian stock markets have offered high mean returns to investors as compared to the global market.

During the globalization and deregulation regime, it has become important to examine the responsiveness of these stock markets to their regional and global trading partners. It has become an area of interest for researchers and policymakers to examine the dynamic linkages among the South Asian markets, as it will facilitate the investors to reduce their portfolio risk by achieving the optimum diversification of funds across the markets. A number of empirical studies have examined the integration of stock markets (Sheng & Tu, 2000; Johnson & Soenen, 2002; Nath & Verma, 2003; Mukherjee & Mishra, 2007) and possible dynamics like interest rate, foreign investment, trade relations and inflation which integrate the markets (Black & Fraser, 1995; Bracker, Docking, & Koch, 1999; Bekaert & Harvey, 2000; Wu, 2001; Bekaert, Harvey, & Lundblad, 2001; Pretorius, 2002; Liu, Lin, & Lai, 2006). The recent liberalization of financial systems and accelerating trade relations have also integrated the South Asian stock markets. Table 11.6 provides the correlation matrix of stock returns of global and South Asian markets. The results clearly report that the returns of Indian stock market are positively correlated with global and other South Asian stock markets. The degree of correlation is very high with the global and Pakistan's stock markets. With India's entry into the liberalization phase in 1992, the Indian stock market has witnessed foreign investment on a large scale, which has promoted its linkages with the other markets. To a lesser degree, it is also correlated with the Sri Lankan stock market. The deteriorating trade relations of India with Bangladesh could be attributed to its weak correlation with the Bangladesh's stock market. Although the Sri Lankan stock market is negatively correlated with the global stock market, the degree of the relationship is not very high. On the other hand, the stock markets of Bangladesh and Pakistan are positively correlated. Table 11.7 exhibits the correlations of conditional volatility of the South Asian stock markets with the global markets. A high correlation is the index of the

Table 11.6 Correlation matrix of stock markets' returns

	India	Sri Lanka	Pakistan	Bangladesh	Global
India	1.00				
Sri Lanka	0.17	1.00			
Pakistan	0.37	0.23	1.00		
Bangladesh	0.09	−0.06	−0.02	1.00	
Global	0.36	−0.05	0.03	0.16	1.00

Source Compiled from Kumar and Dhankar (2009)

Table 11.7 Correlation matrix of stock markets' conditional volatility

India	Sri Lanka	Pakistan	Bangladesh	Global	
India	1.00				
Sri Lanka	0.17	1.00			
Pakistan	0.02	0.06	1.00		
Bangladesh	−0.03	−0.03	−0.11	1.00	
Global	−0.05	0.07	0.62	−0.28	1.00

Source Compiled from Kumar and Dhankar (2009)

Table 11.8 Correlation matrix of stock markets'expected volatility

	India	Sri Lanka	Pakistan	Bangladesh	Global
India	1.00				
Sri Lanka	−0.17	1.00			
Pakistan	0.02	0.06	1.00		
Bangladesh	−0.03	−0.03	−0.10	1.00	
Global	−0.06	0.05	0.64	−0.27	1.00

Source Compiled from Kumar and Dhankar (2009)

high vulnerability of the stock market to international shocks; a low correlation, on the other hand, is the indication of the confidence of investors in the stock market. A high correlation clearly indicates that investors give a weightage to international shocks in their investment decisions. Good news motivates them to take risks in stock market resultant to rise in the stock prices; bad news, contrarily, forces them to alter their stand in line with global developments. The conditional volatilities of Indian, global, and other South Asian stock markets are not along the same lines (Table 11.7). The low correlations of Indian stock market bring out the fact that investors having exposure to Indian stock market are less affected by global developments, whereas the high correlation of Pakistan and Bangladesh stock markets' conditional volatility suggests the sensitiveness of these markets to global shocks. Table 11.8, on the other hand, provides the correlation of expected volatility among the South Asian markets and with the global market. The results reveal that Indian stock market tends to move positively with Pakistan and Sri Lanka, but negatively with global and Bangladesh stock markets with the emergence of expected global economic and non-economic shocks.

Conclusion and Implications of the Study

In this paper, attempts are made to examine the cross-correlations in stock returns, asymmetric volatility, and the relationship of stock returns with expected and unexpected volatility for South Asian stock markets and global stock market. Additionally, the paper also investigates regional integration in the South Asian stock markets and with the global stock market. Liberalization of these stock markets has created enormous opportunities for investment, attracting the attention of foreign institutional investors. The mean returns clearly indicate that these markets have offered higher returns to the investors as compared to the global stock market (Table 11.2). The Ljung–Box statistics which tests the autocorrelation in stock returns strongly rejects the null hypothesis and holds the presence of autocorrelations. The significant autocorrelations question the random walk behaviour of stock returns, suggesting that global and South Asian stock markets are informationally inefficient. The prevailing stock prices have not absorbed the historical and available information pertinent to stocks. Inference can be drawn here that the investors' current investment decisions are strongly influenced by the previous time period decisions. These findings are consistent with that of the previous research, which finds non-linearity and seasonal variations in stock returns in the South Asian stock markets. When serial autocorrelations are found in stock returns, the use of variance as a measure of risk provides inconsistent estimates of volatility. The study has applied ARCH and its extension models to explain the conditional volatility in stock returns under consideration, which have been found to best fit the data adequately.

The study brings out important facts about the stock returns relationship with expected and unexpected volatility. It finds no relationship between stock returns and expected volatility suggesting that investors adjust their risk premium in advance for the expected volatility and that they do not alter their portfolios in response to the expected variations in stock returns. The positive significant relationship between stock returns and unexpected volatility, however, suggests that investors realize extra risk premium for taking advantage of unexpected variations in stock returns. The study also finds that the liberalized trade relations and financial systems have positively integrated the South Asian stock markets with the global stock market. However, regional integration among the markets is not much encouraging, which is an indication of poor trading relations and financial flows among these markets. The results report a positive correlation of Indian stock market with the global and other South Asian stock markets. The degree of correlation is very high with global and Pakistan's stock markets. The accelerating financial flows from institutional investors have promoted its linkages with the markets. To a lesser degree, it is also correlated with the Sri Lankan stock market in view of the expanding trade relations. However, the Indian stock market is weakly correlated with Bangladesh's stock market. The Sri Lankan stock market is negatively correlated with the global stock market, though the degree of relationship is not much low. As against it, Sri Lankan and Pakistan's stock markets are positively correlated to each other. These findings are important for investors and policymakers as they will facilitate them to design investment strategy for maximizing the returns of their portfolios by diversification among the South Asian stock markets.

To conclude, the study reports weak interdependency among the South Asian stock markets and also with the global stock market. Here, we have taken S & P Global 1200 as the benchmark of global stock market which is a value-weighted index, compiled on the basis of a certain number of indices of different leading stock exchanges. As a matter of fact, all the South Asian markets may not be having the same trading relations and financial flows with these markets. The weak interdependency among South Asian markets bring out poor trading relations and financial flows. Though these markets have been liberalized, the interdependency among the markets is not encouraging. However, the scope of the study would widen by including the impact of economic and non-economic explanatory variables on the integration of the South Asian markets. It would also provide a better understanding of the dynamics of the linkages over a period of time.

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Chapter 12
Risk–Return Assessment: An Overview

Life shouldn't be printed on dollar bills.
Clifford Odets

Abstract In the age of globalization, foreign capital has become the wheel of economic development. If a country wants to walk with the rest of the world, foreign capital contributes in achieving a competitive edge. In order to attract foreign capital, all developing countries are working on the principles of liberalization and globalization. India is no exception to it. Being the fifth largest economy of the world with huge potential in all sectors. India can be the most prospective destination for foreign investors. The risk and return are the two parameters of the economy, which attract the fancy of the investors. We do an assessment of these two parameters in Indian Stock market for the period from June 1996 to May 2005. During this 10-year period, the Indian economy has not remained stable throughout, instead passed through three distinct phases successively, i.e. decline, recession and growth. We examine the risk and return profile of the Indian stock market under these different economic conditions, and their futuristic scenario.

Introduction

In investment, risk and return are highly correlated. Increased potential of returns on investment is invariably associated with increased risk. There are various types of risks such as project-specific risk industry-specific risk, business risk, political risk, international risk and market risk. Return refers to either gains and losses made from buying or selling a security. The return on investment is expressed as a percentage and considered a random variable that takes any value within a given

This chapter draws from the author's previous publication (Dhankar & Kumar, 2007), co-authored with Rakesh Kumar, Assistant Professor in the Department of Business Studies, Deen Dayal Upadhyaya College, University of Delhi, New Delhi, re-used here with permission.

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India Studies in Business and Economics,
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range. Many factors influence the type of returns that investors can expect from trading in the markets.

The year 1995 was a major breakthrough in the Indian economy, when India signed WTO charter and thereby aligning economy with liberalization system. To work on liberalization, India took the first step to liberalize the economy in its Industrial Resolution 1991, and EXIM policy 1991, thereafter, a transition has started to liberalize every sphere of the economy. The stock market, which represents the lifeline of the economy, can't remain insensitive to global economic and corporate developments. At present, India has become the hub of foreign investment, as unexplored sectors are attracting huge foreign direct investment, which was $5.6 billion in 2004–2005. Apart from attracting FDI, there is also the huge inflow of foreign institutional investment in equities, which was at an impressive figure of US $8.5 billion in 2004–2005.

Two fundamentals, which affect the investment decisions of a rational investor, are risk and return. Return includes both cash inflows (dividend), and net increase or decrease in the market value of the investment, viz., capital gain or loss. Risk, on the other hand, represents the cyclical variations in the return resultant to domestic and global market events. When an investor decides to park his funds in a market, risk of that market becomes central consideration for him/her. It is a difficult decision, as to which securities should be put in the portfolio because a set of risk/uncertainty is associated with each one. Some securities are riskier than the others, and quite natural some portfolios are riskier than the others. In a well-integrated market, market sensitivity is found between each security and market. Sharpe (1985) developed 'beta' as a measurement of the market sensitivity of security. Beta integrates the return of a security to the return of the market, and is extensively used by both investors and financial academicians to analyse the market. A high beta represents high sensitivity to the market, and vice versa.

Many researchers over the years have gone through the measurement of risk and return of stock market, and have provided a possible explanation of their behaviour. Studies (Balvers, Cosimano, & Mcdonald, 1990; Officer, 1973; Reichenstein & Rich, 1994) relate the behaviour and predictability of return and risk with the macroeconomic variables. Kenneth, Schwert, and Stambaugh (1987) maintain a positive relationship between expected risk premium on common stocks and predictable level of volatility. Schewrt (1990) suggests different reasons for long- and short-term volatility. This paper does not synthesize the risk and return in Indian stock with particular variable/s; rather it provides a broad-based picture of the behaviour of the stock market in terms of risk and return, in response to the collective economic performance of the economy, over a period of time. The study covers the period wherein the Indian economy has passed through three distinct phases successively, i.e. decline, recession and growth. The paper, therefore, attempts to explain the behaviour of the stock market under these different economic situations. Here, the GDP growth rate has been taken to represent the collective performance of the economy, and subsequently, its impact upon the behaviour of the stock market.

Research Methodology

The study examines the risk and return of Indian stock market for the period from June 1996 to May 2005. For the study, Bombay Stock Exchange index BSE 100 having the composite portfolio of 100 stocks, popularly known as National Index, has been taken. BSE 100, which represents 75% market capitalization, includes large-cap, mid-cap and small-cap stocks. For the analysis, the monthly return of BSE 100 over the period has been taken from PROWESS, a database maintained by CMIE. Return (X_{pt}) for BSE 100 on a month t, is calculated as under; Let I_t be the closing price and, I_{t-1} be the opening price of BSE 100 in month $_t$. The natural logarithmic difference between the two times prices will be

$$X_{pt} = Log_e\left(\frac{I_t}{I_{t-1}}\right) * 100 \tag{12.1}$$

Thus, return on a portfolio of 100 stocks on a month, is the value-weighted average of the return stocks in BSE 100 on the month. The monthly return of the composite portfolio of 100 stocks can be symbolically written as

$$X_{pt} = \sum_{i=1}^{100} w_i r_{it} \tag{12.2}$$

where X_{pt} represents the monthly return of the composite portfolio of BSE 100, r_{it} is the expected return on stock $_i$ on month $_t$, w_i is the weight that has been given to stock $_i$ in the BSE 100. To depict the broad-based picture of Indian stock market, the annual return and risk has also been calculated. The other important parameter of the market is the risk, which is dispersion around the average return. Academicians widely agree on the use of standard deviation or variance as the standard measure of risk of the stock market. Standard Deviation of BSE 100 return x_{pt} of sample with n observations is the square root of the square of average deviations from the average return $\overline{X}$. Symbolically, it can be written as

$$\sigma_p = \sqrt{\sum_{i=1}^{n} \frac{1}{n}(X_{pt} - \overline{X})^2} \tag{12.3}$$

The monthly return and risk has been annualized by multiplying with the total number of trading months and the square root of trading months, respectively. Karl Pearson empirical method has been used to calculate the mode of the stock index return. Symbolically, it can be written as

$$Mode = (3 * median - 2 * Mean) \tag{12.4}$$

Capital Asset Pricing Models as developed by Sharpe (1964), Linter (1965) and Mossin (1966) make the assumption of normal distribution return of the stock market. If asymmetry of stock return exists, the normal distribution of return will not be applicable. Skewness (Karl Pearson) is used to test the asymmetry of stock return. Symbolically, it can be shown as

$$\text{Skewness} = (\text{average return} - \text{mode})/\sigma_p \tag{12.5}$$

Economic Review of Indian Economy

Table 12.1 summarizes the performance of all sectors during the study period, the Indian economy grew by a magic growth rate by 7.8% at factor cost (base year 1993) in 1996. The agriculture sector is the major contributor to the overall growth of economy, which grew by 9.8% in the same period. It is worth mentioning here that the Indian agriculture sector is still dependent on the blessing of monsoon. A big slow down has occurred in the economy in 1997–1998 during which the economy registered only 4.8% growth rate because of negative growth rate of the agriculture sector. The industrial sector also registered a very poor growth rate, which indicates that both sectors are correlated; the growth of one sector affects the growth of another sector. The economy revived in 2001–2002, and grew by 5.8% after facing two drought-hit years. The growth recovery in this year was accompanied by continued macroeconomic stability in terms of low inflation, orderly currency market conditions and comfortable foreign reserve. The rupee exchange rate and foreign currency reserve were Rs. 47.69 per dollar and the US $51.05 billion, respectively. Again, there is a big drop in growth rate in 2002–2003, when the economy grew at 4.0%, because of heavy shortfall in the agriculture sector, which registered –7.0% growth rate accompanied with –7.0% growth rate of the industrial sector. However, the economy revived in 2003–2004 and registered a growth rate of 8.5%, mainly attributed to the strong performance of both agriculture and industrial sector. The growth recovery in 2003–2004 was accompanied with economic stability; inflation as measured by the wholesale price index, which was 5.5% on average. The foreign exchange rate and foreign currency reserve were at Rs. 45.95 per dollar and the US $107 billion, respectively. In 2004–2005, the economy registered an impressive growth rate of 7.5%, attributed by the high growth rates of both industrial and service sectors. However, the agriculture sector had shown poor performance in that period. The foreign currency reserve and the exchange rate had been US $123 billion and 45.18 per dollar, respectively. Further, the economy registered an impressive growth rate of 8.1% in 2005–2006. The collective economic performance of economy (GDP growth rate) during the three distinct phases is summarized in Table 12.2.

It is evident from Table 12.1 that during the period June 1996 through December 1999, the Indian economy was on decline phase, as the average GDP growth rate of

Table 12.1 Sectoral real growth rate in GDP at factor cost during 1996–2005

	Items	1996–1997	1997–1998	1998–1999	1999–2000	2000–2001	2001–2002	2002–2003	2003–2004	2004–2005	2005–2006
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	**Agriculture and allied**	**9.6**	**–2.4**	**6.2**	**0.3**	**–0.1**	**6.3**	**–7.0**	**9.6**	**0.7**	**2.3**
2	**Industry**	**7.1**	**4.3**	**3.7**	**4.8**	**6.5**	**3.6**	**–7.0**	**9.6**	**8.6**	**9.0**
	1. Mining and quarrying	0.5	9.8	2.8	3.3	2.4	2.5	9.0	6.4	5.8	1.0
	2. Manufacturing	9.7	1.5	2.7	4.0	7.4	3.6	6.5	6.9	8.1	9.4
	3. Electricity, Gas and Water supply	5.4	7.9	7.0	5.2	4.3	3.7	3.1	3.7	4.3	5.4
	4. Construction	2.1	10.2	6.2	8.2	6.7	4.0	7.3	7.0	12.5	12.1
3	**Services**	**7.2**	**9.8**	**8.4**	**10.1**	**5.5**	**6.8**	**7.9**	**9.1**	**9.9**	**9.8**
	1. Trade, hotels, transport and comm.	7.8	7.8	7.7	8.5	6.8	9.0	9.8	11.8	10.6	11.1
	2. Financial services	7.0	11.6	7.4	10.6	3.5	4.5	8.7	7.1	9.2	9.5
	3. Community, social and personal services	6.3	11.7	10.4	12.2	5.2	5.1	3.9	5.8	9.2	7.9
	Total GDP at factor cost	**7.8**	**4.8**	**6.5**	**6.1**	**4.4**	**5.8**	**4.0**	**8.5**	**7.5**	**8.1**

Source Economic Survey 2005–2006

Table 12.2 Economic phases during the period June 1996–May 2005

Period	Economic phases	Average growth rate
June 1996–December 1999	Decline	6.3%
January 2000–December 2002	Recession	4.7%
January 2003–May 2005	Growth	8.03%

Source Compiled from Dhankar and Kumar (2007)

this period was 6.3%. In the recession phase, which covers the period from January 2000 through December 2002, the economy grew by average growth rate of 4.7%, which is followed by growth phase with average growth rate of 8.03% during January 2003 through May 2005. The market yield of these three phases has a long-term implication for investors, who seek to park their fund in Indian stock market for the long term.

Trend in Growth Rate of the Economy

The institutional investors occupy a dominant place in the volume of total transactions of the stock market. They invariably overlook the trend in the growth of Indian economy. Variations in macroeconomic variables have considerable influence on the price of stocks. Balvers (1990) argues that fluctuations in consumption bring corresponding variations in aggregate output, which in turn affects the investor's expectations about future projections of output, and consequently, they have to readjust their required rate of return accordingly. The trend line in Fig. 12.1, asserts that in near future the economy will grow around with a growth rate of 7.5%. It gives an insight to the investors, whether Indian economy is a prospective destination to park their fund or not.

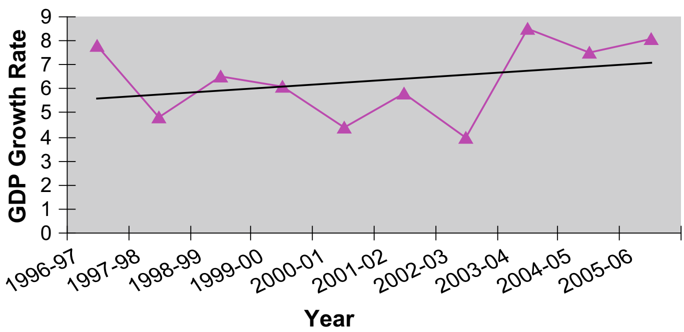

Fig. 12.1 Fitting of the trend line in growth rates of the economy during the period 1996–2006. *Source* Compiled from Dhankar and Kumar (2007)

Empirical Findings

Measurement of Monthly Return and Risk of Three Phases (Decline, Recession and Growth)

The main objective of this study is to provide a broad-based picture of return and risk in three distinct periods, viz., decline, recession and growth. Unlike the developed economies, developing economies grow with instability; therefore, the statistical parameters of these economies do not show consistency over the period. The monthly mean, median, mode, standard deviation and skewness over the period, of the three phases have been summarized in Table 12.3. Table 12.3 clear depicts, during decline phase, Indian stock market has offered 0.91% monthly return. The median and mode of this phase are 1.63 and 3.08%, respectively. The coefficient of skewness of this period is –0.26, which indicates that the return is negatively distributed. The recession phase is offering –1.20% monthly returns over the period with –0.88 and –0.25% median and mode, respectively. The coefficient of skewness of this phase is –0.10. The median and mode of this period are 3.87 and 5.34%, respectively. During the growth stage, a dramatic jump has occurred in the monthly return, it has increased to 3.07%. The coefficient of skewness of this period is –0.32%. The cyclical movement of the monthly return of three periods is depicted in Fig. 12.2. The other factor, which affects investment decision is risk, which indicates the variation in the rate of return. Kenneth, Schewert and Stemabugh, (1987) find that investors make an adjustment to their expected risk premium on common stocks in response to predictable volatility, i.e. a positive relation between the two.

However, a negative relationship exists between unpredictable volatility and return, which in turn increases the future expected risk premium of the investors. It is clear from Table 12.3 and Fig. 12.3 that during decline phase, the volatility (risk) is 8.21%, i.e. 8.21% variation in average monthly return. It has risen to 9.29% in recession period. Generally, in recession, investors become pessimistic about future prospects resulting in large fluctuations in the stock market. In the growth stage, volatility has declined to 7.15%.

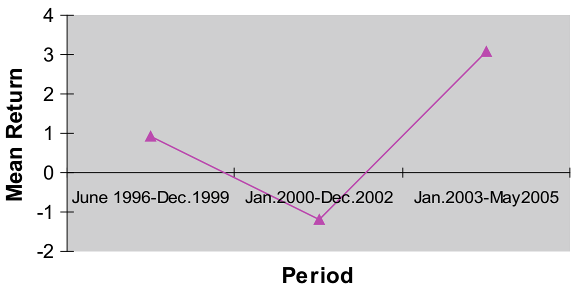

Fig. 12.2 Trend of monthly return of three phases (calculated on the basis of monthly return). *Source* Compiled from Dhankar and Kumar (2007)

Table 12.3 Monthly risk and return profile of the economy during the period June 1996–May 2005

Statistics (1)	Decline (2)	Recession (3)	Growth (4)
Mean	0.91	–1.20	3.07
Median	1.63	–0.88	3.87
Mode	3.08	–0.25	5.43
Standard deviation	8.21	9.29	7.15
Skewness	–0.26	–0.10	–0.32

Source Compiled from Dhankar and Kumar (2007)

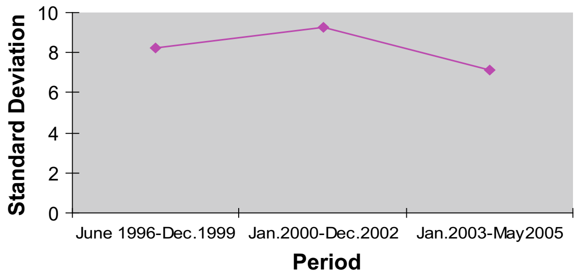

Fig. 12.3 Trend of the volatility of the three phases (calculated on the basis of monthly return over the three phases). *Source* Compiled from Dhankar and Kumar (2007)

Measurement of Monthly and Annual Return and Risk

The calculation of monthly and annualized return and risk will provide a fairly good view of the overall scenario of Indian stock market over the period June 1996 through May 2005. Table 12.4 summarizes the monthly statistical summary, calculated on the basis of monthly return over the year. Figure 12.4 depicts the graphical movement of the monthly return during the study period. It indicates, during the decline phase average monthly return was very low or negative, leaving 1999 year when the return is at an impressive rate of 5.60%. It is also negative in the recession period except for the year of 2000, when the market offered 0.38% monthly return. In the first year of the growth phase, the average monthly return is 5.62%. However, in the next 2 years, it has taken a downward trend. Contrary to Obadullah's (1991) study which maintains the normal distribution of return, and Mariestty and Alayur's (2002) study, which signify the positive distribution of return, here, the negative skewness of all the years of the study period indicates the asymmetry of return, i.e. return is negatively distributed. Table 12.4 indicates that during the recession phase monthly volatility is high, as compared to decline and growth phases.

Volatility in the growth phase is showing decline tendency. In the decline phase, the average monthly volatility is 7.46%. It is 9.2 and 6.63% in recession and growth phases, respectively. The cyclical movement of volatility of monthly return is depicted in Fig. 12.5. Table 12.5 summarizes the annualized return and risk over the years.

Table 12.4 Average monthly risk and return over the years

Statistics (1)	1996 (2)	1997 (3)	1998 (4)	1999 (5)	2000 (6)	2001 (7)	2002 (8)	2003 (9)	2004 (10)	2005 (11)
Mean	–3.22	0.25	–7.74	5.60	–2.41	–1.56	0.38	5.62	1.01	2.24
Median	–2.65	0.75	–0.25	5.71	–4.91	–0.88	1.06	5.67	1.66	4.52
Mode	–1.52	1.73	0.72	5.93	–12.3	0.47	2.42	5.77	2.95	9.07
St. Dev.	5.08	7.80	8.44	8.53	11.59	9.90	6.11	7.91	7.26	4.72
Skewness	–0.33	–0.19	–0.17	-0.04	0.85	–0.20	–0.33	–0.02	–0.27	–1.45

Source Compiled from Dhankar and Kumar (2007)

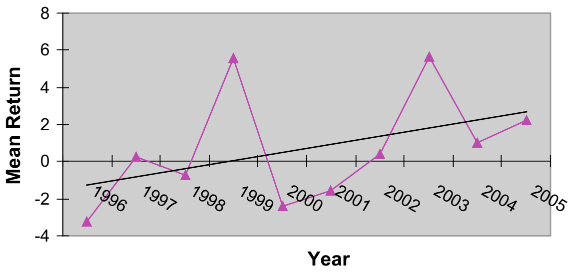

Fig. 12.4 Average monthly returns volatility. *Source* Compiled from Dhankar and Kumar (2007)

Trend in Monthly Return and Risk

A trend line is fitted in historical return and risk to determine the future profile of return and risk of the stock market, i.e. what likely rate of return, the Indian stock market will offer in near future subject to a certain level of risk. Researchers use different tools including the dividend yield and price-earning ratio to predict the short- and long-term return on stocks. Reichenstein and Rich (1994) argue that both dividend yield and price/earning ratio are not good measures to predict the return of short horizon, however, they can partially predict the long horizon return. It is obvious from Fig. 12.4, if everything remains constant, in near future Indian stock market will offer 2% monthly return. The trend line of risk, on the other hand, provides the future outlook of volatility in Indian stock market. Figure 12.5 exhibits that volatility/risk has been declining over the years in Indian stock market, and the market is approaching towards stability. Charles and Wilson (1989) find that volatility of both daily and monthly return has been declining over the period, when it is compared to the volatility of early periods, baring the period of 1980s, when it was on the higher side.

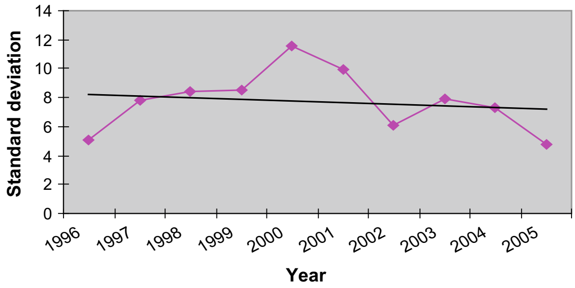

Fig. 12.5 Monthly volatility (calculated on the basis of monthly return in a year). *Source* Compiled from Dhankar and Kumar (2007)

Table 12.5 Annual return and risk

Year (1)	Total months (2)	Average monthly return (3)	Average monthly volatility (4)	Annual return (5) = (2)*(3)	Annual volatility (6) = (2)*(4)
1996	7.0	–3.22	5.08	–22.54	13.44
1997	12	0.25	7.80	3.00	27.22
1998	12	–0.74	8.44	–8.88	29.23
1999	12	5.60	8.53	67.20	29.54
2000	12	–2.41	11.59	–28.92	40.14
2001	12	–1.56	9.90	–18.72	34.29
2002	12	0.38	6.11	4.56	21.40
2003	12	5.62	7.91	67.44	27.40
2004	12	1.01	7.26	12.12	25.14
2005	5.0	2.24	4.72	11.20	10.55

Source Compiled from Dhankar and Kumar (2007)
Note The study is based on June 1996–May 2005. So the years 1996 and 2005 include 7 and 5 months, respectively

Conclusion and Implication of the Study

This paper brings a broad-based picture of risk and return scenario in Indian stock market during the period June 1996 through May 2005. Measurement of return and risk in three phases, viz., decline, recession and growth has provided the bird's-eye view of the stock market in terms of its behaviour. Being a developing economy, the cyclical fluctuations in the return and volatility are common. Worth mentioning to here, despite rapid industrialization since independence, the agricultural sector is the backbone of Indian economy, which contributes nearly one-fourth share to total GDP. With the introduction of liberalization in the Indian economy, it is showing co-movement with the major markets across the world like New York Stock Exchange, American Stock Exchange, and Singapore Stock Exchange, etc. On looking the market profile of return and risk monthly, annual and three phases, an investor can safely project, as to what will be the behaviour of Indian stock market in the near future. Trend lines of both return and risk, as indicated by Fig. 12.4 and 12.5, respectively, depict on the whole, return is showing an increasing tendency, whereas the downward slope of risk indicating that risk/volatility in the stock market is declining with passage of time.

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Part IV
Portfolio Selection, Performance and Risk-Return Relationship

Chapter 13
Market Efficiency, Diversification and Portfolio Performance

Goodness is the only investment that never fails.
Henry David Thoreau

Abstract The study attempts to validate efficient market hypothesis in Indian stock market by examining the relationship between risk and return. It also examines the possibility of diversification effect on portfolio risk, which is the composite of market and non-market risk. The study takes daily, weekly and monthly adjusted opening and closing prices of BSE 100 composite portfolios for the period of June1996 through May 2005. The findings suggest that the relationship between portfolio return and risk is very weak, based on daily return. It is moderate in the case of weekly return. However, portfolio risk and return exhibit a high degree of positive relationship when monthly return is used. Portfolio non-market risk shows a declining tendency with diversification.

Introduction

The single-period capital asset model (CAPM) postulates a simple linear relationship between the expected return and the market risk of a security. While the results of direct tests have been inconclusive, evidence suggests the existence of additional factors which are relevant for asset pricing. Studies, for example, have found a significant positive relationship between dividend yield and return on common stocks; and price earning ratios and risk adjusted returns. These results are evidence of market inefficiency and anomalies, which may as well be the result of a mis-specification of the pricing model.

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An efficient capital market fully reflects the available information. It provides unbiased estimates of the underlying stocks, which result in eliminating the possibilities of making an abnormal profit under conditions of certainty. Substantial empirical evidence supports the efficient market hypothesis in developed countries.

Widely quoted Capital Asset Pricing Models of Sharpe (1964), Linter (1965), and Mossin (1966) describe how risky assets are priced in a competitive capital market. By efficient capital market, they mean that risky assets are priced according to risk and return preferences of investors. The return of well-diversified portfolio is composed of regular return (dividend) plus risk weighted return, i.e. appreciation/depreciation in the value of the investment. Portfolio risk, on the other hand, is a weighted average of market and non-market risk of the constituent stocks. Sharpe and Cooper (1972) argue that variations in stock returns are resultant of the market and non-market risks. Market risk is evolved by including factors such as interest rate, inflation and foreign exchange rate. It effects the overall stock market; however, the degree of influence varies across the stocks. With the increasing presence of foreign institutional investors, Indian stock market has become responsive to international market forces. A change in the interest rate prevailing in the international market to a large extent can cause capital inflow or outflow from the Indian stock markets. Non-market risk, on the other hand, is specific to each stock. Variation in investors' expectations to tangible or intangible factors of each stock can cause a change in its value.

Sharpe and Cooper (1972) argu that diversification across the stocks results in decline of portfolio risk, thereby, reduction of non-market risk. As a result, market risk should be assumed as the proper measure of portfolio risk. In an efficient capital market, rational investors, being risk averse, will demand an increasing return for increasing risk. They are ready to take extra risk only with the expectation of gaining extra risk premium. In the bullish market, portfolio returns are likely to increase by purchasing stocks with high market risk, and conversely in the bearish market, can be reduced by holding stocks with low beta value. If this relationship holds true a perfect or efficient capital market will provide an higher return for increasing market risk. Further, diversification across the stocks will lead to the decline of non-market risk. The paper investigate this hypothesis.

Review of Literature

The Efficient Market Hypothesis (EMH) has been researched in various forms in both the developed and developing capital markets. There is not much research evidence that supports the EMH in terms of risk–return relationship and effects of diversification in Indian stock markets. Sharpe and Cooper (1972) examine the market risk and return of securities ranging from 478 (in 1931) to 985 (in 1967) for the period 1931–1967. The study involved the formulation of 10 portfolios from low beta value to high beta value. The study reports a consistent relationship between portfolio market risk and portfolio return by providing low return to low market risk portfolio and high return to high market risk portfolio.

Basu (1977) investigates the efficient capital market by examining the investment performance of common stocks in relation to their P/E ratios. For the analysis, five portfolios are constructed based on the P/E ratios, thereafter, risk and return relationship is examined for the pool period from 1957 through 1971, and two non-overlapping sub-periods, viz., April 1957–March 1964, and April 1964–March 1971. The findings indicate that the average annual rate of return declines with the movement from low P/E ratio portfolio to high PE ratio portfolios. Contrary to capital market theory, no consistency is observed between portfolio expected return and portfolio market risk, viz., portfolio with high market risk fails to give high return to the investors.

Brown (1978) examines the earnings announcement effect on stock prices for the period from 1963 to 1966. The study reports that the adjustment of stock prices to EPS information apparently takes some time. This relationship leads to the conclusion that the market fails to show instantaneous response to new information, and questions the efficient market theory. Gupta and Gupta (1997) conduct run and autocorrelation test over 50 actively traded stocks for the period July 1988 through 1996. The findings do not support the random walk theory and leads to the conclusion that stock prices fail to reflect the information contained in the historical records.

Rao, Nath, and Malhotra (1998) measure the portfolio return and risk relationship using the BSE 100, Sensex and Nifty stocks for the period 1992–1997. To test the relationship the study involves estimation of beta using different market proxies and time intervals. The study reports that a significant relationship exists between portfolio beta and portfolio return on quarterly return than monthly or weekly returns.

Barman and Samanta (2001) examine the EMH in Indian stock market by employing two martingale tests using spectral shape volatility test and co-integration between the real price index and real market proxies rather than looking individual share prices for the period 1984 through 1997, and two sub-periods, viz., 1984–1992, and 1993–1997. The findings do not support the EMH in the stock market. The volatility test also exhibits the presence of excess volatility in the return series. The study also accepts the hypothesis of no integration between the real price and real dividend series indicating the lack of market efficiency.

Debasish and Mishra (2003) investigate Random Walk Hypothesis (RWH) in the Indian stock market. The study examines adjusted daily returns, weekly returns, and monthly returns of six stock indices of the BSE and the NSE for a period of 5 years. It uses two non-parametric techniques such as runs test and Spearman's rank correlation. The rank correlation analysis tests the significance of the rank correlation between stock indices returns of the BSE and the NSE. The runs test examines the randomness of the stock market as a consequence of the occurrence of some events. The empirical results support the information efficiency and RWH more in the case of daily stock return and weekly stock returns as compared to the case of stock indices returns on a monthly basis.

Bodla and Jindal (2006) measure the monthly effect across the CNX Nifty stocks for the pooled period from 1998 to 2005, and three sub-periods including 1998–

2001, 2002–2005, and 1998–2005. The findings reveal that turns of the month and semi-monthly effect are prevalent in the Indian stock market. It concludes that the stocks market remain bullish in the first days of the months resultant to cash inflows in these days in the stock market. As a result, stock returns cannot be said to be normally distributed, which questions the validity of the efficient market theory.

Dhankar and Kumar (2006) examine BSE 100 stocks' monthly adjusted opening and closing prices for the period 1996–2005. The study involves the formulation of 10 portfolios and thereafter estimation of their expected return, market risk, and non-market risk by applying Capital Asset Pricing Model (CAPM). The study reports a high positive significant relationship between portfolios' expected return and market risk. It documents that with increasing market risk of portfolios, investors get increasing return, thereby hold the efficient capital market theory in Indian stock market.

Dhankar and Kumar (2007) also examine the CAPM in Indian Stock market. The study considers the monthly return of composite portfolio of 100 stocks of BSE 100 for the period from June 1996 to May 2005. It involves testing of the relationship between risk and return of 100 companies' stocks, and a set of ten portfolios. The findings are in favour of the model and assert a positive and linear relationship between risk and return. The study also reports that as diversification is carried out, non-market risk considerably declines. These findings support the CAPM in Indian stock market in establishing a trade-off between risk and return.

Chander, Sharma, and Mehta (2007) examine the impact of dividend announcements on stock price behaviour. It considers 188 events of dividends announcement for Group A listed stock of the BSE during the period 2004–2005 by using the event study methodology. The results show consistent incidences of average abnormal returns for CAPM around the dividend announcement, indicating over expectation of investors regarding dividend announcement in the information leakage phase. The study documents evidence on the impact of the dividend announcement. Irala (2007) investigate the relevance of beta value as a measure of market risk in Indian stock market. The study uses monthly returns of 660 companies over a 12-year period and examines the stationarity of betas in the Indian security markets as well as the tendency of betas in successive time period to regress towards mean beta of 1.

Research Methodology

The dataset consists of daily, weekly and monthly adjusted opening and closing prices of the BSE 100 stocks for the period from June 1996 to 2005. These prices are adjusted with the bonus issue, right issue and other corporate actions. The data has been taken from PROWESS, a database maintained by CMIE Ltd.

The BSE 100, which covers stocks of all industry categories, is value-weighted index, which assigns weights to all stocks in proportion to the share of their market capitalization. The sample stocks account for a major part of the market capitalization as well as trading volume. The number and diversity of stocks lead us to conclude that sample stocks taken as a whole is an approximate efficient portfolio of stocks. The natural logarithmic mode is used to measure the return of the stocks. The logarithmic difference of the prices is symmetric between up and down movements and is expressed in percentage terms for easy comparability. Symbolically, it can be written as

$$R_{it} = Log_t\left(\frac{P_t}{P_{t-1}}\right) * 100 \tag{13.1}$$

where R_{it} is the return on stock i in time period t, $\mathrm{Log_t}$, is natural logarithm, $\mathrm{P_t}$ is the closing price and $\mathrm{P_{t-1}}$ is the opening price. This measure of return takes into account only appreciation/depreciation of stock and neglects the dividend yield. This suggests that the value of beta would not change significantly if the dividend yield is excluded (Sharpe & Cooper, 1972). The same method has been used for calculating the return on market index (BSE 100). Symbolically, it can be written as

$$X_i = Log_{\bar{t}}\left(\frac{I_t}{I_{t-1}}\right) * 100 \tag{13.2}$$

where X_i is the return on the index, I is the closing number and I_{t-1} is the opening number.

The Index model assets that expected return on security i, E ($\mathrm{R_{it}}$) in time period t is a linear function of market return $\mathrm{X_t}$ and independent factor unique to security i,$\mathrm{e_i}$ Symbolically, it can be written as

$$E(R_{it}) = \alpha_i + \beta_i X_i + e_{it} \tag{13.3}$$

where (β) can be estimated by regressing the monthly security return to the return of index. It is calculated as

$$\beta_i = \frac{n\sum XR - \sum X \sum R}{n\sum X^2 - \left(\sum X\right)^2} \tag{13.4}$$

Alpha (α) is constant intercept indicating the minimum level of return that is expected from security i, if the market remains flat (neither going up nor going down), is calculated as

$$\alpha_i = \bar{R} - \beta_i \bar{X} \tag{13.5}$$

where α_i is constant intercept of security i, $\bar{R}$ is the mean return of security i, $\bar{X}$ is the mean market return of index, β_i is slope of security i. e_i is an error term representing the residuals (non-market risk) of security i. Given the assumptions that (I) cov (e_{it}, e_{it}) = 0 for all, i ≠ j; (2) cov (X_i, e_{it}) = 0 and (3) constant variance of error term (e) $\sigma_{it} = \frac{\sum e_i^2}{n-k}$ where n is the total number of observations and k is total parameters in the equations. Total risk of a security is the sum of total market risk and total non-market risk. Symbolically, it can be written as

$$\sigma_i^2 = \beta_i^2 \sigma_{x_1}^2 + e_{it}^2 \tag{13.6}$$

where σ_i^2 is variance of stock i representing total risk, $\beta_i^2 \sigma_{xi}^2$ is the total market risk and e_{it}^2 is the non-market risk. To measure portfolio return, equal weights have been assigned to each security in the portfolio. Symbolically, portfolio return can be obtained as

$$E(R_p) = \sum_{t=1}^{N} w_i(\alpha_i + \beta_i X) \tag{13.7}$$

where E (R_p) is portfolio expected return, w_i is weight given to security i in the portfolio. For a portfolio w = 1, the weighted average of portfolio beta can be written as

$$\beta_p = \sum_{i=1}^{N} w_i \beta_i \tag{13.8}$$

where w = 1. So far our main objective is to see the implication of efficient capital market theory by testing the relationship between risk (systematic risk) and return, and effect of diversification on the portfolio risk. Accordingly, the hypotheses to be tested are

H1: There is a significant relationship between stock beta and return, i.e. beta is significant from zero.

For portfolio:

H2: There is a positive and proportional relationship between portfolio beta and portfolio return, i.e. correlation coefficient between the two is significant.

H3: There is a significant effect of diversification on the non-market risk of portfolio.

To measure the reliability of beta statistically and correlation coefficient, 'Z' test is used at 5% level of significance. Where the number of observations is less than 30, 't' test has been widely used. To calculate the expected return of the securities and portfolio, it is assumed that the market will give 2% (24% annual) monthly return in the near future.

Empirical Findings

For the purpose of the study, daily, weekly and monthly adjusted opening and closing prices of BSE 100 have been taken. Stock market efficiency in terms of risk and return relationship for different time intervals is relevant for policymaking point of view. Investors' reaction to market and non-market events and subsequently re-engineering investment strategy is important from a policy point of view for various time intervals. It is based on the idea that stock market efficiency determines the time gap between the occurrence of an event and subsequent investors' reactions. To test the relationship, 100 stocks are arranged in the ascending order on the basis of beta value, and subsequently, ten portfolios are formulated.

In an efficient market, investors evaluate stocks taking into account risk and return. If the capital market is dominated by risk-averse investors, they will incorporate risk premium into portfolio return. Under this condition, the appropriate measure of portfolio performance is risk and return. A well-diversified portfolio composed of varying market risk will provide risk-weighted return. As a result, investors demand higher returns for increasing risk.

In Tables 13.1, 13.2 and 13.3, portfolios are arranged on the basis of increasing market risk. Portfolios coming on the top end are defensive, exhibit a lesser degree of responsiveness to the market risk. Investors having such portfolios observe fewer variations in return with the occurrence of market and non-market risk. Investors who seek regular income prefer these portfolios. Portfolios, on the other hand, coming on the bottom end can be categorized as aggressive. Variations in market events bring multiple changes in expected portfolio return. Speculators and investors who are particular about capital appreciation prefer such portfolios. The middle-end portfolios exhibit a moderate response to market fluctuations. Such portfolios are preferred by investors interested in both capital appreciation of the investment and regular income. Sharpe and Cooper (1972) follow the same methodology to classify different classes of return and risk in the NYSE. Portfolios with high beta value are categorized as high risk class and portfolios with low beta value are categorized as a low-risk class.

Table 13.1 presents the statistical summary of the daily return. All the portfolios which are statistically significant at 5% level are arranged in the ascending order on market risk. The correlation coefficient between portfolio-expected return and portfolio beta is –0.05, which indicates a negative relationship. Investors are not maximizing their return by investing in highly risky portfolios. Non-market risk ($1-R^2$) declines moderately with diversification.

Table 13.2 presents the statistical summary of weekly return. Three portfolios out of ten are significant at 5% level of significance, while three portfolios are significant at 20% level

Table 13.3 presents the statistical summary of monthly return and indicates that beta of eight portfolios are significant at 5% level. Correlation coefficient (0.98) between the expected portfolio return and portfolio beta is significant at 5% level

Table 13.1 Daily returns

Pt	Stocks	Pt_{var}	β_p	α_p	$\beta_i^2 * \sigma_{xi}^2$	e^2	β_{SE}	t_p	R^2	$(1–R^2)$	E (Rp)
P1	10	8.58	0.04*	–0.10	0.08	8.50	0.014	4.92	0.010	0.98	–0.09
P2	10	8.50	0.07*	–0.17	0.10	8.40	0.014	5.51	0.010	0.98	–0.16
P3	10	7.57	0.08*	–0.12	0.34	7.23	0.013	6.21	0.020	0.98	–0.12
P4	10	8.79	0.09*	–0.23	0.14	8.65	0.014	6.35	0.020	0.98	–0.22
P5	10	11.36	0.09*	–0.28	0.17	11.19	0.016	6.34	0.020	0.98	–0.28
P6	10	10.92	0.11*	–0.36	0.35	10.57	0.026	7.08	0.020	0.97	–0.36
P7	10	11.06	0.12*	–0.17	0.94	10.12	0.019	8.33	0.030	0.97	–0.17
P8	10	12.40	0.21*	–0.18	0.42	11.98	0.20	8.94	0.040	0.96	–0.17
P9	10	9.76	0.72*	–0.29	1.10	8.66	0.075	9.99	0.120	0.88	–0.25
P10	10	11.68	1.23*	–0.26	2.17	9.51	0.080	16.11	0.240	0.76	–0.18
Average	10	10.06	0.27	–0.21	0.58	9.48	0.27	7.97	0.053	0.95	–0.20

Source Compiled from Kumar and Dhankar (2008)
Note where Pt is portfolio Pt_{var} is portfolio variance
β_p is portfolio bets: α_p is portfolio alpha
$\beta_i^2 \alpha_{xi}^2$ is portfolio aggregate market risk
β_{SE} is portfolio beta standard error
tp is portfolio t value indicates the statistical significance of portfolio beta
R^2 is the coefficient of determination, i.e., how much variation in portfolio return is explained by market return (BSE 100)
$1–R^2$ indicates variations in portfolio return, which is not explained by market return, i.e. systematic risk; and
E (R_p) portfolio expected return
*Portfolio beta is significant at 5% level of significance

Table 13.2 Weekly returns

Pt	Stocks	Pt_{var}	β_p	α_p	$\beta_i^2\sigma_{xi}^2$	e^2	β_{SE}	t_p	R^2	$(1–R^1)$	E (R_p)
P1	10	8.09	–0.20	0.50	0.56	7.53	0.020	0.33	0.001	0.999	0.49
P2	10	8.98	0.010	–021	0.01	8.97	0.020	0.83	0.002	0.998	–0.20
P3	10	9.33	0.020	–0.30	1.13	8.20	0.020	1.25	0.003	0.997	–0.29
P4	10	12.80	0.020	–0.28	0.05	12.81	0.100	1.23	0.003	0.997	–0.27
P5	10	10.09	0.023	–0.30	0.09	10.00	0.020	1.48	0.004	0.996	–0.31
P6	10	9.69	0.030**	–0.30	0.04	9.65	0.020	1.76	0.006	0.994	–0.38
P7	10	10.69	0.030**	–0.38	0.05	10.64	0.40	1,982.18	0.008	0.992	–0.36
P8	10	11.58	0.080*	–0.48	0.09	11.49	0.014	5.93	0.012	0.988	–0.45
P9	10	9.85	0.710*	–0.29	1.21	8.64	0.120		0.140	0.860	0.03
P10	10	12.03	1.27*	–0.36	3.35	8.68	0.19	7.88	0.29	0.710	0.23
Average	10	10.31	0.22	–0.25	0.66	9.65	0.05	2.48	0.05	0.95	–0.15

Source Compiled from Kumar and Dhankar (2008)
Note where Pt is portfolio
Pt_{var} is portfolio variance
β_p is portfolio beta: α_p is portfolio alpha
$\beta_1^2\sigma_{xi}^2$ is portfolio aggregate market risk
β_{ei} is portfolio beta standard error
tp is portfolio t value indicates the statistical significance of portfolio beta
R^2 is the coefficient of determination, i.e. how much variation in portfolio return is explained by market return (BSE 100)
1-R^2 indicates variations in portfolio return, which is not explained by market return, i.e. systematic risk and
E (R_p) portfolio expected return
*Portfolio beta is significant at 5% level of significance
**Portfolio beta is significant at 20% level of significance

Table 13.3 Monthly returns and risk

Pt	Stocks	Pt_{var}	β_p	α_p	$\beta_1^2\sigma_{xi}^2$	e^2	β_{SE}	t_p	R^2	$(1–R^2)$	$E(R_P)$
P1	10	0.24	–0.35**	0.39	11.30	11.30	0.18	–1.94	0.03	0.97	0.13
P2	10	7.39	0.41**	–0.15	0.60	6.78	0.14	2.92	0.07	0.93	0.68
P3	10	8.27	0.54*	–0.09	0.89	7.38	0.25	2.16	0.12	0.88	0.99
P4	10	12.91	0.62*	–0.09	1.29	11.64	0.16	3.87	0.14	0.86	1.14
P5	10	10.30	0.68*	–0.17	1.56	8.77	0.15	4.53	0.19	0.81	1.20
P6	10	10.06	0.75*	–0.04	1.96	8.19	0.15	5.00	0.20	0.80	1.46
P7	10	12.24	0.83*	–0.21	2.12	10.12	0.21	3.95	0.22	0.78	1.47
P8	10	11.76	0.93*	–0.25	2.72	9.00	0.19	4.90	0.24	0.76	1.61
P9	10	11.05	1.04*	–0.40	2.77	7.97	0.28	3.71	0.28	0.72	1.67
P10	10	15.58	1.40*	–0.19	4.98	10.59	0.32	4.38	0.31	0.69	2.60
Average	10	9.98	0.69	–0.12	3.01	9.17	0.20	3.35	0.18	0.82	1.29

Source Compiled from Kumar and Dhankar (2008)
Note where Pt is portfolio
Pt_{var} is portfolio variance
β_p is portfolio beta: α_p is portfolio alpha
$\beta_1^2\sigma_{xi}^2$ is portfolio aggregate market risk
β_{ei} is portfolio beta standard error
tp is portfolio t-value that indicates the statistical significance of portfolio beta
R^2 is the coefficient of determination, i.e. how much variation in portfolio return is explained by market return (BSE 100)
1-R^2 indicates variations in portfolio return which is not explained by market return, i.e. systematic risk and
E (R_p) portfolio expected return
*Portfolio beta is significant at 5% level of significance
**Portfolio beta is significant at 20% level of significance

signifying a high degree of relationship. Investors are maximizing their return by investing in highly risky portfolios. Non-market risk declines with successive portfolios which signifies the impact of diversification on non-market risk.

Conclusion

The present study is an attempt to measure the efficiency of Indian stock market in terms of risk and return relationship and the effect of diversification, i.e. what time horizon is involved in adjusting the investors' exposure to their risk-weighted portfolios in response to the market and non-market events. As Indian stock market approaches to the efficiency with a longer time horizon for holding of stock; investors do not realize maximum returns by holding risky portfolio for intraday. However, to some extent, they reduce the impact of non-market risk of the portfolio. They get moderately high returns by holding risky portfolios on a weekly basis. However, their return is maximized by holding risky portfolios for a month. These findings support Rao et al. (1998) study, where stock returns of different time horizons are used to establish the relationship between portfolio return and risk. They found no significant relationship between risk and return on weekly return. The relationship is moderate in the case of monthly return. However, the relationship between portfolio expected return and risk is moderate on quarterly return. This tendency of the stock market signifies the fact that investors gradually readjust their holdings of stocks in response to market or non-market events.

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Chapter 14
Price Earning Ratio, Efficiency and Portfolio Performance

Everything in the world may be endured except continual prosperity.
Goethe

Abstract Price earning ratios are widely applied by investors to make investment decisions and to determine the future behaviour of stock price. We measure the performance of a set of portfolios which are based on P/E of stocks. The study examines the monthly price-earning ratios of BSE 100 companies, for the period June 1996–May 2005, and three non-overlapping sub-periods (June 1996–December 1999, January 2000–December 2002, and January 2003–May 2005). It found no consistency between the portfolios' expected return and their corresponding P/E ratios. It is observed that the stock market failed to reflect instantaneous response pertaining to earnings information. However, during the pool and sub-periods', the relationship between portfolio expected return and market risk is found to be positive and significant. These findings question the efficient market hypothesis but hold the application of the capital asset pricing model in the Indian stock market.

Introduction

In an efficient capital market, security prices fully reflect available information in a rapid and unbiased manner and therefore, provide unbiased estimates of the underlying prices. Opponents of this hypothesis question its validity by explaining various anomalies in stock markets. One such anomaly that they elucidate is Price/Earning (P/E) ratio effect, which is based on the premise that P/E ratios are indicators of the investment performance of a security and low P/E stocks have a

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tendency to outperform high P/E stocks even after adjusting for underlying risks. In short, prices of securities are biased, and the P/E ratio is an indicator of this bias.

Investors are interested in predicting the future behaviour of stock market. The efficient market hypothesis, which stresses on the random walk behaviour of the stock market, is yet to be acclaimed in the age of information technology and globalization. This proposition is based on the fact that a group of researchers believe in efficient market hypothesis; on the other hand, others discard it. An efficient capital market is one which reflects fully the effects of all information technology and globalization. An efficient capital market is one which reflects fully the effect of all information and makes it impossible to earn abnormal returns due to inefficiencies. The believers in efficient market hypothesis treat Price–Earning (P/E) ratio as a reflector of the future performance of securities. Investors make their investments after considering the price–earning behaviour of stocks. Stocks with high P/E ratios are put into portfolio on the expectations that their good performance will persist in the future as well.

The paper measures the performance of the portfolios, which are based on the P/E ratios. It is the ratio of the current price of the stock to the latest 12 months earnings. It signifies price paid by the buyer of stock for each rupee of annual earnings. A study by Basu (1977) finds that the low P/E ratio portfolios on an average earned higher absolute return and risk adjusted rate of return than the high P/E securities. The study refutes the efficient market hypothesis because of the poor performance of high P/E portfolios. The study also questions the validity of capital asset pricing model on the basis of an inconsistent relationship between portfolios return and market risk. Portfolios with low market risk have outperformed the portfolios with high market risk. The study of Gupta et al. (1998) is the only comprehensive work regarding the behaviour of P/E in Indian stock market. The study reports interesting findings. The P/E of large companies were found four times higher than that of small companies. The study also reports that in the boom year 1991–92, upper end size companies outperformed the lower end size companies. Brown (1978) finds that adjustment of stock prices to earnings per share information apparently takes some time. The study reports that the market does not instantaneously adjust to new information, which means that efficient market hypothesis does not hold. The study of Niederhoffer and Regan (1972) reports that stock prices are strongly dependent on earning changes.

Research Methodology

The study involves the analysis of monthly data of price earning of the composite portfolio of BSE 100 companies. The data were collected from CMIE's PROWESS for the period from June 1996 to May 2005. The 100 companies of BSE 100 represent 75% market capitalization that includes actively traded large-, mid- and small-cap stocks. All the 100 stocks are arranged in ascending order on the basis of median P/E ratio. Subsequently, ten portfolios each comprising ten stocks were constructed. The portfolio, which occupies the first rank, comprises ten stocks with the least median P/E ratios. Portfolio placed on the second, comprise the next ten stocks with second least median P/E ratios. Basu (1977) also follows the same strategy in ranking the portfolios to measure their efficiency. To depict the characteristics of P/E portfolios, separate estimates were done for quartile 1, quartile 3 and interquartile range. To show the variation in P/E ratio, quartile deviation and coefficient of quartile are estimated. A low coefficient of quartile deviation exhibits uniformity or small variation in the distribution of P/E ratios.

Method of Analysis

According to the efficient market hypothesis, portfolio P10 should comparatively yield a higher return than portfolio P9, portfolio P9 should yield a higher return than portfolio P8 and so on. Portfolio P1 should yield the least return in comparison to other portfolios. The trade-off between portfolio-expected return and market risk implies that the portfolios with higher market risk should yield a higher return, and contrarily, portfolios with low market risk should yield low return to the investors. Consequently, portfolio expected return should go up as one moves from low market risk portfolio P1 to high market risk portfolio P10, which should have the maximum return. The persistence of this relationship stakes the claim of the implication of capital asset pricing model in Indian Stock market. Notwithstanding, capital markets are dominated by risk averse investors. The risk aversion tendency calls for higher risk premium as the market risk increases. To construct market portfolios, the returns of ten portfolios are integrated with the market return. The expected return of stock *i* is regressed to the return of market X_t in time period *t*. Symbolically, it can be written as

$$R_{it}\alpha_i + \beta_i X_i + e_{it} \tag{14.1}$$

where R_{it} is the expected return on security *i*, β_i is slope, which integrates the return of a security to the return of market x_1 and e_{it} is the error term representing the residuals (non market risk) of security *i*. Given the assumptions that (1) E (e_{it}) = 0, (2) cov (e_{it}, e_{it}) = 0 for all, i $\neq$ j, (3) cov (X_{it}, e_{it}) = 0, and (4) constant variance of error term (e) $\sigma_{it} = \frac{\Sigma e_i^2}{n-k}$, where n is total number of observations, k is total parameters in the equation. Here, we make the assumption that equal weights are given to each stock in every portfolio. Symbolically, it can be written as

$$R_p = \sum_{i=1}^{N} w_i(\alpha_i + \beta_i X) \tag{14.2}$$

where R_p is portfolio return, w_i is weight given to security *i* in the portfolio. For a portfolio, w = 1, the estimation of ex-ante return of stock involves the mode of natural logarithmic difference in stock prices. The logarithmic difference between price movements is symmetric and is expressed in percentage terms for the sake of comparison. Symbolically, it can be written as

$$\overset{*}{R}_{it} = Log_t\left(\frac{P_t}{P_{t-1}}\right) * 100 \tag{14.3}$$

where $\overset{*}{R}_{it}$ is return on stock i in time period t, $\mathrm{Log_t}$ is natural logarithm, $\mathrm{P_t}$ is closing price, $\mathrm{P_{t-1}}$ is opening price. This measure of return takes into account only the change in the price of stock and ignores the dividend yield. In developing countries like India, divided yield does not significantly affect the relative return of a stock. Sharpe and Cooper (1972) argue that the value of Beta would not change significantly, if divided yield is excluded. The same method has been used for calculating the return on market (BSE 100). Symbolically, it can be written as

$$X_t = Log_t\left(\frac{I_t}{I_{i-t}}\right) * 100 \tag{14.4}$$

where $\mathrm{X_t}$ is the return on index, $\mathrm{I_t}$ is closing number, $\mathrm{I_{t-1}}$ is the opening number.

In Eq. 14.1, slope (β) integrates the return of a stock with market return. It measures the responsive change in return of a security to that of market. The slope of a stock exhibits market risk. It is non-diversifiable in nature. Portfolio market risk, symbolically can be written as

$$\beta_p = \sum_{i=1}^{N} w_i\beta_i \tag{14.5}$$

Total risk of a portfolio comprises market risk and non-market risk. The portfolio return fluctuates in response to two sets of market risk and non-market risk. Symbolically, it can be written as

$$\sigma_p^2 = \left[\left(\sum_{i=1}^{N} w_i\beta_i\right)^2 \sigma_x\right] + \left[\sum_{i=1}^{N} w_i^2 e_i^2\right] \tag{14.6}$$

where σ_p^2 is the total risk of portfolio, N is the total number of securities, $w_i^2\beta_i^2\sigma_i^2$ is a weighted average of the total market risk of each security, and $w_i^2 e_i^2$ is weighted average of error term of each security in the portfolio, representing the non-market risk of portfolio. The market risk is evolved by fluctuations in macro level factors like inflation, interest rate, exchange rate and so on, which affect the whole economic structure and thereby risk and return prospects of a security. Non-market risk, on the other hand, is unique to a stock and industry. It is influenced by factors like business conditions, capital structure, growth prospects and so on.

Findings and Discussion

Relative Performance of P/E Portfolios

Table 14.1 shows the risk and return profile of ten portfolios and selected summary of other statistics. All the ten portfolio are shown in ascending order along with their median P/E ratios. The difference in the median value of P/E is significant. Coefficients of quartile deviation represent the dispersion of P/E ratios of corresponding portfolios. The validation of efficient market hypothesis calls for consistency of portfolios return with portfolio P/E portfolio ratios. Portfolio return should go up with movement from low P/E portfolio to high P/E portfolio. Furthermore, the risk-aversion tendency of investors requires a high return for high market risk portfolio and low return for low market risk portfolio. Accordingly, the market risk should go on increasing from portfolio P1 through portfolio P10. Holding of this relationship validates the implication of capital asset pricing model in Indian stock market. It is observed from Table 14.1, that the expected return of portfolio P2, P4 and P5 show consistency with their corresponding P/E ratios. There is no doubt that the expected return of portfolios has gone up from low P/E portfolios to high P/E portfolios, but no consistency is observed in the increase of return with corresponding P/E ratios. The relationship between portfolio market risk and return is supposed to be positive and linear. The correlation coefficient between the two (0.31), as shown in Table 14.5, is significant at a 40% level of significance. The important evidence which flows from the results is that, in all the portfolios, beta and return are significant at 5% level.

Performance of P/E Portfolios Under Different Economic Conditions

The statistics shown in Table 14.1 are based on the pool data for the period from June 1996 to May 2005. The ten portfolios which are based on P/E ratios fail to prove efficient market hypothesis. However, a small degree of relationship is observed in portfolio market risk and return. To help provide an insight into the efficiency of these portfolios, and validation of efficient market hypothesis and capital asset pricing model, a set of ten portfolios are tested in three non-overlapping periods. The period from June 1996 to May 2005 is arbitrarily divided into three sub-periods, covering June 1996–December 1999, January 2000–December 2002 and January 2003–May 2005. Testing the P/E portfolios efficiency under these three periods is important from the policymaking point of view. These three sub-periods exhibit successive three economic phases in the Indian economy. The period from June 1996 to December 1999 exhibits decline phase in the economy with a 6.3% average growth rate. The period from January 2000 to December 2002 outlines the recession phase in the economy with 4.3% growth rate.

Table 14.1 Portfolio test (1996–2005)

Portfolio (1)	P1 (2)	P2 (3)	P3 (4)	P 4 (5)	P5 (6)	P 6 (7)	P7 (8)	P8 (9)	P9 (10)	P10 (11)
Mean	4.74	5.0	7.51	9.64	11.50	13.73	16.23	20.56	28.51	44.13
Median	1.68	4.29	6.27	7.55	8.89	12.14	15.25	18.12	23.63	34.43
Quartile 1	0.47	3.08	3.08	5.28	6.33	9.00	11.20	14.58	16.36	23.32
Quartile 3	5.60	6.38	9.87	11.36	13.70	17.71	20.32	2.40	33.27	48.19
Inter quartile range	3.62	3.11	6.72	5.73	7.07	8.11	8.04	8.61	16.68	25.31
Coff. of Qut. deviation	0.45	0.35	0.48	0.35	0.35	0.31	0.26	0.24	0.34	0.35
Quartile deviation	1.01	1.55	3.36	2.86	3.53	4.06	4.02	4.30	8.34	12.65
Variance (Portfolio)	16.0	1.14	1.70	0.88	0.87	0.80	0.80	1.27	0.75	1.34
T (Beta)	0.84	0.83	0.84	0.60	0.71	0.79	0.67	0.65	0.83	0.71
SE (beta)	0.27	0.31	0.20	0.14	0.15	0.14*	0.23	0.21	0.18	0.15
r (beta)	3.11*	2.67*	4.20*	4.28*	4.73*	5.64*	2.91*	3.0*	4.61*	4.73*
Alpha	−0.51	−0.57	−0.41	−0.42	−0.22	−0.13	−0.02	0.13	0.04	0.15
e^2	14.05	8.90	14.77	8.34	8.87	7.13	8.00	6.12	7.73	6.88
e (y)	1.16	1.10	1.27	0.78	1.18	1.44	1.32	1.44	1.70	1.57
SE (return)	0.10	0.07	0.06	0.14	0.06	0.04	0.09	0.06	0.06	0.08
t (return)	11.6*	15.71*	21.16*	5.57*	19.66*	36.0*	14.66*	24.0*	28.33*	19.62*

Note *Significant at 5% level
Source Compiled from Dhankar and Kumar (2007)

Indian economy, on the other hand, was on growth phase during January 2003 to May 2005 with 7.7% average growth rate.

Relative Performance of P/E Portfolios Under Decline Phase

Table 14.2 gives a summary of results under decline phase. No consistency is observed in expected returns of portfolios to their P/E ratios. However, portfolio-expected return is showing an increasing tendency form low P/E to high P/E portfolios. All the portfolios expected return and beta are significant at least at 10% level.

Relative Performance of P/E Portfolios Under Recession Phase

Results of the ten portfolios, obtained under recession phase, are summarized in Table 14.3. The portfolio-expected return goes up as one moves from low P/E portfolio to high P/E portfolio, but no consistency in portfolios returns are observed; as Portfolio P3 and P4 have low P/E, yet yield comparatively high return over the high P/E portfolio P6 and P7. Further, Table 14.5 shows that the correlation coefficient between portfolios expected return and market risk is fairly high. It is significant at 5% level. The trade-off between risk and return motivates the investors to demand high return for increasing risk.

Table 14.2 Portfolio test (1996–2000)

Pt (1)	Alpha (2)	Beta (3)	SE (4)	t (beta) (5)	Var (6)	e^2 (7)	e (y) (8)	SE2 (9)	t (return) (10)
P1	0.14	0.40	0.47	0.85	26.57	25.70	0.93	0.16	5.81
P2	−0.36	0.46	0.25	1.84**	9.03	8.28	0.57	0.06	9.50*
P3	0.05	0.61	0.31	1.96**	19.23	17.54	1.26	0.13	9.69*
P4	0.12	0.41	0.22	1.86**	7.87	6.85	0.94	0.09	10.44*
P5	0.08	0.51	0.25	2.04**	0.81	9.80	1.10	0.06	18.33*
P6	0.05	0.65	0.21	3.09**	7.83	6.06	1.34	0.07	19.14*
P7	0.10	0.39	0.19	2.05**	6.42	5.71	0.87	0.09	9.66*
P8	0.38	0.49	0.20	2.45**	6.84	5.76	1.37	0.12	11.41*
P9	0.70	0.71	0.38	1.86**	10.53	8.08	2.13	0.16	13.30*
P10	0.43	0.63	0.20	3.15*	7.40	5.89	1.68	0.09	18.66*

Note SE1: Standard error of beta; var; Portfolio variance: e_i^2 Non-market risk: e (y): Expected return: SE2; Standard error of return
*Significant at 5% level
**Significant at 10% level
Source Compiled from Dhankar and Kumar (2007)

Table 14.3 Portfolio test (2000–2003)

Pt (1)	Alpha (2)	Beta (3)	SE (4)	t (beta) (5)	Var (6)	e^2 (7)	e (y) (8)	SEZ (9)	t (return) (10)
P1	−0.38	0.68	0.40	1.70	17.31	14.85	0.96	0.17	5.64*
P2	−0.24	0.65	0.30	2.16**	9.10	6.15	1.05	0.09	11.66*
P3	−0.46	1.03	0.31	3.32*	21.35	15.86	1.58	0.08	19.75*
P4	−0.21	0.82	0.26	3.15*	14.76	10.61	1.42	0.10	14.20*
P5	−0.53	0.81	0.25	3.24*	13.36	9.87	1.12	0.08	14.0*
P6	−0.49	0.88	0.23	3.82*	13.02	9.17	1.27	0.07	18.14*
P7	−0.12	0.72	0.25	2.88*	13.13	9.64	1.32	0.14	9.42*
P8	−0.03	0.81	0.21	3.85*	10.50	7.42	1.58	0.11	14.36*
P9	−0.15	0.94	0.38	2.47*	13.95	9.34	1.73	0.11	15.72
P10	0.21	0.93	0.24	3.87*	15.12	10.16	2.06	0.16	12.87*

Note SE1: Standard error of beta; var; Portfolio variance: e^2 Non-market risk: e (y): Expected return: SE2; Standard error of return
*Significant at 5% level
**Significant at 10% level
Source Compiled from Dhankar and Kumar (2007)

Table 14.4 Portfolio test (2003–2005)

Pt (1)	Alpha (2)	Beta (3)	SE 1 (4)	t (beta) (5)	Var (6)	e^2 (7)	e (y) (8)	SEZ (9)	t (return) (10)
P1	−0.85	1.07	0.45	2.37*	10.48	9.63	3.96	0.60	6.60*
P2	−0.90	1.16	0.50	2.32*	11.64	10.76	2.75	0.43	6.39*
P3	−0.92	0.90	0.37	2.43*	7.47	6.06	0.83	0.08	10.37*
P4	−0.35	0.88	0.37	2.37*	7.40	6.03	1.42	0.08	17.75*
P5	−0.42	1.03	0.35	2.94*	5.90	5.14	2.47	0.30	8.23*
P6	−0.06	0.98	0.33	2.96*	6.58	4.70	1.89	0.10	18.90*
P7	−0.08	0.60	0.34	1.76*	6.12	5.45	0.99	0.09	11.0*
P8	0.03	0.65	0.35	1.85	6.27	5.20	1.32	0.07	18.85*
P9	−0.15	0.63	0.35	1.80**	6.41	4.52	1.11	0.07	15.85
P10	−0.03	0.39	0.35	1.11	5.26	4.77	0.76	0.07	10.85*

Note SE1: Standard error of beta; var; Portfolio variance: e^2 Non-market risk: e (y): Expected return: SE2; Standard error of return
*Significant at 5% level
**Significant at 10% level
Source Compiled from Dhankar and Kumar (2007)

Relative Performance of P/E Portfolios Under Growth Phase

Results of P/E portfolios, under growth phase, are shown in Table 14.4. It is found that under growth phase, portfolio-expected return exhibits declining tendency with movement from low P/E portfolio to high P/E portfolio. The observation is consistent with Basu (1977) findings, where he observed that the average annual rate of

Table 14.5 Correlation coefficients between portfolios expected return and portfolio market risk

Periods (1)	Correlation (2)	t-value (3)
June 1996–May 2005	0.30	0.89*
June 1996–December 1999	0.83	4.19*
January 2000–December 2002	0.74	3.08*
January 2003–May 2005	0.74	3.40*

Source Compiled from Dhankar and Kumar (2007)
Note *Indicates significance at 5% level

return declines as one moves from low P/E portfolio to high P/E portfolio. Under such a situation, low P/E stocks will tend to outperform high P/E stocks. The correlation coefficient between portfolios' expected return and market risk, as indicated in Table 14.5 is high and significant at 5% level. It indicates that the risk aversion tendency of investors makes them demand a high return for high market risk.

Conclusion

The study examines the relationship between the performance of portfolios corresponding to their P/E ratios. The results of the research work are relevant from investment decisions and policymaking point of view, as a large number of investors make their investment decision and forecast the future performance of stocks by considering the P/E ratios. The findings of the present study question the validation of investment decisions based on the P/E ratios. The cross-sectional tests of 10 P/E portfolios under decline and recession phases in Indian economy bring out that portfolio-expected return has increased, as one moves from the low P/E portfolio to high P/E portfolio, however, the rise in return is not continuous. On the contrary, in the growth phase, portfolios expected return show declining tendency as one moves from low P/E portfolio to high P/E portfolio. An important finding of the study is that Indian stock market has failed to absorb new information, and has not reflected instantaneous response in stock returns. The inefficient behaviour of stock market raises the question of the validation of efficient market hypothesis. However, Dhankar (1991), finds that Random Walk Hypothesis (RWH) holds in Indian stock market. Dhankar and Chakraborty (2005), using VR test and ARIMA process, found the dependency of the aggregate market series, which violates the assumption of RWH. However, the test results manifest mixed behaviour of the return generating process for individual companies. The findings are also consistent with Brown (1978) study, wherein the market does not adjust instantaneously to the information pertaining to earnings per share. Basu (1977), could not find any significant relationship between portfolio return and market risk for the period 1956 to 1971 in New York Stock Exchange. But in the present study, the cross-sectional analysis brings out a significant relationship between portfolios' expected return and market risk. This relationship exhibits the trade-off between risk and return, and indicates that investors want risk premium for increasing risk. This finding is consistent with the studies of Sharpe and Cooper (1972), Srinivasan (1988), and Rao et al. (1998). This relationship signifies the validation of capital asset pricing model in Indian stock market.

The findings of the pooled period and three sub-periods fail to establish any relationship between P/E ratios and their portfolios' performance. This leads to question the validity of efficient market hypothesis. The findings of all the four periods, however, show a significant relationship between portfolios' expected return and market risk. It holds the validation of capital asset pricing model in Indian stock market, as the descriptor of portfolio return corresponding to market risk.

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Chapter 15
Risk Diversification and Market Index Model

Beware of little expenses; a small leak will sink a great ship.
Benjamin Franklin

Abstract The study attempts to measure the relationship between risk and return, and the effect of diversification on non-market risk in Indian stock market by applying Market Index Model. For the analysis, monthly adjusted opening and closing prices of composite portfolio of BSE 100 companies for the period June 1996 through May 2005 have been taken. We find a high positive correlation between portfolio return and risk. It also signifies that portfolio non-market risk declines with diversification. The results, so obtained, are fully coinciding with the generalization of market index model, and thereby hold it applicable in Indian stock market, in establishing the trade-off between risk and return.

Introduction

Diversification is an important concept because of the risk–reward relationship. Individual stocks have several kinds of risk including firm risk, industry risk, and market risk. Firm risk and industry risk are diversifiable risks—in a portfolio, they can be substantially reduced by diversifying among different stocks and different industries. Market risk is non-diversifiable—all stock portfolios to some degree contain market risk. It is also a proven fact that diversification risk is not consistently rewarded with higher expected returns. On the other hand, bearing overall market risk does tend to be consistently rewarded. Thus, investors with poorly diversified portfolios would be far better off by diversifying those risks and, if desired, taking on the risks that do tend to be rewarded. In other words, by

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diversifying, one can increase the expected return of your stock portfolio without increasing the risk (Burnside 2004).

Markowitz Mean–Variance Model (Markowitz 1952) was the beginning of portfolio theory which states investors' preference for return and risk. Investors demand a higher return for higher risk. Markowitz argues that portfolio risk is not the weighted average risk of individual securities in the portfolio, but it is the aggregation of the co-variability of individual securities' returns. Portfolio risk gets reduced with the process of diversification, resultant inclusion of securities having low co-variability in their return. The existence of risk-free security led Sharpe (1964, 1995), Lintner (1965), and Mossin (1966) to develop the Capital Asset Pricing Model, which deals with the determination of required rate of return of a risky security in an efficient capital market, and thereby determination of the price of a security. An efficient capital market provides a higher return for higher risk. Capital Asset Pricing Model enables investors to price a risky asset under conditions of risk and uncertainty. Knight (1921) argues that risk refers to the situation, where decision makers project the outcome by assigning probabilities to the situation; whereas outcome cannot be projected under uncertainty by assigning probabilities to the situation.

An efficient capital market exhibits the instantaneous response to market and non-market factors. A time lag between corresponding reactions motivates the speculators to take advantage of the opportunity and make an abnormal profit. In fact, variability in interest rate prompts investors to keep a portion of their money for a speculative motive. In such a situation, they will prefer to park their funds in money market securities.

Prelude

Sharpe and Cooper (1972) argue that variability in stock return is a result of the market and non-market risk. Market risk is the product of variation in factors like interest rate, inflation, foreign exchange rate, gross domestic product, etc. With the presence of foreign institutional investors, Indian stock market has become responsive to international market factors. A change in U.S. Federal interest rate can cause upswing or downswing in the Indian stock market. Non-market risk, on the other hand, is specific to each stock. Change in investors expectations to tangible or intangible factors of each stock can cause a change in its value. Sharpe (1964, 1995) argues that diversification results in the decline of portfolio risk and more specifically the non-market risk. When some securities in the portfolio respond undesirably to the market or non-market factors, it is likely that the rest of the securities may perform better under the same conditions. Stocks return necessarily shows a co-movement with market index (BSE 100). Variability in market return resultant to market risk brings the corresponding variation in stocks return. Consequently, market index model is widely used as a tool to project the expected return and risk of securities. This paper examines the hypotheses of the proportional and linear relationship between portfolio return and risk, and process of diversification results in decline of portfolio non-market risk.

Many researchers have examined the risk and return relationship, and the effect of diversification on the portfolio risk. Sharpe and Cooper (1972) maintain that as the number of securities in a portfolio increases, the non-market risk goes on declining. Srinivasan uses two-phase regression to test the relationship, and effect of diversification in Indian stock market. The first phase consists of time series regression of 85 companies listed on Bombay Stock Exchange, where stocks return is regressed to the market return. The second phase involves cross-sectional regression of portfolio return to portfolio beta. He finds a significant relationship between portfolio return and portfolio market risk. Stocks, which have least beta values, include Modi Xerox (0.05), Shankey (0.08) and Finlay (0.11). Stocks, whereas, with high beta values are Barr Welco. (1.87), Com Prod. (1.92) and Indo Burma (2.26). Dhankar (1988, 1996) shows a significant relationship between portfolio beta and portfolio expected return. Further, Dhankar (1988, 1996) reports that APT provides a better indication of asset risk and required rate of return than CAPM. However, the findings of Sehgal (1997) do not support the risk and return relationship and effect of diversification in Indian stock market. Yet another study deals with 593 New York Stock Exchange stocks for the period ranging from 1946 through 1965. The study supports the hypothesis that realized returns are significantly positively related to market risk. Klemlosky and Martin (1975) maintain that diversification can be achieved by enlarging the portfolio size. A high beta value portfolio needs a large number of stocks to achieve a diversification level equal to low beta value portfolio.

Methodology Used

The dataset consists of monthly adjusted opening and closing prices of BSE 100 stocks for the period from June 1996 through May 2005. These prices are adjusted with the bonus issue, right issue and other corporate actions. The data has been taken from PROWESS, a database maintained by the CMIE. The sample period exhibits a mixed set of the economic environment in the Indian economy. The early period (June 1996–December 1999) of the study can be categorized as decline phase with a 6.3% average low growth rate. However, the later period (January 2003–May 2005) was growth-oriented, when the economy started to register an impressive 7.7% average growth rate. BSE 100, which covers all industry-category stocks, is value-weighted index, assigns weights to all stocks in proportion to the share of their market capitalization. The sample stocks account for a major part of the market capitalization as well as trading volume. The number and diversity of stocks lead us to conclude that sample stocks, taken as a whole, is an approximate efficient portfolio of stocks. The natural logarithmic mode is used to measure the return of stocks. The logarithmic difference between the movements of prices is symmetric and is expressed in percentage terms for ease of comparability. Symbolically, it can be written as

$$R_{it} = Log_t\left(\frac{P_1}{P_{t-1}}\right) * 100 \tag{15.1}$$

where R_{it} is the return on stock i in time period t, $\mathrm{Log_t}$ is natural logarithm, $\mathrm{P_t}$ is closing price, $\mathrm{P_{t-1}}$ is opening price. This measure of return takes into account only appreciation/depreciation of stock and neglect the dividend yield. This suggests that the value of beta would not change significantly, if the dividend yield is excluded (Sharpe). The same method has been used for calculating the return on market index (BSE 100). Symbolically, it can be written as

$$X_t = Log_t\left(\frac{I_1}{I_{t-1}}\right) * 100 \tag{15.2}$$

where $\mathrm{X_t}$, is the return on index, $\mathrm{I_t}$, is closing number and $\mathrm{I_{t-1}}$ is the opening number.

The market index model asserts that expected return on security i, i.e. E ($\mathrm{R_{it}}$), in time period t, is a linear function of market return $\mathrm{X_t}$ and an independent factor unique to security i, i.e. $\mathrm{e_1}$. Symbolically, it can be written as

$$\mathrm{E(R_{it}) = \alpha_i + \beta_t\, X_t + e_{it}} \tag{15.3}$$

Beta (β) can be estimated by regressing the monthly security return to the return of index. It is calculated as

$$\beta_i = \frac{n\sum XR - \sum X \sum R}{n\sum X^2 - \left(\sum X\right)^2} \tag{15.4}$$

Alpha (α) is a constant intercept indicating the minimum level of return that is expected from security i, if the market remains flat, is calculated as follows:

$$\alpha_i = \overline{R} - \beta_i \overline{X}_i \tag{15.5}$$

where α is constant intercept of security *i*, $\overline{R}$ is mean the return of security i, $\overline{X}$ is mean the market return of index, β_i is the slope of security *i* and $\mathrm{e_{it}}$ is error term representing the residuals (non-market risk) of security *i*. Total risk of a security is the sum of market risk and non-market risk. Symbolically, it can be written as

$$\sigma_i^2 = \beta_i^2 \sigma_{x_t}^2 + e_{it}^2 \tag{15.6}$$

where σ_i^2 is the variance of stock *i* representing total risk, $\beta_i^2 \sigma_{x_t}^2$, is total market risk and e_{it} is the total non-market risk. To measure portfolio return, equal weights have been assigned to each security in the portfolio. Symbolically, portfolio return can be obtained as

$$E(R_p) = \sum_{t=1}^{N} W_i(\alpha_i + \beta_i X) \tag{15.7}$$

where E (R_p) is portfolio expected return, w_i is weight given to security i in the portfolio. For a portfolio, w = 1. In the same fashion, the total risk of a portfolio is the weighted average of total risk of individual securities which is composite of the market and non-market risks. Symbolically, it can be written as

$$\sigma_p^2 \left[\left(\sum_{i=1}^{n} (w_i \beta_i)^2 \sigma_x^2 \right) \right] + \left[\sum_{i=1}^{N} W_i^2 e_i^2 \right] \tag{15.8}$$

where σ_p^2 is total risk of portfolio, N is the total number of securities, $w_p^2 \beta_p^2 \sigma_p^2$ is a weighted average of total market risk of each security $w_i^2\, e_1^2$ and is weighted average of error term of each security in the portfolio, representing the non-market risk of portfolio. Portfolio's beta which is a function of the summation of the weight of each security in the portfolio multiplied by its beta, can be written as

$$\beta_p = \sum_{i=1}^{N} w_i\, \beta_1 \text{ where, w} = 1 \tag{15.9}$$

To measure the relationship between portfolio risk and return, and the effect the diversification, all the securities have been arranged in ascending order on the basis of their beta values, and thereafter ten portfolios have been constructed.

The main objective of the study is to test the relationship between risk (systematic risk) and return, and the effect of diversification on the portfolio risk.

Accordingly, the hypotheses to be tested are:

H_1: There is a significant relationship between stock beta and return, i.e. beta is significant from zero.
H_2: There is a positive and proportional relationship between portfolio beta and portfolio return, i.e. correlation coefficient between the two is significant.
H_3: There is a significant effect of diversification on the non-market risk of portfolio.

To measure the reliability of beta and correlation coefficient, 'Z' test is used at 5% level of significance. Where the number of observations is less than 30, 't' test has been used. To calculate the expected return of the securities and portfolios, it is assumed that the market will give 2% (24% annual) monthly return in the near future.

Relationship Between Individual Security Risk and Return: Characteristic Line

Table 15.1 outlines the statistical summary of all the stocks. To establish the risk and return relationship between stocks, all the securities are arranged in ascending order on the basis of their beta values. Out of 100 stocks, 90 stocks beta is statistically significant, which means null hypothesis is rejected. Spearman's correlation

Table 15.1 Individual securities return and risk: Indian stock market

Sl. No.	Company	Var_{at}	β_1	α_1	$\beta_i^2\sigma_i^2$	e_i^2	β_{SE}	R^2	E (R)
1.	Reliance Capital	20.00	0.12	−3.07	2.08	17.82	0.04	0.10	−2.85
2.	MICO	6.21	0.12*	0.40	0.05	6.16	0.13	0.00	0.64
3.	Pizer Ltd.	11.20	0.22*	0.10	0.16	11.09	0.18	0.01	0.54
4.	MRPL	17.90	0.23*	−0.29	0.17	17.74	0.22	0.00	0.17
5.	Matrix Lab	24.80	0.24*	0.13	0.20	24.61	0.26	0.00	0.61
6.	Container Corp	9.86	0.27	−0.19	0.24	9.62	0.16	0.02	0.35
7.	Indian Rayon	7.61	0.29	0.20	0.28	7.33	0.14	0.03	0.78
8.	Wockhardt	7.96	0.30	−0.21	0.30	7.66	0.14	0.03	0.39
9.	Indian overseas Bank	9.21	0.32*	−0.51	0.25	8.97	0.26	0.02	0.13
10.	Patni Computer	2.15	0.32*	−0.09	0.11	2.04	0.36	0.02	0.55
11.	HDFC Bank	4.79	0.33	0.41	0.36	4.44	0.11	0.05	1.06
12.	IDBI	9.99	0.37	−0.81	0.46	9.53	0.16	0.07	−0.07
13.	Indian Oil Corp.	7.02	0.38	0.03	0.49	6.54	0.14	0.04	0.79
14.	Cummins India.	6.80	0.39	0.16	1.05	5.75	0.13	0.06	0.94
15.	Novartis India	7.49	0.41	0.13	0.55	6.94	0.14	0.07	0.95
16.	Asian Paints	3.89	0.42	0.02	0.58	3.31	0.10	0.07	0.86
17.	VSNL	8.80	0.43	−0.32	0.61	8.19	0.15	0.02	0.54
18.	HDFC	9.00	0.46	0.02	0.72	8.28	0.15	0.07	0.94
19.	Raymond Ltd.	8.38	0.47	−0.51	0.72	7.65	0.14	0.08	0.43
20.	Cadila Health Centre	7.81	0.48	−0.61	0.55	7.26	0.22	0.07	0.35
21.	Bharat Forge	12.50	0.51	−0.06	0.88	11.60	0.18	0.07	1.08
22.	Nicholas Pirmal	7.58	0.51	0.48	0.86	6.71	0.14	0.11	1.50
23.	Vijaya Bank	11.10	0.51*	−1.40	0.63	10.45	1.14	0.05	−0.38
24.	Blocon Ltd.	3.26	0.52	−0.68	0.31	2.95	0.29	0.09	0.36
25.	GE Shipping Co.	7.71	0.52	−0.53	0.92	6.79	0.14	0.11	0.51
26.	ABB Ltd.	8.73	0.54	0.48	0.99	7.75	0.07	0.11	1.56
27.	J & K Bank	14.50	0.55	−0.08	1.01	13.51	0.22	0.06	1.02
28.	Nestle India	6.93	0.57	0.31	1.08	5.85	0.13	0.15	1.45
29.	Bajaj Auto	4.48	0.59	0.22	1.17	3.31	0.10	0.26	1.40
30.	Glaxosmith	5.97	0.59	0.23	1.06	4.91	0.12	0.17	1.41

(continued)

Table 15.1 (continued)

Sl. No.	Company	Var_{at}	β_1	α_1	$\beta_i^2\sigma_i^2$	e_i^2	β_{SE}	R^2	E (R)
31.	HLL	5.23	0.60	0.19	1.21	4.02	0.11	0.23	1.39
32.	SCI	1.50	0.60	−0.37	1.18	10.31	0.17	0.10	0.83
33.	ITC Ltd.	5.94	0.61	0.09	1.23	4.71	0.12	0.20	1.31
34.	Kochi Refinery	9.76	0.61	−0.50	1.22	8.54	0.16	0.12	0.72
35.	Colgate Palmolive	4.48	0.62	−0.29	1.29	3.19	0.09	0.28	0.95
36.	Ashok Leyland	12.30	0.63	−0.73	1.32	10.98	0.18	0.10	0.53
37.	Lupin Ltd.	18.30	0.63	−0.52	1.33	17.01	0.21	0.09	0.74
38.	Tata Tea Ltd.	6.73	0.63	0.01	1.34	5.39	0.12	0.19	1.27
39.	United Phosphor	45.60	0.64	1.13	1.37	44.17	0.35	0.03	2.41
40.	Hero Honda Motor	9.29	0.65	0.01	1.43	7.86	0.15	0.07	1.31
41.	Chennai Petroleum	11.70	0.66	−0.36	1.46	10.22	0.17	0.12	0.96
42.	Tata Chemical	9.23	0.66	−0.58	1.45	7.77	0.14	0.15	0.74
43.	Sun Pharmaceutical	7.69	0.67	−0.26	1.51	6.20	0.13	0.19	1.08
44.	Bharat Petroleum	11.70	0.68	−0.28	1.53	10.53	0.17	0.13	1.08
45.	Hindalco Industries	6.38	0.68	−0.01	1.54	4.84	0.12	0.24	1.35
46.	KM Bank	12.6	0.68	0.58	1.53	11.08	0.18	0.12	1.94
47.	Ranbaxy Lab	5.67	0.69	0.08	1.60	4.08	0.10	0.28	1.46
48.	Dr. Reddy Lab	6.03	0.71	0.09	1.67	4.37	0.11	0.27	1.51
49.	Rashtirya Chemical	21.60	0.71	−0.87	1.68	19.92	0.23	0.28	0.55
50.	TVS Motor	10.50	0.71	−0.14	1.71	8.75	0.15	0.16	1.28
51.	M &M	7.22	0.72	0.24	1.72	5.49	0.12	0.23	1.68
52.	ONGC	8.28	0.72	−0.21	1.72	6.56	0.14	0.20	1.23
53.	OBC	8.48	0.72	−0.17	1.72	6.73	0.14	0.20	1.27
54.	Indian Hotels	7.98	0.74	−0.18	1.84	6.14	0.13	0.23	1.30
55.	National Alum.	1.70	0.74	−0.25	1.83	15.13	0.21	0.10	1.23
56.	Siemens Ltd.	9.08	0.74	0.30	1.84	7.24	0.14	0.20	1.78
57.	Cipla Ltd.	7.02	0.78	0.24	2.01	5.01	0.13	0.28	1.80
58.	Moser Baer	18.50	0.78	−0.46	2.05	16.47	0.22	0.11	1.10
59.	GAIL India	7.53	0.79	−0.08	1.86	5.66	0.14	0.24	1.50
60.	MTNL	9.61	0.79	0.13	3.07	7.54	0.15	0.21	1.71
61.	Divi's Laboratory	12.70	0.80	0.07	1.08	11.57	0.51	0.08	1.67
62.	Neyveli Lignite	41.50	0.81	−0.25	2.26	39.19	0.31	0.10	1.35
63.	Hind. Petroleum	11.90	0.83	−0.42	2.18	9.73	0.17	0.18	1.20
64.	Tata Motors	8.48	0.84	−0.12	2.30	6.19	0.15	0.27	1.54
65.	G. Ambuja Cement	8.22	0.84	−0.11	2.36	5.86	0.13	0.28	1.57
66.	Tata Power	8.72	0.85	−0.50	2.36	6.39	0.10	0.26	1.18
67.	Arvind Mills	9.00	0.86	−0.72	2.43	6.56	0.16	0.27	0.98
68.	Reliance Energy	8.33	0.87	−0.39	2.45	6.56	0.16	0.27	0.98
69.	Tata Iron & Steel	8.16	0.88	0.10	2.51	5.64	0.12	0.30	1.84

(continued)

Table 15.1 (continued)

Sl. No.	Company	Var_{at}	β_1	α_1	$\beta_i^2\sigma_i^2$	e_i^2	β_{SE}	R^2	E (R)
70.	Maruti Udyog Ltd.	5.48	0.88	0.21	1.330	4.15	0.33	0.24	1.97
71.	Grasim Industries	9.13	0.89	0.09	2.64	6.49	0.14	0.28	1.87
72.	Infosys Technology	11.10	0.90	0.54	2.71	8.38	0.15	0.24	2.34
73.	Sterlite Industries	12.10	0.90	−0.08	2.78	9.35	0.16	0.22	1.72
74.	I-Flex Solutions	13.60	0.91	−0.54	1.17	12.24	0.49	0.08	1.28
75.	UTI Bank	14.00	0.92	−0.80	2.88	11.11	0.20	0.20	1.04
76.	Larsen & Turbo	7.93	0.93	−0.11	2.86	5.07	0.12	0.36	1.75
77.	Reliance Industries	7.51	0.94	0.26	2.90	4.54	0.11	0.39	2.14
78.	Bank of Baroda	13.50	0.97	−0.44	3.30	10.23	0.17	0.24	1.50
79.	ICICI Bank	11.10	0.97	−0.54	2.87	8.26	0.17	0.25	1.40
80.	SAIL	17.60	0.97	−0.87	3.16	14.38	0.20	0.18	1.07
81.	BHEL	12.10	0.98	−0.65	3.22	8.90	0.16	0.26	1.31
82.	Satyam Computers	13.80	0.98	0.50	3.22	10.57	0.17	0.23	2.46
83.	Indian Petrochemical	10.90	1.01	−0.24	3.41	7.50	0.17	0.31	1.78
84.	Bharti Televenture	10.00	1.02	−0.27	1.92	8.10	0.34	0.19	1.77
85.	Corporation Bank	11.70	1.02	−0.45	3.22	8.51	0.18	0.27	1.59
86.	PNB	11.40	1.03	−0.16	1.47	9.96	0.43	0.12	1.90
87.	Bank of India	9.87	1.04	−0.63	3.22	6.65	0.90	0.32	1.45
88.	State Bank of India	8.42	1.05	−0.26	0.71	4.70	0.11	0.44	1.84
89.	Tata Teleservices	10.60	1.11	−1.74	2.99	7.56	0.23	0.26	0.48
90.	ACC	11.70	1.14	−0.13	4.32	7.33	0.14	0.37	2.15
91.	Wipro	13.40	1.16	0.48	4.52	8.86	0.15	0.33	2.80
92.	Jaiprakash Asso.	11.10	1.20	0.35	1.78	9.35	0.84	0.15	2.75
93.	Zee Telefilm	20.40	1.21	0.52	4.86	15.48	0.20	0.23	2.94
94.	HCL Infosystems	18.00	1.28	0.33	5.45	12.55	0.19	0.30	2.89
95.	Polaris Software	18.20	1.30	−0.10	5.83	12.34	0.23	0.32	2.50
96.	Andhra Bank	13.80	1.45	−1.06	4.01	9.80	0.32	0.29	1.84
97.	Bharat Electronics	16.90	1.48	−0.48	7.44	9.49	0.17	0.43	2.48
98.	HCL Technology	19.90	1.53	−0.25	7.70	12.24	0.24	0.38	2.81
99.	Canara Bank	13.23	1.70	−1.09	4.19	9.13	0.45	0.31	2.80
100.	Union Bank	10.90	1.70	−0.60	4.19	6.70	0.37	0.38	2.80
Weighted average		11.12	0.74	−0.20	1.93	9.17	0.20	0.18	129

Source Compiled from Dhankar and Kumar (2007)

*Notes *Beta is not significant at five percent level of significance: Var_{at} variance of stocks: β_{SR} Standard error of beta. R^2 Coefficient of determination, showing how much variation in stock return is explained by the index. E (Rp)—Expected return on stocks when the market is supposed to give 2% monthly return* coefficient value of (0.75) between the beta and expected return; and the value of (0.62) between total market risk and expected return of each stock show a very high degree of relationship. The proposition of the market model that high risk yields high return and low risk yields low return seems to be proving correct. Mean–Variance model has also established the same kind of relationship between the two.

Stocks which fall in the first end of ranking can be categorized as less volatile. They remain less responsive to the market upswings and downswings. Stocks, on the other hand, which come in the second end of ranking are highly volatile and exhibit a high degree of market sensitivity. Coefficient of determination, which measures how much variation in stock return is explained by the index return, depicts that major portion of the total risk of stocks is non-market risk. The value of r_{Rx} 0.90 with R^2 0.81 means that 81% variation in the stock return is explained by index return. On the other hand, $1\text{-}R^2$ indicates the percentage of variation in the security return which is not explained by the index return, and this can be termed as non-market risk.

Industry Risk and Return

All the 100 stocks have been grouped industry-wise in Table 15.2. Industries have been arranged in ascending order on the basis of their beta values. The industry beta is simply the weighted average of the betas of different stocks in that industry. All the industries betas are statistically significant at 5% level of significance. Risk and return expectations of investors across the stocks in an industry should be affected equally by market factors. As a result, stocks beta values should move close to each other subject to any significant differences. But the observed betas of different stocks from the same industry question this hypothesis. There is a significant difference between the beta values across the stocks from the same industry. Finance and banking stocks have betas ranging from 0.32 (Indian Overseas Bank) to 1.70 (Union Bank of India) and Oil and Gas stocks have betas ranging from 0.23 (MRPL) to 0.94 (Reliance Industries). Beta value, in fact, of different industries exhibits their response to the market risk. Transport Services industry has the least beta value, exhibits its defensive nature from the upswing and downswing of market factors. Investors don't expect any significant appreciation/depreciation in the value of stocks from this industry. As a result, the expected return of this industry is comparatively low (0.56).

Media and Publishing has the highest beta (1.21), exhibiting high responsiveness to market factors. In other words, any variation in market factors would have a huge effect on the investment value of the investors of this industry. Investors have received, on an average 1.15% monthly return, by investing in the composite portfolio of this industry. Further investors have got highest return (2.94) from the composite portfolio of the tourism industry. The low beta value (0.74) indicates that investors observe low variation in composite portfolio of stocks of this industry due to variation in market factors. It can be categorized as a defensive industry.

Table 15.2 Industry risk and return: Indian stock market

	Industry	Var_{at}	β	α	$\beta_i^2\sigma_i^2$	e_{i1}^2	β_{SE}	R^2	$(1-R^2)$	E (Rp)
1.	Transport Services	9.68	0.46	−0.36	0.78	8.90	0.16	0.08	0.92	0.56
2.	Health Care	8.86	0.53	−0.02	0.92	7.95	0.19	0.13	0.87	1.05
3.	Diversified	8.37	0.59	0.15	1.46	6.91	0.14	0.16	0.85	1.32
4.	FMCG	5.55	0.60	0.07	1.19	4.35	0.11	0.22	0.78	1.26
5.	Finance and Banking	11.46	0.83	−0.58	2.04	9.25	0.26	0.19	0.81	1.08
6.	Agriculture	6.33	0.62	0.05	1.28	5.05	0.12	0.20	0.80	1.29
7	Transport Equipment	8.49	0.63	0.02	1.32	7.16	0.17	0.16	0.84	1.27
8.	Textile	8.69	0.66	−0.62	1.58	7.11	0.15	0.18	0.82	1.30
9.	Oil and Natural Gas	9.99	0.67	−0.21	1.61	8.41	0.15	0.18	0.82	1.13
10.	Chemical and Petrochemical	7.32	0.68	−0.20	1.61	15.70	0.19	1.15	0.13	0.87
11.	Tourism	7.98	0.74	−0.18	1.84	6.14	0. 13	0.23	0.77	2.94
12.	Capital Goods	10.18	0.83	−0.03	2.18	8.01	0.22	0.21	0.79	1.63
13.	Power	8.72	0.84	−0.50	2.36	6.39	0.10	0.26	0.74	1.18
14.	Telecom	9.74	0.84	−0.55	2.14	7.84	0.22	0.18	0.82	1.13
15.	Metal, Metal products and Mining	16.13	0.85	−0.14	2.51	13.61	0.18	0.22	0.78	1.56
16.	Information Technology	13.16	1.02	0.08	3.61	9.52	0.26	0.24	0.76	2.10
17.	Consumer Durables	17.82	1.18	−0.21	4.98	12.83	0.19	0.31	0.69	0.71
18.	Media and Publishing	20.35	1.21	0.52	4.86	15.48	0.20	0.23	0.77	1.15

Source Compiled from Dhankar and Kumar (2007)
Note Where β *industry beta value;* Var_{at} *Industry Variance* β_{SE} *Standard error of industry beta* $\beta_1^2\sigma_x^2$ *Aggregate systematic risk of industry;* R^2 *Variation in industry return which is explained by market return;* $1-R^2$ *Variation in industry return which is not explained by market return; E (Rp) Industry expected return*

Relationship Between Portfolio Return and Risk

Table 15.3 depicts the statistical summary of ten portfolios constructed on the basis of beta value of hundred stocks. All portfolios betas, except the Pl, are statistically significant. Portfolio‘s total risk is not exhibiting consistency with the market risk of respective portfolios, as one moves from low market risk portfolio P1 to high market risk portfolio P10. Total risk of portfolio P2 and P3 is low as compared to preceding portfolios. The expected return of successive portfolio is, however, consistent with its market risk. Investors have realized a 13% monthly return by investing in portfolio Pl, whereas those who invested in portfolio P10 have got only a 2.60% monthly return. Sharpe and Cooper also adopt the same methodology in classifying the different classes of return and risk of stocks, ranging from 478 (1931) to 985 (1967), listed on New York Stock Exchange. Their study involves construction of ten portfolios on the basis of beta value. Portfolio with high beta value is termed as high risk–return class and portfolio with low beta value is termed as a low risk–return class.

Correlation coefficient values of (0.96) and (0.98), between portfolio total market risk ($\beta_i^2 \sigma_{xi}^2$) and portfolio expected return, and between portfolios beta (β_i) and expected return, respectively, are significant at 5% level of significance, and do exhibit a very high positive and linear relationship. Rao, Nath, and Malhotra (1998) provide a moderate relationship between monthly return and beta, but a very high degree of positive relationship when quarterly returns are used. Solnik and Bruno (1974) argue that because the prices of long array of stocks move together and show relationship with market, the rate of return, on any reasonably well diversified portfolio will be highly correlated with that of the market as a whole. The declining values of l-R^2 with successive portfolios, indicate that non-market risk declines with diversification. From Table 15.3, it is evident that an investor has the 10 alternative portfolios with different returns subject to different risks. Which portfolio an investor will pick up depends upon his/her risk–return trade-off. One would choose a portfolio, where one's risk–return preference curve will intersect with each other.

Table 15.3 Portfolio Return and risk: Indian stock market

Pt	Stocks	Var_{at}	β_1	α_1	$\beta_1^2 \sigma_{xi}^2$	e_1^2	β_{SE}	R^2	(1-R^2)	E (R_P)
P1	10	11.69	0.24	−0.35	0.39	11.30	0.18	0.030	0.97	0.13
P2	10	7.39	0.41	−0.15	0.60	6.78	0.14	0.074	0.93	0.68
P3	10	8.27	0.54	−0.09	0.89	7.38	0.25	0.12	0.88	0.99
P4	10	12.91	0.62	−0.09	1.29	11.64	0.16	0.14	0.86	1.14
P5	10	10.30	0.68	−0.17	1.56	8.77	0.15	0.19	0.81	1.20
P6	10	10.06	0.75	−0.04	1.96	8.19	0.15	0.20	0.80	1.46
P7	10	12.24	0.83	−0.21	2.12	10.12	0.21	0.22	0.78	1.47
P8	10	11.76	0.93	−0.25	2.72	9.00	0.19	0.24	0.76	1.61
P9	10	11.05	1.04	−0.40	2.77	7.97	0.28	0.28	0.72	1.67
P10	10	15.58	1.40	−0.19	4.98	10.59	0.32	0.31	0.69	2.60
Average	10	11.12	0.74	−0.20	1.93	9.17	0.20	0.18	0.82	1.29

Source Compiled from Dhankar and Kumar (2007)

Notes where, beta is not significant; Var_{at} Variance of stocks of the portfolio; β_{SE} Standard error of portfolio beta; $\beta_1^2 \sigma_{xi}^2$ Aggregate systematic risk of the portfolio; R^2 Variation in portfolio return which is explained by market return; 1-R^2 Variation in portfolio return which is not explained by market return; $E(R_p)$ Portfolio expected return

Security Market Line

The relevant risk measure, of an individual risky asset, is its covariance with the market portfolio. Klemkosky and Martin (1975) argue that market risk of individual security should be equal to the aggregate risk of a portfolio, as non-market risk tends to decline with diversification. The return of a market portfolio should be consistent with its own risk. An efficient market provides a high return for high risk to investors. Investors will prefer risky portfolio, when it tends to give high return. The security market line helps investors to determine the required rate of return for the given level of risk. Figure 15.1 depicts the observed SML, which is obtained, by joining the portfolio's expected return and market risk. In Fig. 15.1, the observed SML exhibits a very highly positive and linear relationship between portfolio expected return and portfolio market risk. This relationship validates the efficient market hypothesis in Indian stock market. Investors have earned an increasing return by investing in high market risk portfolio.

Non-market Risk and Process of Diversification

Portfolio risk, which is composite of market and non-market risks, tends to decline with the process of diversification. Black (1969) maintains that if diversification is carried out effectively, the portfolio risk will be significantly less than the weighted average risk of individual stocks in it. The study involves diversification on the basis of market risk of sample stocks. In Table 15.3 the portfolios are arranged on the basis of increasing market risk. Portfolio Pl which comprises ten securities having least value of betas can be categorized most defensive portfolio, as it exhibits the least response to the market. The return of this portfolio is not significantly related to the market return. The holders of this portfolio will observe

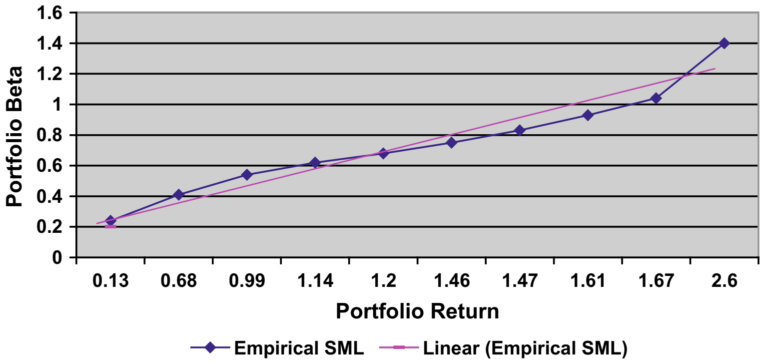

Fig. 15.1 Relationship between portfolio'S BETA and expected return: Indian stock market. *Source* Compiled from Dhankar and Kumar (2007)

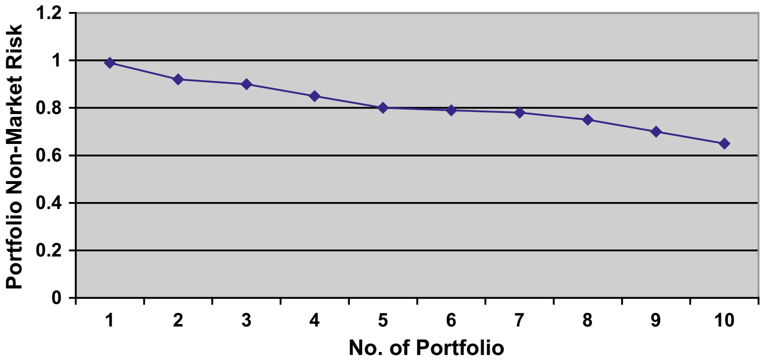

Fig. 15.2 Relationship between portfolios non-market risk and diversification: Indian stock market. *Source* Compiled from Dhankar and Kumar (2007)

fewer fluctuations in their returns with the upward and downward movement of the market. Such portfolio is preferred by regular income seeker investors. Portfolio P2, in the same way, covers the next ten securities having the second least value of betas and so on. Portfolio P10, which comprises high beta values, on the other hand, can be categorized as most aggressive portfolio. It shows a greater degree of response to the market. The return of this portfolio is highly integrated to the market return. Investors interested in appreciation of their investment will prefer such portfolio. Table 15.3 shows that with movement from low market risk portfolio to high market risk portfolio, the value of $1\text{-}R^2$ successively declines. It exhibits that variation in the stock return resulting due to variation in market return successively declines. Figure 15.2 depicts the negative trend of non-market risk as one moves from portfolio Pl to portfolio P10.

Klemkosky and Martin find that an investor needs to have a fairly large number of securities in the portfolio, if its beta is high, and the reverse is the case for a low beta portfolio, to achieve the same level of effect of diversification. A class of researchers suggests time diversification instead of non-market risk diversification. In case of time diversification, if stocks are held for a long period, the risk will be lower, and if they held for a shorter period, risk will be higher. Madhusoodan (1998) argues that if the stock return is normally distributed, then the losses from bad periods will be offset by the good periods. Time diversification can be viewed in relation to variability in market factors, which tend to vary with business cycles in the economy. In today's world of globalization, with the upward movement of business cycle, investors tend to realize a high return. The reverse holds true in the downward movement. Higher returns realized by investors in the upward phase of business cycle do offset the lower returns realized in downward movement. Portfolio P10 will offer a higher return to investors in the upward movement of the business cycle compared to portfolio Pl, whereas, in the downward movement, portfolio P10 will depreciate the value of investment much faster in comparison to portfolio P1.

Conclusions

Our objective in the paper was to test the relationship between risk and return, and effect of diversification on portfolio‘s non-market risk, by applying the market index model. Variability in the market and non-market factors is necessarily absorbed by the market index. Consequently, stocks return exhibit corresponding response to market movement. The efficient capital market enables investors to earn a higher return for higher risk. In the study, results so obtained are consistent with the efficient capital market theory and thereby proves the usefulness of market index model in pricing the risky securities. The significant correlation coefficient between stock’s market risk and expected return exhibits a linear and positive relationship. Stocks with high beta values have given high returns to investors. A similar relationship is also observed for portfolio market risk and expected return. Investors have realised higher returns as the market risk of a portfolio increases. As investors move from low market risk portfolio to high market risk portfolio, their exposure to non-market risk gets reduced. Coefficient of determination of individual stocks and portfolios indicate that major portion of risk is a non-market risk.

In conclusion, it can be said that Indian stock market has offered an increasing return to those investors, who invested in high risk portfolios. This tendency validates the efficient market theory in the Indian stock market. Thus, we can say that market index model is applicable in Indian Stock Market.

Implications for Policy

The study has wide-ranging implications to the investors and policymakers. Risk and return quantify the attractiveness of capital market. An efficient capital market deters to earn an abnormal profit because of having additional information, and other speculative activities. The positive relationship between portfolio risk and return validates the efficient market hypothesis in Indian Stock Market. Investors, being risk evaders, demand a higher return for higher risk. There are, basically, three categories of investors. One class of investors is highly risk evaders, mainly interested in regular income instead of capital appreciation of their investment. They should prefer portfolio with low market risk. Investors, on the other hand, who are high risk-takers, and are mainly interested in the capital appreciation of their investment, should prefer a portfolio with high market risk. The third category belongs to moderate risk-takers, who invariably are interested in both regular income plus the market appreciation of their investment, they should ideally prefer portfolios with moderate market risk.

The study reports that non-market risk is subject to decline with diversification and more so if we diversify internationally, therefore, market risk should be assumed as a proper measure of portfolio risk. As a result, portfolio return is more responsive to market factors like interest rate, inflation, foreign exchange, gross domestic product, etc. Investors and fund managers, therefore, would be better off, if they diversify their portfolio and consider market risk as a major factor in their investment strategy.

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Chapter 16
Mean–Variance Approach and Portfolio Selection

How many millionaires do you know who have become wealthy by investing in savings accounts? I rest my case.
Robert G. Allen

Abstract We make an attempt to examine the performance of portfolios formulated on the basis of Mean–Variance approach. For the analysis, monthly adjusted opening and closing prices of composite portfolio of BSE 100 companies have been taken for the period ranging from June 1996 to May 2005. The study has wide-ranging implications for finance professionals and policy makers. Ten portfolios have, first, been formulated and then evaluated by using Sharpe's excess return to beta approach. Nine portfolios' expected returns out of ten are significant at 5% level of significance. A cross-sectional analysis of the same set of ten portfolios carried out for three non-overlapping sub-periods (June 1996–December 1999, Jan 2000–December 2002, and Jan 2003–May 2005). The three sub-periods exhibit successive different economic conditions in the Indian economy, viz. decline, recession and growth, respectively. The results so obtained exhibit that portfolio-expected return of all ten portfolios, in three different economic conditions, are optimal.

Introduction

The portfolio selection problem is based on a single period model of investment. The investor has to choose and allocate his available capital among various securities such that the investment can be achieved. Markowitz initialized the problem by mean–variance methodology and that has been serving as the basis of modern financial theory. The mathematical formulation of the Markowitz's portfolio

This chapter draws from the author's previous publication (Dhankar & Kumar, 2006) Rakesh Kumar, Assistant Professor in the Department of Business Studies, Deen Dayal Upadhyaya College, University of Delhi, New Delhi, and re-used here with permission.

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selection problem is the trade-off between risk and return, which combines probability theory and optimization theory to model the behaviour of the economic agents. The classical mean–variance model is valid if the return is a multi-variate normally distributed and the investor is averse to risk and always prefers lower risk, or it is valid if for any given return which is multi-variate distributed and the investor has a quadratic objective function (Qin, Kar and Li).

Modern portfolio theory of investment strategy regards risk as an integral part of the investment and portfolio analysis. It provides that diversification across the securities reduces the overall risk of the portfolio. The risk aversion tendency of an investor makes him choose the set of assets, which give him higher return at minimum risk. Mean–Variance model, the pioneer work of Markowitz (1952), establishes a direct and proportional relationship between risk and return. It is widely used for effective allocation of wealth to different investment alternatives. The approach assumes that an investor compares the risk and return of alternative portfolios. A portfolio with the higher expected return will be preferred over others when two or more portfolios have identical risk. A Mean–Variance approach provides for the construction of portfolio in preference to putting all money in one security. Formulation of portfolio is an effective measure to minimize the risk. Such a portfolio requires estimation of expected return, correlation coefficients, standard deviations and co-variances. The theoretical justification for the risk measure can be derived from the insight of the portfolio approach that investors evaluate risk of a portfolio as a whole rather than the risk of assets individually.

Capital Asset Pricing Models, formulated by Marokowitz (1952), Sharpe (1964), Lintner (1965) and Mossin (1966) deal with determining the price of risky security in a competitive market, subject to risk. These models make the assumption of market efficiency. Efficiency presumes that stock prices have discounted the effect of all kinds of information pertaining to market and non-market. The return of a well-diversified portfolio can be viewed in relation to market risk only. It is based on the assumption that rational investors, being risk averse, will demand a high return for increasing risks. In the bullish market, return can be maximized by picking stocks with high market risk. Conversely, in a bearish market, losses can be minimized by holding stocks with low market risk. Total risk, which is composed of market-risk and non-market risk can be minimized, when different classes of securities having varying degrees of integration with the market, are put into the portfolio. Markowitz (1952) maintains that the portfolio risk is not simply the weighted risk of individual stocks but it is also the co-variability of returns of different stocks in the portfolio. The effective diversification requires putting securities into portfolio, which show a lesser correlation in their return. Diversification will lead to decline of total portfolio risk, resulting reduction of non-market risk. Sharpe and Cooper (1972) argue that when some securities in the portfolio perform undesirably with respect to market movement, it is likely that another set of securities will perform better under the same conditions. Diversification enables stock price changes resulting in specific company and industry factors tend to offset one another. While, stock price changes due to the market factors, are common to all stock, the random effect will not be eliminated through diversification. Sharpe (1995) proposes diversification based on market sensitivity of stocks, measured by stock's beta. A well-diversified portfolio of high beta value will be risky and return of this portfolio will co-vary with the movement of the market. In an efficient market, it gives relatively high returns. As this portfolio is highly integrated with the market, it will be very risky. A well-diversified portfolio of low beta value, contrarily, will have relatively low risk. In an efficient market, it gives a relatively low and flat return subject to market fluctuations. As a matter of fact, the capital asset pricing model recognizes the resulting importance of market risk in diversified portfolios. It provides that investors do the capital budgeting of the expected cash inflows at the cost of the market risk. The model asserts a positive and linear relationship between risk and return.

Many researchers have examined the trade-off between risk and return, and the effect of diversification on the portfolio risk. Mehta (2005) formulate 54 portfolios by using Mean–Variance model for a period from April 1995 to March 2002. Formulated portfolios were then evaluated using risk adjusted performance measures of Sharpe, Treynor, Jenson and Fama during one year immediately following their formation. The study indicates that the performance of the majority of portfolios is superior than the market. Sehgal (1997) study does not support the implication of capital asset pricing model in determining the price of risk securities. The relationship between portfolio return and market risk is not significant. Sharpe and Cooper (1972) examine the market risk and return of securities ranging from 478 (in 1931) to 985 (in 1967) for the period from 1931 to 1967. The study involves the formulation of ten risk and return classes from low beta value to high beta value. The study reports a consistent relationship between portfolio market risk and portfolio return by providing low return to low market risk class and high return to high market risk class. Rao, Nath, and Malhotra (1998) measure the portfolio return and risk relationship using the BSE 100, Sensex and Nifty stocks for the period from 1992 to 1997. The study involves estimation of portfolio beta and return using different market proxies and time intervals. The study reports a significant relationship between portfolio beta and portfolio return on quarterly return than monthly or weekly returns. Dhankar (1996) reports a significant relationship between beta and return. Srinivasan (1998) observes a significant relationship between risk and return, and effect of diversification on portfolio risk. Grinold (1999) argues that a portfolio, which is based on Mean–Variance approach, is more optimal and easy to implement.

Research Methodology

The study measures the effectiveness of Mean–Variance model in portfolio construction in Indian stock market. For the analysis, monthly adjusted opening and closing price of Bombay Stock Exchange Index (BSE 100), which is composite portfolio of hundred stocks including large-cap, mid-cap and small-cap has been taken for the period ranging June 1996 through May 2005. These prices have been adjusted with the bonus issue, right issue and other corporate actions. The study period involves a mixed set of the economic environment. For the calculation of ex-ante return of all stocks, natural logarithmic mode is used. The logarithmic difference of price movements is symmetric and is expressed in percentage term for the ease of comparability. Symbolically, it can be expressed as

$$r_{it} = Log_e\left(\frac{P_t}{P_{t-1}}\right) * 100 \tag{16.1}$$

where r_{it} is the return on stock i in time period t, Log_e is natural logarithm, P_t is closing price, P_{t-1} is opening price. This measure of return takes into account only appreciation or depreciation of stock and neglects the dividend yields. In developing countries like India, dividend yield doesn't significantly affect the relative return of a stock. Gupta (2000) argues that ignoring dividends has little impact on the analysis as the Indian companies do not pay significant dividend yields. The expected return of stocks has been calculated by regressing time series return of stocks with market (BSE 100) return. Symbolically, it can be written as

$$E(R_{it}) = \alpha_i + \beta_i X_t + e_{it} \tag{16.2}$$

where $E(R_{it})$ is the return on stock i, X_t is the return on market index and e_i is an independent factor unique to security i. It also exhibits non-market risk of the same security. The logarithmic method is also used for calculating the return on market index (BSE 100). Symbolically, it can be written as

$$X_t = Log_e\left(\frac{I_t}{I_{t-1}}\right) * 100 \tag{16.3}$$

where X_t is the return on index, I_t is closing number and I_{t-1} is opening number.

Weighted average return of portfolios, symbolically cab be written as

$$E(R_p) = \sum_{i=1}^{N} w_i R_{it} \tag{16.4}$$

where $w_i = 1$.

In market portfolio the risk is widely measured by the covariance of the stocks returns, which symbolically can be written as

$$Portfolio\ Risk = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j r_{ij} \sigma_i \sigma_j \tag{16.5}$$

Since $r_{ij\sigma_j}\sigma_j = Cov_{ij}$. It can, therefore, be further simplified:

$$Portfolio\,Risk = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j Cov_{ij} \tag{16.6}$$

For portfolio formulation, all the stocks have been arranged in ascending order on the basis of Sharpe's risk adjusted performance measure, which is described as an excess return to beta ratio.

Empirical Findings

Portfolio Formulation: A Test of Optimization

Table 16.1 summarizes the successive 10 portfolios and their test for performance. The expected return of nine portfolios out of ten is significant at 5% level of significance. For a given level of expected return, investors will prefer to minimize portfolio risk. The correlation coefficient between portfolio expected return and portfolio risk is 0.22, which is statistically not significant. However, correlation coefficient (0.87) between portfolio expected return and portfolio market risk is significant at 5% level of significance, which indicates that high market risk portfolio provides high return to investors (Fig. 16.1).

Table 16.1 Portfolio performance for the period 1996–2005

Portfolio (1)	α_p (2)	β_p (3)	e^2 (5)	E(R) (6)	$SE_{E(R)}$ (7)	$[E(R) - r_f]/\beta$ (8)	$t_{E(R)}$ (9)	Portfolio risk (10)
P1	0.54	0.91	13.49	2.36*	0.05	2.15	47.20	3.76
P2	0.28	0.63	5.11	1.54*	0.05	1.74	30.80	2.05
P3	0.03	0.93	7.56	1.89*	0.05	1.55	37.80	9.89
P4	–0.15	0.96	6.95	1.77*	0.05	1.38	35.40	2.75
P5	–0.05	0.69	7.23	1.32*	0.04	1.27	33.00	9.98
P6	–0.31	0.84	12.34	1.36*	0.03	1.11	45.30	4.39
P7	–0.41	0.82	7.91	1.23*	0.03	0.96	41.00	2.63
P8	–0.49	0.75	11.21	1.00*	0.02	0.75	50.00	7.18
P9	–0.58	0.58	9.98	0.59*	0.01	0.29	59.00	2.54
P10	–0.82	0.35	9.96	–0.11**	0.10	–3.60	1.10	2.83

Source Compiled from Dhankar and Kumar (2006)
where α_p portfolio alpha
β_p portfolio beta
e^2 portfolio non-market risk
E(R) portfolio expected return
$SE_{E(R)}$ Standard error of portfolio return
$[E(R) - r_f]/\beta$ Sharpe portfolio performance measure
$t_{E(R)}$ t value of portfolio return
*portfolio expected return is significant at 5% level of significance
**Portfolio expected return is not significant at 5% level of significance

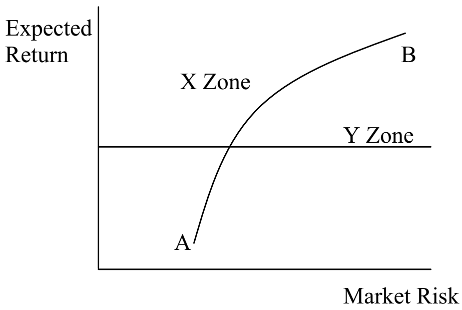

Fig. 16.1 Efficient market frontier

Levitz (1974), however, argues that the test has little significance for institutional portfolio managers. The risk–return preference of the investors will determine the number of portfolios they would pick up. A rational investor will determine it by developing an efficient market frontier. This is depicted in Fig. 16.1, where AB is the market efficient frontier of investors indicating the positive and linear relationship between expected return and market risk, which indicates that all the portfolios lie on this curve are optimum. RR measures the desirable expected return at the given level of market risk. Portfolios, which lie in the Zone X are undesirable to investors. However, portfolios, lie in Zone Y are desirable to the investors, and are likely to be picked up. Some researchers advocate time diversification in place of market diversification. It is based on the idea that above-average return tend to offset below-average return over long horizons. However, very less research has been carried out to measure the performance of time diversification in the Indian stock market. Madhusoodanan (1996a, 1996b) studies show that Indian stock market is not efficient. Risk and return trade-off is commonly not found, and is different from the theoretical predictions. There is a good scope to examine the efficiency of time diversification in Indian stock market. It would be interesting to find out as to whether investing for the long run will make the investors better or worse. Lee (1990) finds that long-horizon return is effective in establishing strategic norms for the portfolio weightings of specific asset classes.

A Test of Optimization Under Different Economic Conditions

The economic environment of an economy undergoes changes. Economic cyclical sets the value of some securities up or down, depending upon their market sensitivities. A set of stocks which performed well in one set of economic conditions may perform badly in another. A portfolio which is based on Mean–Variance approach may not be optimal in all economic scenarios. Such a portfolio requires a periodic review. In the study, all portfolios are formulated in the random economic environment for the period from June 1996 to May 2005 as depicted in Table 16.1. A cross-sectional analysis of optimality of the same set of portfolios with the same set of stocks has important implications for finance professionals and investors.

Table 16.2 Portfolio performance in decline period

Portfolio (1)	α_p (2)	β_p (3)	e^2 (4)	E(R) (5)	$SE_{E(R)}$ (6)	$t_{E(R)}$ (7)	Portfolio risk (8)
P1	0.88	0.68	12.18	2.23*	0.10	22.30	3.40
P2	0.38	0.55	5.21	1.47*	0.08	18.30	2.00
P3	0.51	0.51	7.90	1.89*	0.15	12.60	3.41
P4	0.30	0.94	7.56	2.18*	0.13	16.76	3.75
P5	0.28	0.40	5.78	1.07*	0.08	13.37	1.73
P6	0.22	0.57	17.80	1.35*	0.11	12.27	4.93
P7	–0.19	0.48	5.80	0.76*	0.07	10.85	2.07
P8	–0.26	0.48	13.40	0.61*	0.06	10.16	3.71
P9	–0.35	0.41	10.50	0.47*	0.08	5.87	3.10
P10	–0.09	0.22	8.20	0.36*	0.07	5.14	2.12

Source Compiled from Dhankar and Kumar (2006)
where α_p portfolio alpha
β_p portfolio beta
e^2 portfolio non market risk
E(R) portfolio expected return
$SE_{E(R)}$ Standard error of portfolio return
$t_{E(R)}$ t value of portfolio return
*Portfolio expected return is significant at 5% level of significance

A test of optimality of all ten portfolios have been carried out in three non-overlapping sub-periods, which depicts three economic cyclical phases, viz., decline, recession and growth, respectively. The early period (January 1996–December 1999) of study exhibits decline phase with a 6.3% average growth rate. The middle period (January 2000–December2002) can be categorized decline phase with 4.7% average growth rate. However, later period (January 2003–May 2005) exhibits growth phase with 7.7% average growth rate.

Table 16.2 exhibits the statistical summary of ten portfolios in decline phase. All ten portfolios are significant at 5% level of significance. The lower correlation coefficients (0.35) between portfolio expected return and portfolio risk indicates a weak relationship. However, correlation coefficient (0.72) between portfolio expected return and portfolio market risk (beta) is significant at 5% level of significance, which exhibits that investors are getting a higher return for high market risk portfolios. These findings lead to the implication that a diversified portfolio provides risk weighted return to the investors.

Table 16.3 provides a statistical summary of ten portfolios in recession phase. The expected return of all ten portfolios is significant at 5% level of significance. Table 16.5 indicates that correlation coefficient (0.75) between portfolio expected return and portfolio risk is significant at 5% level of significance, indicates a diversified portfolio on Mean–Variance approach provides risk weighted return to investors. The high correlation coefficient (0.86) between portfolios expected return and portfolio market risk is significant, which exhibits investors get higher return

Table 16.3 Portfolio performance in recession period

Portfolio (1)	α_p (2)	β_p (3)	e^2 (4)	E(R) (5)	$SE_{E(R)}$ (6)	$t_{E(R)}$ (7)	Portfolio Risk (8)
P1	0.75	1.14	19.0	3.03*	0.16	18.93	6.18
P2	0.06	0.65	6.05	1.38*	0.08	17.25	2.65
P3	–0.06	1.13	9.27	2.21*	0.11	20.00	6.07
P4	–0.33	0.59	6.78	0.85*	0.09	9.44	2.62
P5	0.01	0.91	9.34	1.82*	0.08	22.75	3.02
P6	–0.38	0.83	8.14	1.32*	0.09	14.66	3.75
P7	–0.46	0.98	10.58	1.51*	0.98	1.54	3.68
P8	–0.70	0.90	12.10	1.10*	0.05	22.00	4.22
P9	–0.93	0.71	13.64	0.48*	0.06	8.00	3.94
P10	–0.41	0.31	1.51	0.18*	0.06	3.00	2.34

Source Compiled from Dhankar and Kumar (2006)
where, α_p portfolio alpha
β_p portfolio beta
e^2 portfolio non-market risk
E(R) portfolio expected return
$SE_{E(R)}$ Standard error of portfolio return
$t_{E(R)}$ t value of portfolio return
*Portfolio expected return is significant at 5% level of significance

Table 16.4 Portfolio performance in the growth period

Portfolio (1)	α_p (2)	β_p (3)	e^2 (4)	E(R) (5)	$SE_{E(R}$ (6)	$t_{E(R)}$ (7)	Portfolio Risk (8)
P1	–0.11	0.75	7.91	3.12*	0.52	6.00	2.28
P2	0.42	0.63	4.78	1.53*	0.07	21.85	1.45
P3	–0.13	0.81	5.48	1.48*	0.04	37.00	2.13
P4	–0.24	1.01	5.18	2.73*	0.34	8.02	1.67
P5	–0.54	0.75	5.57	0.96*	0.08	12.00	1.61
P6	–0.68	1.07	8.52	3.64*	0.50	7.28	2.90
P7	–0.54	0.97	6.16	1.39*	0.07	19.85	1.63
P8	–0.69	0.96	6.15	1.24*	0.11	11.27	2.27
P9	–0.49	0.78	7.96	1.02*	0.08	12.75	2.22
P10	–0.93	0.59	7.98	0.24*	0.09	2.66	1.87

Source Compiled from Dhankar and Kumar (2006)
where α_p portfolio alpha
β_p portfolio beta
e^2 portfolio non-market risk
E(R) portfolio expected return
$SE_{E(R)}$ Standard error of portfolio return
$t_{E(R)}$ t value of portfolio return
*Portfolio expected return is significant at 5% level of significance

Table 16.5 Statistical significance of correlation coefficients

Periods	Correlation coefficients	t value
June 1996–May 2005	$r_{E(R_p).Portfolio\,Risk} = 0.22$	0.64
	$r_{E(R_p).\beta_p} = 0.87^*$	5.00
January 1996–December 1999	$r_{E(R_p).Portfolio\,Risk} = 0.35$	1.06
	$r_{E(R_p).\beta_p} = 0.72^*$	2.94
January 2000–December 2002	$r_{E(R_p).Portfolio\,Risk} = 0.75^*$	3.20
	$r_{E(R_p).\beta_p} = 0.86^*$	4.75
January 2003–May 2005	$r_{E(R_p).Portfolio\,Risk} = 0.52^{**}$	1.72
	$r_{E(R_p).\beta_p} = 0.58^{**}$	2.01

Source Compiled from Dhankar and Kumar (2006)
*Significant at 5% level of significance
**Significant at 20% level of significance

for increasing market risk portfolios. It leads to the conclusion; Mean–Variance approach is quite suitable in portfolio formulation during recession time.

Table 16.4 provides the statistical summary of ten portfolios in growth period. The expected return of all ten portfolios is significant at 5% level of significance. Table 16.5 indicates that the correlation coefficient (0.52) between portfolio expected return and portfolio risk is significant at 20% level of significance. The correlation coefficient (0.58) between portfolio expected return and portfolio market risk is significant at 20% level of significance. These findings show that investors get moderately increasing return if they diversify their portfolio during growth period.

Conclusion and Implication of the Study

The study attempts to provide an insight into a trade-off between risk and return of portfolios constructed on the basis of Mean–Variance approach. The study has important implications. Findings show that the formulation of portfolios using Mean–Variance approach resulting from the ranking of stocks on the basis of Sharpe's excess return to beta ratio is optimal in Indian stock market. The optimality test of all ten portfolios in different economic conditions exhibits that portfolios of the same set of stocks will be optimal in different economic scenarios. The weak correlation coefficients between portfolio expected return and portfolio risk during the pool and decline period show that investors are unable to diversify their portfolio risk and fail to get risk weighted return. Correlation coefficients, however, during the recession and growth phase are significant, which point out that investors can successfully diversify their portfolio risk and do get risk weighted return. The significant finding of the study is that there are high correlation coefficients between portfolio expected return and portfolio market risk. A portfolio which is diversified provides good risk adjusted weighted average return to the investors.

Appendix 1

List of companies of BSE 100

Code	Company	Code	Company	Code	Company	Code	Company
c1	ABB Ltd.	c20	Colgate Pamolive Ltd.	c39	ICICI Bank	c58	Lupin Ltd.
c2	Andhra Bank	c21	Container Corporation	c40	I-Flex Solution	c59	Patni Computers
c3	Arvind Mill	c22	Corporation Bank	c41	Kochi Refinery	c60	Pfizer Ltd.
c4	Ashok Leyland	c23	Cummins Ltd.	c42	Kotak Mahindra Bank	c61	Polaris Software Ltd.
c5	Asian Paints	c24	Divi's Laboratory	c43	Larsen & Turbo	c62	Punjab National Bank
c6	ACC	c25	Dr. Reddy Lab	c44	MTNL	c63	Ranbaxy Ltd.
c7	Bajaj Auto Ltd.	c26	GAIL	c45	Mahindra & Mahindra	c64	Rashtriya Chemical
c8	Bank of Baroda	c27	Glaxosmithkline	c46	Mangalore Refinery	c65	Raymond Ltd.
c9	Bank of India	c28	Grasim Industries Ltd.	c47	Maruti Udoyg Ltd.	c66	Reliance Capital
c10	Bharat Electronics	c29	Great Eastern shipping Ltd.	c48	Matrix Laboratory	c67	Reliance Energy Ltd.
c11	Bharat Forge Ltd.	c30	Gujarat Ambuja Cement	c49	Moser Baer	c68	Reliance Industries
c12	BHEL	c31	HCL Infosystem	c50	MICO	c69	Satyam Computers
c13	Bharat Petroleum	c32	HCL Technologies	c51	National Aluminium	c70	Shipping Corporation
c14	Bharati Televenture	c33	HDFC Bank	c52	Nestle India	c71	Siemens Ltd.
c15	Biocon Ltd.	c34	Hero Honda	c53	Neyveli Lignite	c72	State Bank of India
c16	Cadila Health care Ltd.	c35	Hindalco	c54	Nicholas Piramal	c73	SAIL
c17	Canara Bank	c36	Hindustan Lever Ltd.	c55	Novartis India	c74	Sterlite Industries Ltd.
c18	Chennai Petroleum Ltd.	c37	Hindustan Petroleum	c56	ONGC	c75	Sun Pharmaceuticals
c19	Cipla Ltd.	c38	HDFC	c57	Oriental Bank of Commerce	c76	Tata Chemicals
c77	Tata Iron & Steel	c83	Indian Hotels	c89	Jaiprakash Associate	c96	VSNL

(continued)

(continued)

Code	Company	Code	Company	Code	Company	Code	Company
c78	Tata Motor	c84	Indian Oil Corporation	c90	Jammu & Kashmir Bank	c97	Vijaya Bank
c79	Tata Power	c85	Indian Overseas Bank	c91	TVS Motors	c98	Wipro Ltd.
c80	Tata Tea Ltd.	c86	Indian Petrochemicals	c92	Tata Teleservices	c99	Wockhardt
c81	Indian Rayon Ltd.	c87	IDBI c93 UTI Bank	c94	Union Bank of India	c100	Zee Telefilm
c82	ITC Ltd.	c88	Infosys Technologies	c95	United Phosphorus Ltd.		

Appendix 2

Correlation Matrix for Portfolio 1

c95c42 = 0.18, c95c88 = 0.24, c95c54 = 0.12, c95c1 = 0.1, c95c100 = 0.12, c95c0.05 = –0.01, c95c98 = 0.13, c95c89 = 0.16, c95c31 = 0.14
c42c88 = 0.58, c42c54 = –0.28, c42c1 = 0.08, c42c100 = 0.05 c42c69 = 0.34, c42c98 = 0.08, c42c89 = –0.03, c42c31 = 0.17
c88c54 = –0.28, c88c1 = 0.08, c88c100 = 0.05, c88c69 = –0.13, c88c98 = 0.33, c88c89 = 0.08, c88c31 = –0.11
c54c1 = 0.17, c54c100 = 0.22, c54c69 = 0.18, c54c98 = 0.10, c54c89 = 0.18, c54c31 = 0.27
c1c100 = 0.25, c1c69 = 0.23, c1c98 = 0.24, c1c89 = 0.19, c1c31 = 0.23
c100c69 = 0.29, c100c98 = 0.02, c100c89 = 0.16, c100c31 = 0.36
c69c98 = –0.02, c69c89 = 0.08, c69c31 = 0.35
c98c89 = 0.15, c98c31 = 0.16
c89c31 = 0.32

Correlation Matrix for Portfolio 2

c33c71 = 0.13, c33c68 = 0.18, c33c52 = 0.12, c33c19 = 0.12, c33c47 = 0.25, c33c45 = 0.10, c33c50 = 0.21, c33c27 = 0.11, c33c7 = 0.18
c71c68 = 0.34, c71c52 = 0.10, c71c19 = 0.24, c71c47 = 0.30, c71c45 = 0.61, c71c50 = 0.13, c71c27 = 0.29, c71c7 = 25
c68c52 = 0.18, c68c19 = 0.41, c68c47 = 0.29, c68c45 = 0.37, c68c50 = 0.21, c68c27 = 0.38, c68c7 = 0.43
c52c19 = 0.24, c52c47 = 0.1, c52c45 = 0.09, c52c50 = 0.19, c52c27 = 0.35, c52c7 = 0.26
c19c47 = 0.35, c19c45 = 0.36, c19c50 = 0.09, c19c27 = 0.4, c19c7 = 0.29
c47c45 = 0.61, c47c50 = 0.09, c47c27 = 0.05, c47c7 = 0.13

c45c50 = 0.06, c45c27 = 0.05, c45c7 = 0.29
c50c27 = 0.24, c50c7 = 0.16
c27c7 = 0.39

Correlation Matrix for Portfolio 3

c77c44 = 0.31, c77c28 = 0.48, c77c61 = 0.06, c77c36 = 0.12, c77c32 = 0.28, c77c24 = 0.04, c77c25 = 0.41, c77c6 = 0.43, c77c63 = 0.27
c44c28 = 0.31, c44c61 = 0.19, c44c36 = 0.14, c44c32 = 0.33, c44c24 = –0.33, c44c25 = 0.19, c44c6 = 0.52, c44c63 = 0.28
c28c61 = 0.27, c28c36 = 0.22, c28c32 = 0.50, c28c24 = –0.04, c28c25 = 0.35, c28c6 = 0.51, c28c63 = 0.39
c61c36 = 0.28, c61c32 = 0.53, c61c24 = 0.35, c61c25 = 0.20, c61c6 = 0.28, c61c63 = 0.31
c36c32 = 0.34, c36c24 = 0.14, c36c25 = 0.28, c36c6 = 0.14, c36c63 = 0.33
c32c24 = 0.27, c32c25 = 0.36, c32c6 = 0.43, c32c63 = 0.32
c24c25 = 0.41, c24c6 = 0.18, c24c63 = 0.40
c25c6 = 0.37, c25c63 = 0.54
c6c63 = 0.43

Correlation Matrix for Portfolio 4

c82c74 = 0.01, c82c62 = -0.06, c82c43 = 0.23, c82c94 = 0.31, c82c10 = 0.28, c82c30 = 0.21, c82c26 = 0.12, c82c34 = 0.06, c82c35 = 0.27
c74c62 = 0.12, c74c43 = 0.33, c74c94 = 0.03, c74c10 = 0.25, c74c30 = 0.29, c74c26 = 0.13, c74c34 = 0.20, c74c35 = 0.34
c62c43 = 0.37, c62c94 = 0.07, c62c10 = 0.24, c62c30 = 0.10, c62c26 = 0.16, c62c34 = 0.20, c62c35 = 0.15
c43c94 = 0.12, c43c10 = 0.41, c43c30 = 0.41, c43c26 = 0.38, c43c34 = 0.26, c43c35 = 0.36
c94c10 = 0.22, c94c30 = 0.16, c94c26 = 0.-0.05, c94c34 = –0.03, c94c35 = 0.16
c10c30 = 0.36, c10c26 = 0.35, c10c34 = 0.24, c10c35 = 0.38
c30c26 = 0.24, c30c34 = 0.21, c30c35 = 0.32
c26c34 = 0.27, c26c35 = 0.16
c34 c35 = 0.16

Correlation Matrix for Portfolio 5

c72c86 = 0.21, c72c78 = 0.51, c72c80 = 0.02, c72c14 = 0.50, c72c23 = 0.31, c72c11 = 0.28, c72c55 = 0.45, c72c91 = 0.44, c72c81 = 0.18
c86c78 = 0.05, c86c80 = 0.08, c86c14 = 0, c86c23 = –0.02, c86c11 = 0.03, c86c55 = 0.12, c86c91 = –-0.12, c86c81 = 0.18
c78c80 = 0.27, c78c14 = 0.41, c78c23 = 0.30, c78c11 = 0.08, c78c55 = 0.28, c78c91 = 0.21, c78c81 = 0.31
c80c14 = 0.01, c80c23 = 0.12, c80c11 = 0.11, c80c55 = 0.09, c80c91 = –0.05, c80c28 = 0.28
c14c23 = 0.12, c14c11 = 0.15, c14c55 = 0.43, c14c91 = 0.51, c14c81 = –0.36

c23c11 = 0.18, c14c55 = 0.17, c23c91 = 0.20, c23c81 = 0.10
c11c55 = 0.23, c11c91 = 0.23, c11c81 = 0
c55c91 = 0.44, c55c81 = 0.20
c91c81 = –0.26

Correlation Matrix for Portfolio 6

c83c57 = –0.08, c83c53 = 0.10, c83c22 = 0.10, c83c56 = 0.26, c83c8 = 0.23, c83c38 = 0.16, c83c51 = 0.14, c83c17 = 0.26, c83c90 = 0.06
c57c53 = 0.18, c57c22 = 0.24, c57c56 = 0.21, c57c8 = 0.41, c57c38 = 0.22, c57c51 = 0.19, c57c17 = 0.29, c57c90 = 0.37
c53c22 = 0.15, c53c56 = 0.36, c53c8 = 0.27, c53c38 = 0.10, c53c51 = 0.07, c53c17 = –0.11, c53c90 = 0.35
c22c56 = 0.07, c22c8 = 0.53, c22c38 = 0.09, c22c51 = 0.30, c22c17 = 0.44, c22c90 = 0.38
c56c8 = 0.32, c56c38 = 0.20, c56c51 = 0.22, c56c17 = 0.42, c56c90 = 0.16
c8c38 = 0.31, c8c51 = 0.21, c8c17 = 0.63, c8c90 = 0.24
c38c51 = 0.12, c38c17 = 0.42, c38c90 = 0.22
c51c17 = 0.32, c51c90 = 0.18
c17c90 = 0.39

Correlation Matrix for Portfolio 7

c67c65 = 0.28, c67c39 = 0.14, c67c9 = 0.27, c67c2 = 0.46, c67c75 = 0.29, c67c13 = 0.22, c67c37 = 0.31, c67c40 = 0.02, c67c84 = –0.11
c5c39 = 0.05, c5c9 = 0, c5c2 = –0.08, c5c75 = 0.27, c5c13 = 0.16, c5c37 = 0.26, c5c40 = –0.14, c5c84 = –0.28
c39c9 = 0.38, c39c2 = 0.18, c39c75 = 0.13, c39c13 = 0.33, c39c37 = 0.22, c39c40 = 0.23, c39c84 = –0.18
c9c2 = 0.58, c9c75 = 0.32, c9c13 = 0.36, c9c37 = 0.24, c9c40 = 0.12, c9c84 = 0.43
c2c75 = 0.14, c2c13 = 0.23, c2c37 = 0.18, c2c40 = –0.06, c2c84 = 0.30
c75c13 = 0.24, c75c37 = 0.23, c75c40 = 0.32, c75c84 = –0.13
c13c37 = 0.69, c13c40 = –0.09, c13c84 = 0.15
c37c40 = –0.05, c37c84 = 0.03
c40c84 = 0.28

Correlation Matrix of Portfolio 8

c12c79 = 0.22, c12c49 = 0.28, c12c20 = 0.51, c12c18 = 0.33, c12c48 = 0.33, c12c93 = 0.50, c12c70 = 0.42, c12c73 = 0.29, c12c3 = 0.17
c79c49 = 0.35, c79c20 = 0.36, c79c18 = 0.08, c79c48 = 0.35, c79c93 = 0.06, c79c70 = –0.12, c79c73 = 0.14, c79c3 = 0.31
c49c20 = 0.32, c49c18 = 0.21, c49c48 = 0.10, c49c93 = 0.06, c49c70 = –0.013, c49c73 = 0.10, c49c3 = 0.18
c20c18 = 0.29, c20c48 = 0.05, c20c93 = –0.15, c20c70 = 0.19, c20c73 = 0.35, c20c3 = 0.36

c18c48 = 0.17, c18c93 = 0.21, c20c70 = 0.07, c18c73 = 0.43, c18c3 = 0.27
c48c93 = 0.26, c48c70 = 0.02, c48c73 = 0.14, c48c3 = –0.01
c93c70 = 0.18, c93c73 = 0.22, c93c3 = 0.28
c70c73 = 0.16, c70c3 = 0.22
c73c3 = 0.37

Correlation Matrix of Portfolio 9

c58c41 = 0.01, c58c60 = 0.15, c58c76 = 0.18, c58c59 = 0.41, c58c96 = 0.09, c58c64 = 0.29, c58c4 = 0.21, c58c29 = 0.41, c58c29 = 0.22
c41c60 = 0.09, c41c76 = 0.43, c41c59 = –0.05, c41c96 = 0.18, c41c64 = 0.21, c41c4 = 0.36, c41c29 = 0.29, c41c92 = 0.30
c60c76 = 0.22, c60c59 = –0.25, c60c96 = –0.03, c60c64 = 0.03, c60c4 = 0.08, c64c29 = –0.01, c60c92 = –0.04
c76c59 = 0.04, c76c96 = 0.19, c76c64 = 0.20, c76c4 = 0.34, c76c29 = 0.37, c76c92 = 0.19
c59c96 = 0.40, c59c64 = –0.35, c59c4 = –0.48, c59c29 = 0.08, c59c92 = –0.51
c96c64 = 0.03, c96c4 = 0.15, c96c29 = 0.21, c96c92 = 0.58
c64c4 = 0.02, c64c29 = 0.15, c64c92 = 0.08
c4c29 = 0.35, c4c92 = 0.30
c29c92 = 0.43

Correlation Matrix of Portfolio 10

c65c15 = 0.47, c65c99 = 0.09, c65c16 = 0.20, c65c21 = –0.06, c65c85 = 0.39, c65c46 = 0.04, c65c87 = 0.13, c65c97 = 0.14, c65c66 = 0.46
c15c99 = –0.20, c15c16 = 0.01, c15c21 = –0.40, c15c85 = 0.26, c15c46 = 0.56, c15c87 = –0.15, c15c97 = 0.00, c15c66 = 0.61
c99c16 = 0.01, c99c21 = 0.05c61, c99c85 = 0.22, c99c46 = 0.0, c99c87 = 0.48, c99c97 = 0.45, c99c66 = 0.33
c16c21 = 0.26, c16c85 = 0.16, c16c46 = –0.13, c16c87 = 0.07, c16c97 = 0.33, c16c66 = 0.20
c21c85 = 0.04, c21c46 = 0.08, c21c87 = 0.11, c21c97 = 0.23, c21c66 = 0.20
c85c46 = 0.35, c85c87 = 0.16, c85c97 = 0.19, c85c66 = 0.32
c46c87 = -0.06, c46c97 = 0.02, c46c66 = 0.29
c87c97 = 0.56, c87c66 = 0.35
c97c66 = 0.

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Part V
Contemporary Topics

Chapter 17
Islamic Finance, Growth and Investing

Financial peace isn't the acquisition of stuff. It's learning to live on less than you make, so you can give money back and have money to invest. You can't win until you do this.
Dave Ramsey

Abstract Islamic finance is one of the most rapidly growing segments of the global financial system. The emergence of Islamic finance can be traced back to 1963 in Egypt, while its importance comes to the global financial system only after the global financial crisis occurred in 2008. It has been reported that the continuing volatility in bond and equity markets, combined with the uncertainty surrounding the Euro Zone, has opened up the Islamic finance industry to a new segment of potential investors looking to diversify away from traditional investments. However, despite the increasing importance of Islamic finance, particularly in developing economies in the Middle East and Southeast Asia, religious and social complexity has acted against a holistic understanding by policymakers, researchers and practitioners. The study provides a review and analysis of the definition, principles, and instruments of Islamic finance that is provided by most Islamic banks. Also, the study tries to answer the question as to what are the key principles of Islamic finance, which led to economic growth. We find that the Islamic finance principles are conducive to the growth of the economy as they help in reducing inflation, monetary volatility, and unemployment, besides in achieving social justice and optimum allocation of resources.

This chapter draws heavily from the author's previous publication (Tabash & Dhankar, 2014), co-authored by Mosab I. Tabash, Faculty of Management Studies (FMS)University of Delhi, India and re-used here with permission.

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Introduction

Islamic economics is part of the Islamic fundamentalist movement gaining ground in large parts of the Muslim world. Various shades of fundamentalism have always existed in Islam. But the attention around Islamic fundamentalism, as well as the number of supporters, received a great boost after the Six-Day War of 1967. Many Muslims felt that this humiliating defeat was caused by the Arabs turning away from God and embracing foreign ideologies such as communism or capitalism—ideologies which are viewed as inherently opposed to Islam and therefore unable to solve the problems of the Muslim world. The fundamentalists call for a return to Islam law, Shari'a, which is believed to offer solutions to economic and social problems of all times and all places (Bjorvtn, 1998).

Islamic finance is growing as a source of finance for Islamic and other investors around the world. During the past years, one of the rising stars in the world of finance has been Islamic finance. From the skyscrapers of Dubai and Kuala Lumpur to the twenty-first century palaces of Paris, there has been a growing interest in this business. Islamic finance involves structuring financial instruments and financial transactions to satisfy traditional Muslim strictures against the payment of interest and engaging in gambling. It is a field of growing importance for conservative muslims, especially in the Middle East and large Muslim population in Southeast Asian countries, who are uncomfortable with western-style of financial system and banking that involve explicit payments of interest.

The year 2012 marked a turning point for interest-free banking growth, as new markets and new regulations in the Middle East, helped the sector to flourish. According to Ernst and Young, globally assets of Islamic finance managed in line with Shariah (The Path term of Islamic law consists of Islamic instructions based on the Holy Quran and Sunnah) reached in 2013 to U.S. $ 1.8 trillion, from U.S. $ 1.2 trillion in 2012. Neither the ongoing turmoil in the Middle East nor the Euro Zone debt crisis could prevent Islamic banks in the Middle East from reaching out to new markets and more businesses. This rapid growth has been fuelled by surging demand for Shariah-compliant products not only from financiers in the Middle East and other Muslim countries but also by investors globally, thus making it a global phenomenon.

Lately, the Osservatore (2009) noted that western banks should look at the rules of Islamic finance to restore confidence amongst their clients at a time of global economic crisis. Despite the financial crisis which has plagued the economies of both industrialized and developing nations, the interest-free banking industry has been flourishing, and has enjoyed a 29% growth in assets and reached more than U. S. $ 1300 billion in 2011 (Fig. 17.1).

In recent years, growth in Islamic financial assets has generally outperformed conventional financial instruments, particularly following the onset of the financial crisis that has been gripping the world since 2008. The performance and relative stability of Islamic financial institutions during the financial crisis that hit the world in 2008 stem from the distinctive features of the instruments they offer. Islamic

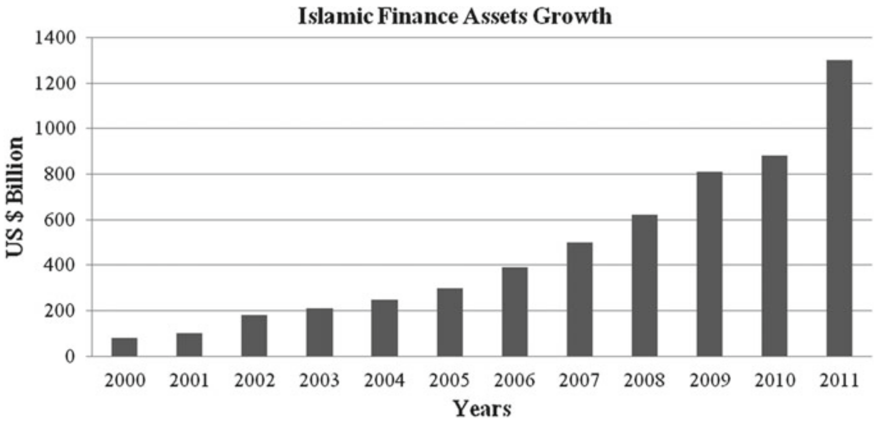

Fig. 17.1 Global Shariah-compliant financial assets (2000–2011). *Source* Deutsche Bank (2011)

finance emphasizes asset backing and the principle of risk sharing, prohibition of interest, ensuring a direct link between financial transactions and real sector activities. The return on savings and investment is closely linked (determined by the real sector, not the financial sector); giving Islamic finance modes a flexible adjustment mechanism in the case of unanticipated shocks. The adjustment mechanism ensures that the real values of assets and liabilities will be equal at all points in time, and prohibits excessive risk taking, thereby avoiding several forms of complicated securitization (Chapra, 2008).

Despite the rapid growth of Islamic finance, and its importance in the global financial finance, many financial researchers and policymakers don't understand the key principles of Islamic finance and their advantages to the economy. The present study tries to explain and discuss the principles and modes of Islamic finance, and how these principles participate in economic growth and social justice in the society.

Research Problem and Objectives

Many studies have focused on the impact of finance on economic growth. However, few studies have examined the impact of Islamic finance principles on economic growth. To fill this gap in the literature, this paper investigates the potential effects of Islamic finance principles and its instruments of economic growth. We believe that the results of this paper will help decision-makers and finance scholars to understand the advantages of Islamic finance principles and their role in enhancing growth of the economy of any nation.

Research Methodology

The qualitative methods have been used to carry out the research. The qualitative approach is also used to review the existing literature from all resources such as academic, scholarly journals, magazines, documents, workshops and other related literature of Islamic finance industry.

Islamic Finance Definition

The term Islamic finance refers to a system of financing that is consistent with the principles of the Islamic Shariah, which in turn is based on the Quran (the holy book of Islam) and the Sunnah (the recorded life, times and deeds of Prophet Mohammad). All forms of Islamic financing must comply with certain Islamic Shariah principles. Most notably, Islamic Shariah prohibits riba (interest) and particularly the payment or receipt of interest. Warde (2000) defines Islamic finance as, roughly, 'all financial practices that are based, in their objectives and operations, on Qu'ranic principles'. This is a broad definition, but it captures the essential nature of Islamic economics as an attempt to reconcile religious principles with economic activities. This goes far beyond interest-free banking to include, for example, refusing to do business with companies that operate in morally impermissible sectors (such as gambling). That said, in the actual operations of Islamic financial institutions, and for the purposes of this paper, the essential defining feature of Islamic finance is the explicit prohibition of transactions that involve riba (interest).

The Development of Islamic Finance in the World

Since the mid-50s, a debate on the possibility of a finance model consistent with the Shariah law (Shariah compliant) has been opened in Muslim societies. Islamic finance originated in the Egyptian village of Mit Ghamr. It was the year 1963 when an agricultural bank, created to copy German agricultural banks, started to provide small private entrepreneurs with microloans, thus also promoting the individual habit of saving. Both the recipient of funds and the investors were members of the bank and shared its profits in accordance with Islamic ethic. The economist Ahmad El Najjar, founded the first religious oversight board composed of "ulama" (i.e. Muslim legal scholars). The first oil crisis in 1973–1974 provided Arab countries with the necessary capital to establish Islamic financial institutions. In 1975, the Islamic Development Bank was created by the Organization of Islamic Conference.

The aim was to promote the development of all Muslim communities in accordance with the principles of Shariah. In the same year, the Dubai Islamic

Bank, the first Islamic commercial bank not owned by a government, was established. Other Islamic banks were then established in Arab countries, the Philippines, Malaysia and so on. In 1979, Iran has Islamized the entire national banking system, followed by Pakistan in the early 80s and then Sudan in 1992. In 2003, the first Islamic bonds (Sukuk) were issued in dollars by sovereign countries and then by companies. In 2004, the German state of Saxony-Anhalt issued the first €100 million Sukuk outside a Muslim country. The same year, the commercial bank, Islamic Bank of Britain was established, while the first bank in Europe of this type was established in 1978 in Luxembourg. In 2006, the first investment bank of the continent, the European Islamic Investment Bank, was fully operational (Gabriella, 2012).

Today, there are more than 20 traditional institutions offering Islamic products in London. In addition, there are several Islamic credit banks in the US. During the past three decades, the number of Islamic financial institutions has risen from one institution in one country in 1963 to over 300 institutions operating in more than 75 countries worldwide (Qorchi, 2005). The sector is increasingly open, innovative, sophisticated and competitive. The major western banks operate in Muslim countries either with traditional and Shariah-compliant credit or through branches dedicated to Islamic financial products. In short, the importance of Islamic finance in the world depends on its extraordinary growth rate and its management model, which is subordinate and/or competitive with the traditional one.

The Key Principles of Islamic Finance

Islamic finance theory promotes economic development in three main ways: its direct link to the real economy and physical transactions, its prohibitions against harmful products and activities and its promotion of economic and social justice. Islamic finance cannot support such conventional finance activities as debt rescheduling, debt swap, speculation and other purely monetary or financial activities that do not add to the real economy (Kahf, 2007).

Shariah is the body of Islamic religious law that determines the legal framework within which the public and private lives of Muslims are regulated. A large portion of Shariah is dedicated to how the economy of Muslim societies should operate. Part of the body of law regarding the economy forms the foundation of what has become the modern Islamic finance industry. The root of the Islamic financial system is the prohibition of riba (interest) in society besides many other viable principles that if applied, not only Muslim economies have grown but also the global economy will become stronger. Islamic finance is based on the themes of community banking, ethical banking, and socially responsible investing. Its goal is to be an ethical, indigenous and equitable mode of finance. If global banking practices adhere to the principles of Islamic finance, which are based on noble ideas of entrepreneurship and transparency, global financial crisis would have been prevented. The following are the main principles of Islamic finance:

1. ***Prohibition of Riba (interest)***: Riba is an Arabic word for 'growth' or 'increase' and denotes the payment or receipt of interest for the use of money. The Qur'an expressly forbids riba, which includes any payment of interest (not only excessive interest) on monetary loans. The Quran states, 'O You who believe! Fear Allah and give up what remains of your demand for usury, if you are indeed believers'. Usury encompasses any payment of interest. Muslim scholars have interpreted riba to mean any fixed or guaranteed interest payment on cash advances or on deposits (Mahmud, 2004). In prohibiting riba, Islam seeks to foster an environment based on fairness and justice. A loan with a fixed return to the lender regardless of the outcome of the borrower's course of action is viewed as unfair. Riba is also believed to be exploitative and unproductive because it is considered to represent a sure gain to the lender without any possibility of loss as well as a reward in return for no work.

These factors are believed to lead, in turn, to inflation and unemployment and to stifle the social and infrastructural development of a nation. Dependence on interest prevents people from working to earn money, since the person with dollars can earn an extra dollar through interest, either in advance or at a later date, without working for it. The value of work will consequently be reduced in his estimation, and he will not bother to take the trouble of running a business or risking his money in trade or industry. This will lead to depriving people of benefits, and the business of the world cannot go on without industries, trade and commerce, building and construction, all of which need capital at risk. Further, permitting the taking of interest discourages people from doing good to one another, as is required by Islam. If interest is prohibited in a society, people will lend to each other with goodwill, expecting back no more than what they have loaned, while if interest is made permissible, the needy person will be required to pay back more on loans (than he has borrowed), weakening his feelings of great goodwill and friendliness towards the lender. This is the moral aspect of the prohibition of interest.

Finally, the lender is likely to be wealthy and the borrower poor. If interest is allowed, the rich will exploit the poor, and this is against the spirit of mercy and charity. This is the social aspect of the prohibition of interest. Thus, in a society in which interest is lawful, the strong benefits from the suffering of the weak. As a result, the rich become richer and the poor become poorer, creating socio-economic classes in society. Naturally, this generates envy and hatred among the poor towards the rich, and contempt and callousness among the rich towards the poor. Conflicts arise, the socio-economic fabric is dented, revolutions are born, and social order is threatened (Warde, 2000).

Recent history illustrates the dangers to the peace and stability of nations inherent in interest-based economies. Friedman (1969) has demonstrated that a zero nominal interest rate is a necessary condition for an optimal allocation of resources. Fixing a zero interest rate, traders will have no reason to substitute real resources for money, so more resources will be used for investments. Therefore, when fixing a positive price for money, traders would economize money for a fixed return and to reduce their transaction costs. It is demonstrated empirically that the zero interest rate is both necessary and sufficient for efficient allocation in general equilibrium models (Wilson, 1979). Thus, Islam prohibits interest in the finance system to promote economic and social justice.

2. ***Risk and Return Sharing***: Shariah prohibits Muslims from earning income by charging interest but permits income generation through the sharing of risks and rewards between the parties to a transaction (no pain no gain strategy). This profit-sharing mechanism is believed to encourage people to become partners and work together rather than to enter into a creditor–debtor relationship. Partnership promotes mutual responsibility for the outcome of the financed project, which is believed to increase the likelihood of success of the venture. A tangential aim of the partnership approach is to help increase the growth of successful projects, also provide stimulus to the economy. On the basis of 'z-scores' analysis, Cihák and Hesse (2008) proved that the Islamic financial system is financially stronger and less risky than conventional banks. In the conventional system, depreciation of assets due to an exogenous shock downgrade the bank equity capital, since its depositors have fixed value securities (the deposits), and which may lead to risks to provoke the bankruptcy. In an Islamic system, the possessors of investment accounts don't have fixed value securities, in macroeconomic or bank-specific crises investment depositors automatically share the risk, which allows an adjustment of the liability, in case of asset reduction.
3. ***Avoidance of Gharar***: Shariah prohibits financial transactions that involve Gharar, which is often translated as 'deception', 'excessive risk', or 'excessive uncertainty'. Gharar refers to any transaction of probable items whose existence or characteristics are not certain, due to lack of information, ignorance of essential elements in the transaction to either party, or uncertainty of the ability of one party to honour the contract. Islam has forbidden the purchase of the unborn animal in the mother's womb, the sale of the milk in the udder without measurement, the purchase of spoils of war prior to distribution, the purchase of charities prior to their receipt and the sale of fish in the sea.

All Islamic finance scholars agree that Gharar should be avoided in commercial exchange contracts. As Islamic Shariah forbid Riba (interest) because it leads to exploitation and injustice in the society, it also forbids Gharar in any transaction to protect the two parties from deceit, ignorance, and uncertainty. All Islamic financial and business transactions must be based on transparency, accuracy and disclosure of all necessary information, so that no one party has advantages over the other party. Islam has clearly forbidden all business transactions, which cause injustice in any form to any of the parties. It may be in the form of hazard leading to uncertainty in any business, or deceit or fraud or undue advantage. The rationale of the prohibition of Gharar is to ensure full consent and satisfaction of the parties in a contract. Without full consent, a contract may not be valid. Full consent can only be achieved through certainty, full knowledge, full disclosure and transparency.

4. ***Shariah Approved Activities***: Islamic finance integrates Islamic moral and ethical principles and, as such, prohibits financing harmful products and activities. For example, Islamic banks prohibit financing to such industries as alcoholic beverages, tobacco, casinos and pornography. Islamic banks do not participate in financing activities that are harmful to society and that would consequently hinder development. By following this principle, Islamic banks improve the productivity in the economy and reduce the social and economic costs of such harmful products and services (Siddiqi, 1999). To ensure that all products and services offered are Shariah compliant, each Islamic bank has an independent Shariah supervisory board.
5. ***Sanctity of Contract***: Islam views contractual obligations and the related full disclosure of information as a sacred duty. Full disclosure is intended to reduce financial speculation (gambling), which is strictly prohibited by Islam, by providing as much information as possible for investors to make accurate assessments about the risks and rewards of an investment. The conditions that are necessary for a contract to be valid include a good understanding of the underlying assets and the profit-sharing ratio, as well as the presence of a willing buyer and seller. Contracts must also not offend Islamic religious and moral principles; if they do, they will be deemed illegal and unenforceable (Shanmugam, 2009).
6. ***The Usage of Money***: Money is a means for conducting transactions and not a commodity to be traded, is another important principle in Islamic finance. Islam recognizes money as a medium of exchange and prohibits the sale of money as a commodity. The Islamic concept of money is such that the value of money is the reflection of the value of the commodity and has no value of its own. Therefore, it is not to be traded but to be used as a medium of exchange in order to facilitate the transactions undertaken by the society.
7. ***Paying and Collecting of Zakah (payments to the poor)***: Metwally (2006) provides a comprehensive definition of Zakah as follows: 'Zakah is the cornerstone of the financial structure in an Islamic economy'. Literally, Zakah means purification. Technically, it means a contribution of a proportion of wealth for the use of the poor and needy people. Also, it is important to notice the experience of Islamic banks in alleviating poverty through the use of Zakah funds to improve the socio-economic development in the society. This is by either making the poor and needy people more productive, which in turn contribute to the economic development and financing of human welfare activities.

Based on the above principles, the Islamic finance system has the following advantages over the conventional finance system as shown in Fig. 17.2.

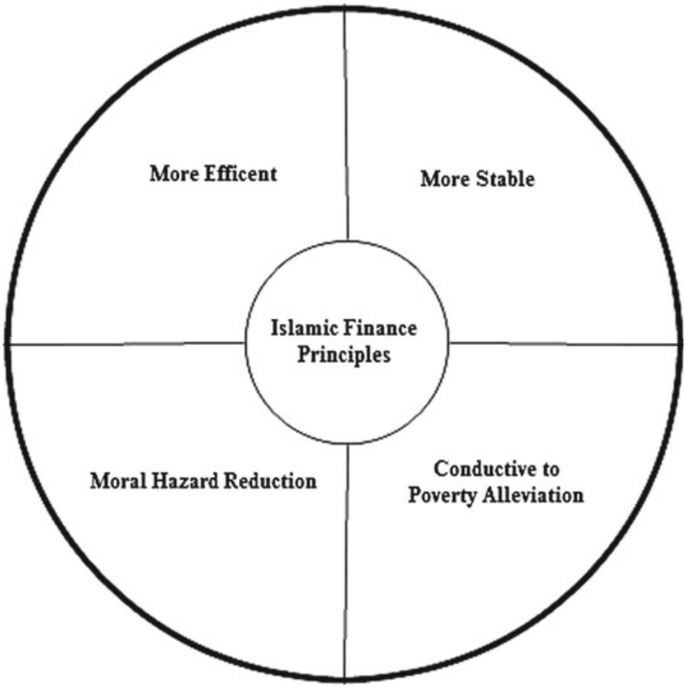

Fig. 17.2 Islamic finance principles advantages. *Source* Compiled from Tabash and Dhankar (2014)

Key Islamic Finance Instruments

Central to Islamic finance is the fact that money itself has no intrinsic value. As a matter of faith, a Muslim cannot lend money to, or receive money from someone and expect to benefit. This means that interest is not allowed and making money from money is forbidden. Money must be used in a productive way, by which wealth can only be generated through legitimate trade and investment in assets. The principal means of Islamic finance are based on trading. Any gains relating to the trading are shared between the party providing the capital and the party providing the expertise. As a result, the Islamic banks have developed six main Islamic financing techniques, which are: Mudaraba, Musharaka, Murabaha, Ijara, Istisna and Salam (Karim, 2002).

1. ***Mudarabah (Trust financing)***: Contracts are profit-sharing agreements, in which a bank provides the entire capital needed to finance a project, and the customer provides the expertise, management and labour. The profits from the project are shared by both parties on a pre-agreed (fixed ratio) basis, but in the case of losses, the total loss is borne by the bank (Schaik, 2001).

2. ***Musharakah (Partnership)***: Contracts are similar to joint venture agreements, in which a bank and an entrepreneur jointly contribute capital and manage a business project. Any profit-and-loss from the project is shared in a predetermined manner. The joint venture is an independent legal entity, and the bank may terminate the joint venture gradually after a certain period or upon the fulfillment of a certain condition (Alam, 2003).
3. ***Murabahah (Cost-plus mark-up)***: Murabaha financing is based on a mark-up (or cost-plus) principle, in which a bank is authorized to buy goods for a customer and resell them to the customer at a predetermined price that includes the original cost-plus a negotiated profit margin. This contract is typically used in working capital and trade financing (Suleiman, 2000).
4. ***Ijara (Sale and leaseback)***: A bank buys an asset for a customer and then leases it to the customer for a certain period at a fixed rental charge. Shariah (Islamic law) permits rental charges on property services, on the precondition that the lessor (bank) retain the risk of asset ownership.
5. ***Salam (Future delivery)***: Salam is structured based on a forward sale concept. This method allows an entrepreneur to sell some specified goods to a bank at a price determined and paid at the time of contract, with delivery of the goods in the future.
6. ***Istisna (Construction/Manufacturing)***: Istisna contracts are based on the concept of commissioned or contract manufacturing, whereby a party undertakes to produce a specific good for future delivery at a predetermined price. It can be used in the financing of manufactured goods, construction and infrastructure projects. All above instruments are based on the principle of Riba (interest) prohibition, and all seek to maintain Islamic business ethics.

Conclusion

In this paper, we have explained and discussed theoretically the role of Islamic finance principles, and its modes of financing in enhancing the growth of the economy. It contributes to the literature by reviewing the main principles, advantages and key modes of Islamic finance industry. The main principles of Islamic finance include the prohibition of Riba (interest), Gharar, Speculation and encompassing the full disclosure of information and removal of any asymmetrical information in a contract. Islamic finance theory promotes economic development through its direct link to the real economy and physical transactions, its prohibitions against harmful products and activities, and its promotion of economic and social justice.

The study has revealed that the Islamic finance industry is a more stable, efficient, less moral hazard and conducive to poverty alleviation than conventional finance, due to its principles of prohibition of interest, Gharar and use the risk and return sharing in any form of transactions. Islamic modes of financing like

Murabahah and Mudarabah have many advantages for the society like creating new jobs, reduce unemployment and achieve poverty alleviation. The findings of the research will be of interest to western and Islamic financial practitioners, policy-makers and academicians, who are interested in Islamic finance industry.

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Chapter 18
Value at Risk and Mutual Funds

Wide diversification is only required when investors do not understand what they are doing.
Warren Buffett

Abstract G-30, Basel Committee on Banking Supervision, Bank of International Settlements and most Central Banks across the globe have endorsed Value at Risk (VaR) as a standard for measuring risk. Though VaR is widely accepted as a true measure of risk for the banking industry, it is yet to find enough acceptance in the investment industry. VaR reporting on a periodic basis could help investors in better understanding of risks of loss to their investments. We have tried to review different methods of estimating VaR, and their applications. Many variants of VaR propagated by researchers seem to work in patches. Risk Metrics developed by J. P. Morgan, which uses exponentially weighted moving average (EWMA) method, has become a standard tool for VaR estimation. Till the time another more effective method is developed, VaR is likely to continue attracting a lot of interest.

Introduction

The concept of Value at Risk (VaR) was used for the first time by large financial institutions at the end of the 80s for measuring risks in portfolios. This period was characterized by huge exchange rate volatility and rapid growth in the use of derivatives useful for managing currency and interest-rate risks. Modern derivatives such as forwards, future swaps and options assist in managing exchange-rate and interest-rate volatility. Since these times, there has occurred a boom in the use of VaR, which has ceased to be merely a matter of internal interest to financial institutions—regularity authorities have begun to take interest in them too.

Sections of this chapter draw from the author's previous publication (Srinivasan & Dhankar, 2015), co-authored by R Srinivasan, Professor (Finance& Accounts), Indus Business Academy, Greater Noida, India; re-used here with permission.

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Value at Risk (VaR) has become the standard measure that financial analysts use to quantify market risk. VaR is defined at the maximum potential loss in use of a portfolio due to adverse market movements, for a given probability. The great popularity that this instrument has achieved is essentially due to its conceptual simplicity: VaR reduces the market risk associated with any portfolio to just one number, the loss associated to a given probability.

Risk is a function of change, and in managing investments, when this change gets more frequent and rapid we need to manage with techniques for coping with the effects of change (Crockford, 2005). Although in modern parlance the term risk has come to mean 'danger of loss', finance theory defines *risk* as the dispersion of unexpected outcomes owing to movements in financial variables; thus viewing both positive and negative deviations as sources of risk (Jorion, 2007). *Risk* is the volatility of unexpected outcomes, generally in the value of assets or liabilities of interest (Jorion, 2002). Financial risk is often defined as the unexpected variability or volatility of returns; and thus includes both potential worse-than-expected losses as well as better-than-expected returns. Risk can be broadly classified as Credit Risk, Market Risk, Operational Risks, Legal Risk, Regulatory Risk, Political Risk, etc. Risks can come from many sources, such as business cycles, inflation, changes in government policies, wars, unforeseen natural phenomena, technological changes, etc. All these may lead to volatility in the markets and uncertainty in business revenues. Volatility, as such, cannot be controlled, but exposure to the underlying factor needs to be managed. *Risk Management* is the process by which various risk exposures are identified, measured and controlled. It has formed the core of every business activity. Clarke and Brown (2009) feel that now is the time for corporate leadership to consider a disciplined approach to risk management at the highest level: the board. Financial risk management has taken a central role since the first Basel Accord was established in 1996. Since Markowitz (1952) seminal work on financial risk/volatility, the variance (or, equivalently, standard deviation $\boldsymbol{\sigma}$) of a random return/loss has been frequently used as a measure of risk. Exposure to movements in different underlying variables is known by different notations. Interest-rate volatility is called *duration*; in market forces and its effect on stock return is *systematic* risk and denoted by $\boldsymbol{\beta}$ (*beta*); and in derivatives market $\boldsymbol{\delta}$ (*delta*) is used; change in duration, due changes in interest rates, is measured by *convexity*; and *gamma* measures the changes in $\boldsymbol{\delta}$ as the underlying price changes.

Indiscriminate actions on the part of individuals and professionals from the financial sector driven more by greed for money and for power had spelt disaster wiping out trillions of dollars. Similarly, natural disasters and political disturbances have caused economies to come crashing down, causing '*too big to fail*' banks to fail. Therefore, the companies need to adopt a comprehensive risk management practice for their entire enterprise, such as Goldman Sachs, helped protect their firms against the worst of the downturn (Mcdonald, 2009). A study by Chiu (2007) on corporate diversification and magnitude of risk through the channel of Cash Flow-at-Risk (C-FaR) models indicate that diversified firms have smaller C-FaR than non-diversified firms, and cash flow distributions are more volatile for related diversification firms than unrelated ones.

After the series of financial disasters caused harm to the economies, it was felt necessary to look at enterprise-wide risk management practice, which paved the way for Value at Risk (VaR). Jorion (1996) described VaR as the quantile of the projected distribution of gains and losses over the target horizon. Leippold (2004) opines that compressing all aspects and dimensions of risk into a single number is untenable and may lead to loss of information. The accelerating trend towards measuring and monitoring risk at a firm-wide level has increased the focus on Value at Risk (VaR) and the need for consistent firm-wide approach (Minnich, 1998).

Jorion (2002) investigated the relation between the trading VaR disclosed by a small sample of U. S. commercial banks and the subsequent variability of their trading revenues, and suggested that VaR disclosures are informative in that they predict the variability of trading revenues. Hence, VaR has been widely and quickly accepted as a true risk measure for the banking industry, but it is yet to find enough acceptances for the investment industry (Deb & Banerjee, 2009). Morgan Guaranty Trust Company (1995) in its report has observed that VaR methods use historical returns to forecast volatilities and correlations, which are then used to estimate the market risk. Many VaR models have been propagated by researchers. Although VaR models are being used extensively, especially in the financial markets, but there are still debates, whether these models do really measure downside risk properly and accurately.

In section “Research Motivation, Objectives and Methodology” we discuss the motivation behind this research, and the research methodology. Risk management practices and Value at Risk (VaR) is discussed in brief in section “Risk Management Practices and VaR”. Section “Risk and Risk Estimation” consists of a review of the work of other researchers on VaR. Section five “conclusion” sums up the discussions.

Research Motivation, Objectives and Methodology

VaR as a risk measurement tool has been in existence since it was popularized in the early 1990s and after endorsement by International bodies like G-30, Basel Committee on Banking Supervision, and Bank of International Settlements (Group of Thirty, 1993). International bodies like Basel Committee, Bank for International Settlements recommend adoption of VaR for assessment of capital adequacy ratio in commercial banks. But its suitability needs to be looked from the perspective of other industries, and whether it can be helpful as an enterprise-wide risk management tool.

Under the premise stated above, the study aims at using new sets of data, variables and approaches for examining the following aspects:

- To discuss the role of VaR in the financial markets, in general.
- To look into the literature about VaR’s applicability in other industries.
- To recommend the best VaR methods for enterprise-wide risk assessment; and
- To look at ways to augment VaR in enterprise-wide risk management.

As the objective here is to find various VaR methods adopted by financial and other industries, we have used the secondary sources for work already published by various researchers.

Risk Management Practices and VaR

'All of life, is management of risk, not its elimination' said Walter Wriston, former chairman of Citicorp. At every corner of our lives we are faced with risk. Some are natural and others are man-made. It is thus, safe to conclude that change is the only constant, and this constant change cannot be avoided, but only needs to be managed (Fung & Hsieh, 2011). VaR as a tool for risk management, at the hands of risk managers, has become increasingly important, and acts as a stabilizing agent in stock markets. Broadly risk managers have been able to use it to control risk. But, in some cases due to the gambling strategy of VaR-based risk managers, large exposures to stocks are taken, thus jacking up the prices and creating a hump in the market. This characteristic of risk managers may artificially increase the probability of extreme losses, and impact the VaR estimation (Berkelaar, Cumperayot, & Roy, 2002).

Extreme value theory (EVT) or Expected shortfall (ES) concentrate on the left tail at a given confidence level and try to compute the average value of the losses falling within the confidence interval. Another popular and one of the most important risk management tools is Value at Risk (VaR). VaR is widely used in the banking and financial sector. It can be described as the quantile of the projected distribution of gains and losses over the target horizon. The seeds of VaR were sown by the shocks felt after the US stock market crash in 1987, called the black Monday, when the US markets went down by twenty-three percent in single a day, spelling a global disaster; and other financial disasters followed it in the US in the early 1990s. To manage something, we need to measure it first. This is where Value at Risk (VaR) comes to our rescue.

Philippe Jorion, who has done a pioneering work on VaR, defines it as '*VaR summarises the worst loss over a target horizon that will not be exceeded with a given level of confidence*'. Supposing c is the confidence level, then VaR can be estimated as 1-c level of the left tail (Jorion, 2007). The term *Value at Risk* was coined at J. P. Morgan in the late 1980s, by Till Guldimann, who was head of research at the bank. The bank decided to concentrate on 'value risk' rather than 'earnings risk'. Later at a G-30 (a group of 30), the international body's meeting; it was taken up and later included in the G-30 report, published in 1993. VaR is measured through a challenging set of complex statistical methods that keep changing with the change in time, change in portfolio structure, change in market conditions, etc., and typically requires statisticians that understand the financial markets well (Damodaran, 2014) (Fig. 18.1).

In 1995, J. P. Morgan proposed the Risk-metrics exponential weighted moving average model (EWMA) to estimate this time-varying conditional volatility.

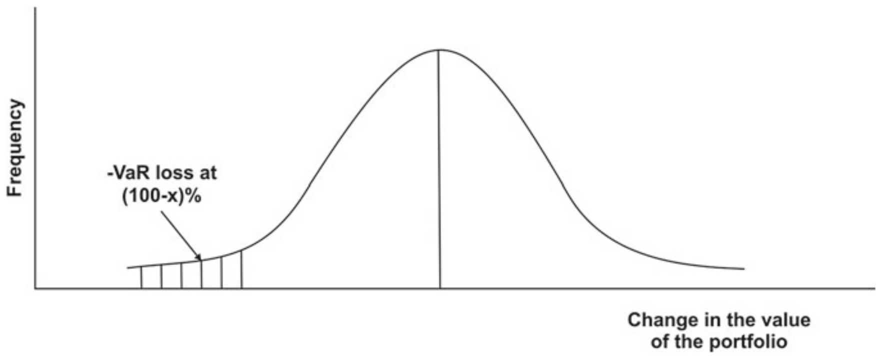

Fig. 18.1 Graphical Presentation of VaR at x% Confidence Level. *Source* Compiled from Srinivasan and Dhankar (2015)

Analysis of a portfolio of stock and option returns revealed that at the 5% level the Risk-metrics analysis gave best results, but at lower probability the semi-parametric method was more accurate (Danielsson & De Vries, 2000). Exponential weighted moving average (EWMA) or GARCH models, observed highest VaR and VaR sensitivity in Indonesian and Korean markets, but lower values in Australian market; and that EWMA underestimated VaR for a single series (Su & Knowles, 2006).

Risk and Risk Estimation

With the advent of Markowitz (1952) pioneering work on risk estimation; variance and standard deviations are used for risk estimation. Even today it is the most popular measure for estimation of risk. Rockafellar and Uryasev (2002) have argued that it does not discriminate between abnormal profits and abnormal losses. With the substantial growth in financial markets and increased interest of the participants, risk estimation has become more diverse and complex (Hwang, 2007). Hence, an assessment of trading revenues from such activities, and examination of the statistical accuracy of the VaR forecasts is absolutely essential. Basel Committee on Banking Supervision has endorsed the use of VaR models, and the same has been implemented in the financial sector across the globe. Rockafellar and Uryasev (2002) proposed another risk measure 'conditional Value at Risk' (CVaR) that satisfies four desirable axioms like, translation invariance, subadditivity, positive homogeneity, and monotonicity lead to a tractable form of a portfolio optimization problem.

The beauty of VaR is that it does not depict the risk as an abstract figure or as a combination of several risk factors; rather it conveys risk associated with a portfolio of assets as an absolute figure in one number (Kiohos & Dimopoulos, 2004). It means it states in absolute terms the likely dollar loss of a portfolio over the next 'n' days, which enables even a layman to understand and helps him in making his decision about the future course of action with regard to his portfolio (Marshall & Siegel, 1997). There is an increasing awareness about the use of VaR models in estimation of risk, and several policy groups have also started recommending the use of these models. The VaR of each stock traded on the National Stock Exchange (NSE), is reported on a daily basis, which can be used by the investors for making their investment decisions.

Tripathi and Gupta (2008), applied portfolio-normal method, on the daily data of thirty stocks from the Indian equity market and two market indices, and concluded that the VaR predictions were not accurate, due to non-normality, leptokurtosis and negative skewness. Ghaoui, Oks, and Oustry (2003) tried to reduce the problem of extreme sensitivity to errors in data posed by the traditional approaches, such as mean–variance or Value at Risk (VaR) models, by assuming that the distribution of returns are partially known, defined the worst-case Value at Risk as the largest VaR attainable, and have tried to show how to compute an upper bound on the worst-case VaR via semi-definite programming (Krokhmal, Palmquist, & Uryasev, 2002). An application of 12 Value at Risk approaches on 1,000 foreign-exchange portfolios produced almost perfect risk estimates at the 95th percentile, but not as perfect results at the 99th percentile (Hendricks, 1996). Leippold (2004) argues that by defining the best of the five percent worst losses, VaR completely misses the tail distribution, which could be the most important part for risk assessment, which can be more misleading, especially if the markets start moving decisively in the negative zone.

Deb and Banerjee (2009) observed that the moving average and random walk models are not well suited for analysis, whereas exponential weighted moving average and historical simulation models are free from downward bias. Zhao (2004) showed that the application of dynamics of VaR estimation in the mutual fund industry, and propagated the idea of designing the dynamic portfolio construction strategies. Researchers exploring the usefulness of Value at Risk models to 1,000 randomly chosen foreign-exchange portfolios over the period 1983–94, selected 3 from exponentially weighted moving average approaches, and 4 from historical simulation approaches; and finally concluded that none of the 12 approaches was superior on every count (Leon & Lin, 2004).

Al Janabi (2006), used descriptive statistics and performed the test of normality on the daily returns data, the daily and annual volatility of foreign-exchange rates of the sample currencies, concluded that USD/EURO has the highest volatility and MAD/EURO has the lowest volatility. Application of techniques like skewness and kurtosis revealed that in general all foreign-exchange rates show slightly asymmetric behaviour, and have flat distributions (Aniūnas, Nedzveckas, & Krušinskas, 2009). Reddy and Rath (2005) concluded that almost all tests on sample currencies showed clear asymmetric behaviours in the distribution of returns, and a clear departure from normality in the distribution of returns mainly in emerging and illiquid markets were observed.

Ordinary, Rankit and Tukey methods, were applied in computation of VaR on hedge funds at 1% (and 5%) quantiles of distribution, and revealed that EVT (a semi-parametric quantile-based estimation of risk capital) was most appropriate in arriving at the VaR value (Nazarova & Teïletche, 2006). Degen and Embrechts (2008) argue that despite the claims of many researchers, it has its own problems and pitfalls when second-order tail behaviour is analysed. Combining the two aspects of dynamism in volatility clustering, and non-normality in the estimation of VaR, Bhattacharyya and Ritolia (2008) develop a combinatorial model of EVT to analyse non-normal behaviour and volatility clustering using GARCH.

The conditional autoregressive value at risk (CAVaR) model that does not put any restriction on the shape of the distribution, was applied on 5 stock indexes and 20 stocks, showed better results than GARCH models and moving averages (Taylor, 2005). Range-based stochastic volatility model and other known forecasting models, were applied on daily futures prices of the S&P 500, ten year US government bond series, crude oil and US/Canada dollar rates, to estimate value at risk measure like, conditional coverage, independence and unconditional coverage, estimated that moving average, exponential smoothing and AR5 models had better forecasting ability (Sadorsky, 2005). With the introduction of CAVaR model, Engle and Manganelli (2004), propose the dynamic quantile (DQ) test that dynamically specifies the quantile over time, and best fit the VaR estimation.

To account for market conditions, where highly volatile values are followed by high volatility and low volatility are followed by low volatile trades, Nelson (1991), and Bollerslev (1987) advocated the use of the General Autoregressive Conditional Heteroskedastic (GARCH). Bhattacharyya, Chaudhary, and Yadav (2008) studied the stock indices of 14 countries, for estimation of VaR, the authors have proposed the use of a combination of Pearson's Type IV distribution and GARCH (1,1) for getting superior predictive results.

Research on 'principle of optimality' of dynamic programming, has demonstrated that conditional Value at Risk (CVaR) need not be time-consistent in multi-stage case, and hence, suggest a formula for target-percentile risk measure (Boda & Filar, 2006). Berkowitz and O'Brien (2002) applied different techniques for estimation of VaR forecasts on the profitability of six large commercial banks, and concluded that the bank VaRs did not adequately reflect changes in P&L volatility.

Fishman (1996) observed that VaR models are helpful on normally distributed data, but most economic data on many occasions exhibit excess kurtosis and fat tails. He suggested Principal Component VaR and Monte Carlo VaR, to overcome these conditions. Tsai and Shih (2007) discussed the principal components with higher eigenvalues, and the ones with higher correlation with the response variable, and concluded that mean square error matrix of estimators for regression coefficients and method of ordinary least squares in the multiple regression models, can determine the best regression estimator. Lin, Chu-Hsiung, and Shen (2006) presented (student-t) VaR-t and (EVT) VaR-x models, and compared them with VaR-n model, and revealed that using the student-t distribution for estimating VaR can offer accurate VaR estimates for confidence level exceeds 98.5 percent. Markov

Switching ARCH (SWARCH) models admit parameters based on various states to control structural changes in the estimating periods, may help mitigate kurtosis, tail-fatness and skewness problems in estimating VaR, when applied on returns of stock market indexes like Dow Jones, Nikkei, Frankfurt Commerzbank index and FTSE, and show that the more generalized SWARCH outshines both ARCH and GARCH in capturing non-normalities with respect to both in-sample and out-of-sample VaR violation rate test (Leon & Lin, 2004). Chang, Hung, and Wu (2003) after surveying various existing procedures proposed several new estimators in measuring the risk involved in VaR estimation; and compared the performance of these VaR models through Monte Carlo simulation studies and found that the newly proposed methods provide better accuracy and robustness in the estimation of the risk in VaR estimator.

Garcia, Renault, and Tsafack (2007) argue that individual traders possess richer information on their specific market segment to fetch superior returns and better control over risk. Alexander and Baptista (2004), applied VaR constraint on the single-period mean–variance model and compared them with those arising from application of CVaR constraint, to conclude that VaR had perverse effect on highly risk-averse agents, and likely to force them to choose the portfolio with higher risk. Fuh and Yang (2007) used the bootstrap method for VaR estimation on nine emerging stock markets indices, US S&P 500 composite index, and MSCI EM Index; and concluded that VaR estimates do not deviate very much from the true VaR; and also that estimates were relatively low in Turkey, India, Mexico, Russia and Indonesia.

Lewis and Okunev (2009) observe that life cycle investment funds are winning favour in recent times, and if well integrated with VaR constraints, they tend to provide better capital gains to the investors, than income returns. Mathematical provision modelling was applied on a life annuity portfolio, and observed that for dynamically estimating proper interest rate term structure, use of Cox–Ingersoll–Ross model is appropriate and Ornstein–Uhlenbeck collection, embodies even negative returns, and add that it may be more appropriate for the investigation of the investment risk (Cocozza, Lorenzo, & Sibillo, 2007).

After due consideration of the conditional measures of market risk, measured by VaR, applied on an oil producer stock price dependent on some of the economic variables, it was observed that the return distribution get affected in a very differential and nontrivial fashion, and the Dow Jones Index (DJI) was found to be only statistically significant determinant of external risk (Chernozukhov & Umentzev, 2001). Using the likelihood ratio, independence, and conditional coverage tests, the performance of VaR is tested on S&P100, Nasdaq100, and S&P index performances, in bull and bear markets; and high and low volatility periods; and did not find any real difference across historical sub-periods, but showed the robustness of VaR models even during difficult market conditions (Giot, 2005).

Dowd and Blake (2006) compare Quantile-Based Risk Measure (QBRM) with other risk estimation techniques like VaR, coherent risk measures, spectral risk measures, and distortions risk measures, and point out that VaR is seriously flawed. An analysis of the credit VaR for allocation of credit risk capital, was observed to be poor in estimating the probability of default, and makes no reference to unexpected loss (Kupiec, 2002). For credit risk measurement and management, Woo and Siu (2004), proposed a discrete-time dynamic extension to the BET in order to incorporate the time-dependent and time-varying behaviour of default probabilities for measuring the risk of a credit-risky portfolio, to obtain closed-form predictive loss distributions for credit-risky portfolios, so that the expected credit loss and Credit Value at Risk (CVaR) can be estimated.

The data envelopment analysis (DEA), a variant of linear programming approach, when applied on the American mutual fund performance, reveals that combining VaR and CVaR, is very helpful in describing skewness and kurtosis, to better estimate the fund performance (Lin & Chen, 2008). Stochastic Dynamic Programming (DP) applications are useful for risk-neutral decision-makers, and for assessment of short-term risk as well as return, but the same cannot be said for assessment of long-term risks (Krautkraemer, Kooten, & Young, 1992). A study conducted by Cao, Chang, and Wang (2008) reveals that there is a negative correlation between the intraday inflow of funds in the mutual fund sector and volatility in the market portfolio. It is further revealed that this negative relation between the inflow of funds and intraday volatility becomes weaker as the day progresses.

Bali (2007) developed an unconditional and conditional extreme value approach in calculating value at risk (VaR), and showed that the maximum likely loss for financial institutions can be more accurately estimated using the statistical theory of extremes, yielding more precise VaR estimates than the normal and skewed t distributions. Anthony Seymour and Daniel Polakow (2003), while expressing their reservations about established methods such as historical simulation, incorporated EVT method and volatility updating (via GARCH-type modelling), Nelson (1990). Cherubini and Giovanni (2001) have presented the fuzzy measure model, well suited to price options when the distribution of the underlying asset is not known precisely. Wilson, Nganje, and Hawes (2007), applied Value at Risk methods to a bread baking company and observed that Value at Risk, when complemented with management goals, competition, and conduct within the industry, provides an effective tool in setting risk limits. For a sample of large bank holding companies, Berkowitz and O'Brien (2002) evaluated the performance of banks' trading risk models by examining the statistical accuracy of the VaR forecasts and came up with a detailed analysis of the performance of models in real life situation; and concluded that their VaR forecasts did not outperform forecasts based simply on an ARMA + GARCH model of the banks' P&L.

To provide preliminary evidence on the informativeness of these new disclosures, Jorion (2002) investigated the relation between the trading VAR disclosed by a small sample of U.S. commercial banks and the subsequent variability of their trading revenues and suggested that VAR disclosures are informative in that they predict the variability of trading revenues.

Using daily flow data and a VAR approach, for studying the dynamic relation between aggregate mutual fund flow and market-wide volatility; it was found that market volatility is negatively related to concurrent and lagged flow (Poon & Granger, 2003). American equity mutual funds of varying investment styles investing in Europe was examined, using Value at Risk (VaR) and expected tail loss (ETL) models developed through three (parametric, nonparametric and style-based approach) techniques, it was found that the least diversified funds that overweight growth and underweight value stocks, the style-based risk model produce significantly lower VaR and ETL estimates than do the other models; whereas, the results for the well-diversified fund show an opposite significance pattern (Papadamou & Stephanides, 2004). Fuss et al. (2007), while examining the conditional volatility characteristics of daily management style returns and comparing the out-of-sample forecasts of different Value at Risk (VaR) approaches, namely, the normal, Cornish–Fisher (CF), and the so-called GARCH type VaR; concluded that the GARCH-type VaR outperforms the other VaRs for most of the hedge fund style indices.

Rajesh (2009) used GARCH and TGARCH models on the Nifty and the Nifty Junior daily returns, for analysing the performance of VaR techniques by subjecting his prediction to elaborate backtesting, and found that the TGARCH model performed better than the GARCH model in predicting VaR.

Conclusion

VaR is not a recent phenomenon, and has been on the horizon now for a couple of decades. A good amount of research has taken place on VaR, but, even today the best measure of estimating VaR is getting debated. Some have declared it as the ultimate measure of risk, others have discarded it as useless and the debate goes on. Despite all the criticism of VaR and its estimation techniques, it seems relevant to the financial sector and continues to evolve. International bodies like G-30, Basel Committee on Banking Supervision, and Bank of International Settlements, have endorsed it as a standard, for measuring the value at risk in financial institutions. In India too, RBI has mandated its implementation in the Banking Sector for assessment and reporting of VaR based regulatory capital in the Indian commercial banks. The equity markets in India, report the daily VaR of each stock traded on the exchanges. Similarly, as we observe from the above literature, it seems to be more of an academic exercise than a serious application. The application of VaR methods have also been largely limited to banking and to a lesser extent in the equity markets. Deb and Banerjee (2009) reaffirm our notion that VaR has been widely accepted as a true risk measure for the banking industry, but it is yet to find enough acceptances for the investment industry. In the stock exchanges the VaR reporting on a periodic basis, may come handy, and make it possible to communicate in a clear language to the investors. If the quantum of loss an investor's portfolio may suffer is reported on periodic basis, it will help the investor in better financial planning. Despite the apparent advantages, there does not seem to be much work on VaR.

Many variants of VaR have also been propagated by researchers, which seem to be working in patches. There does not seem to exist any one specific VaR method for a specific use or industry. Risk Metrics developed by J.P. Morgan for VaR estimation, seemingly gained much popularity, which was then spun-off and listed as a separate entity, before being acquired by MSCI. Risk Metrics has provided a lot of impetus to risk estimation using VaR methods. Till the time another more effective method is created, VaR is likely to remain in limelight and seemingly will continue to attract a lot of interest of the practitioners as well as academicians.

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Chapter 19
Adaptive Markets Hypothesis

A man always has two reasons for what he does—a good one, and the real one.
J. P. Morgan

Abstract The purpose of the study is to critically examine the empirical evidence of Efficient Market Hypothesis (EMH) that pose challenges to the concept of perpetual informational efficiency of financial markets and to provide a context in which a better understanding of behavioural biases can be attained through the evolutionary perspective provided by Adaptive Market Hypothesis (AMH). The defence proffered to various anomalies of EMH has been examined and the weaknesses in the justification provided to reinstate the confidence in the concept of informational efficiency of markets have been re-emphasized. We find that EMH is a description of an ideal scenario of stock market functionality; however, real world is rarely as ideal. Financial markets are a creation of human beings without any restrictions to the selection of market participants. EMH is very abstract in its framework and does not accommodate the possibility of an alternative to informational efficiency in which market inefficiency can persist. It is observed that AMH provides a better financial paradigm than EMH to describe the behaviour of stock returns.

Introduction

The adaptive market hypothesis (AMH), proposed by Lo (2004) is an attempt to reconcile economic theories based on the efficient market hypothesis with behavioural economics, by applying the principles of evolution to financial interaction: competition, adaptation and natural selection. According to Lo, the adaptive market hypothesis can be viewed as a new version of the efficient market hypothesis,

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derived from evolutionary principles: prices reflect as much information as dictated by the combination of environmental conditions and the number and nature of 'species' in the economy. By species, he means a distinct group of market participants, each behaving in a common manner-pension fund managers, retail investors, market makers, hedge funds managers, etc. (Lo, A. W).

The main idea behind the adaptive markets hypothesis is that financial markets are governed by the law of biology than the laws of physics. The AMH applies the framework of evolutionary biology to specific financial contexts. If one follow that perspective to its logical conclusions for any given issue in finance, one will get answers that are quite different than what one would get from either an efficient market hypothesis (EMH) or a behavioural finance perspective (Lo, A. W.).

One of the most contested issues in the finance literature has been the Efficient Market Hypothesis (EMH) proposed by Fama (1970). After its early acceptability, few cracks began to appear in EMH which questioned the validity of the concept of informationally efficient markets in practice. EMH has undergone numerous tests to examine its validity in the financial markets, but a consensus has never been reached. This has led to a polarization among academics either defending EMH or favoring the behavioral biases that might influence the financial markets. In an attempt to reconcile these two schools of thought, Lo (2004) proposed the Adaptive Markets Hypothesis (AMH) taking into consideration an evolutionary perspective of human behavior that influences the informational efficiency of markets. Under AMH, the level of informational efficiency of markets depends upon the ability of market participants to adapt to the changing market conditions.

The purpose of this study is to critically examine the empirical evidence of EMH that pose challenges to the concept of perpetual informational efficiency of financial markets and to provide a context in which a better understanding of behavioral biases can be attained through the evolutionary perspective provided by AMH. We critically examine the defence proffered to various anomalies of EMH and re-emphasize the weaknesses in the justification provided to reinstate the confidence in the concept of informational efficiency of markets. AMH has generated a lot of interest in recent years, as it provides a framework for reconciliation of contradictions between EMH and behavioral biases. In the real-world financial markets, there are uncertainties about the ability of stock prices to fully reflect all available information corroborated by the occurrence of booms and crises along with persistent attempts of market participants to gain informational advantage. We furnish the utility of AMH in illustrating the continually evolving market conditions in which absolute efficiency and outright irrationality are two extremes. Specifically, we provide a description of empirical studies that analyze the practicality of AMH by examining varying levels of efficiency in various stock markets.

The amount of literature pertaining to the concept of informational efficiency of stock markets is so vast that a full coverage of this issue is beyond the scope of this paper. Thus, we focus on reviewing the literature that detects inconsistencies in the concept of perpetual informational efficiency and suggests prevalence of considerably more complex market dynamics than those suggested under EMH. An evolutionary perspective of market efficiency can accommodate major events such as panics, manias, bubbles and crashes that impact the state of efficiency of financial markets. There have been several studies which examine the notion of major events having an impact on the informational efficiency of markets. Lim and Brooks (2011) provide a comprehensive review of the empirical literature related to informational efficiency of stock markets, along with a description of studies that test market efficiency based on events such as opening of stock markets to foreign investors, adoption of electronic trading system, implementation of price limits system, occurrence of financial crisis, changes in regulatory framework and technological advances.

We organize the paper to give emphasis to topics essential for the understanding of AMH, which implies variable efficiency (or varying levels of efficiency) and non-periodic cyclical profitability in stock markets. We provide a brief review of issues regarding EMH in section two of the paper. Section "AMH and Its Implications" discusses progression of the concept of adaptive markets, AMH and its implications. In section "Relevance of AMH", we provide various arguments that elaborate on the relevance of this relatively new proposition and discuss possible explanation of recent financial crises based on variable efficiency. The proposition of adaptive markets did not happen instantaneously, but transpired over several decades, with concepts of evolving efficiency, relative efficiency, time-varying efficiency and Adaptive Markets Hypothesis being tested in different markets. Section "Empirical Evidence of Testable Implications Associated with AMH" provides empirical evidence of the studies which focus on these concepts. Finally, section "Conclusion" concludes the discussion.

Efficient Market Hypothesis and Its Associated Issues

The idea that prices fluctuate randomly was discussed by the likes of Samuelson (1965), who explained the randomness by taking examples of agricultural commodities. However, Fama (1970) discusses it in terms of stock prices and makes categorizations[1] of Weak form, Semi-strong form and Strong form efficiency in markets. A central theme of EMH as formalized by Fama (1970) is investor rationality, due to which prices always reflect all the available information. The implication of EMH was that there is no predictability in asset prices, as any change in prices was the result of a random event. This implication leaves no room for mispriced assets or profit opportunities which can be exploited by investors. This suggests that a passive strategy to invest in the financial markets is much more suitable, as any form of active management ought to be considered as speculative trading.

In an informationally efficient market, rigorous competition among investors restricts them from generating profits through information-based speculative trading. The idea of informational efficiency of markets in itself is intuitively appealing

[1]Although, Fama (1991) tried to reclassify the levels of informational efficiency as Tests of return predictability, Event Studies and Tests for private information, respectively; the initial categorization is the most widely recognized. Informational efficiency, commonly referred to as market efficiency, represents the ability of stock prices to fully reflect all available information.

and serves as a necessary tool for the development of asset pricing models. EMH garnered a lot of attention after its conception and was subjected to several empirical tests. The early evidence suggested that EMH holds true in the market. Jensen (1978, p. 95) remarked ‘there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis’. However, starting with the work of Rozeff and Kinney (1976), researchers started exploring other inconsistencies in the concept of market efficiency. Rozeff and Kinney (1976) tested the seasonality of monthly stock returns on NYSE over a period of seven decades and reported significant differences in mean returns with large returns in the month of January (known as ‘January effect’). Over the years, various other inconsistencies were reported that were categorized as market anomalies. Basu (1977) reported the ‘Value effect’ in which low P/E stocks were found to outperform high P/E stocks. French (1980) presented the ‘Weekend effect’ (also known as ‘Day-of-the-week effect’) in which stock returns on Monday were found to be consistently negative over the study period. Banz (1981) examined the ‘Size effect’ in which smaller firms on an average were found to give higher risk adjusted returns than larger firms. Harris and Gurel (1986) documented the index inclusion effect indicating stocks that are included in the S&P 500 index experience economically and statistically significant price increases on the day of inclusion into the index. Saunders (1993) examined the ‘Weather effect’ in which prices of stocks listed on New York City exchanges were observed to be systematically influenced by local weather.

The common defence to these anomalies was the joint-hypothesis problem, in which the inconsistencies in tests of market efficiency might either be due to the efficient markets model or due to the use of an incorrect asset pricing model (Fama 1991). The other set of market anomalies are related to under-reaction and over-reaction of stock prices to information. De Bondt and Thaler (1985) examine the phenomenon of stock price over-reaction that can be exploited by a contrarian strategy, in which stocks that garner capital gains (losses) over an initial period, amass capital losses (gains) over the subsequent period. In contrast to this, Jegadeesh and Titman (1993) associate under-reaction to momentum strategy of return persistence in past winners as well as losers. Although evidence suggests that contrarian strategies are profitable over long horizons of 3–5 years and momentum strategies are profitable over short horizons of up to 12 months, Fama (1998) asserts that over-reaction and under-reaction counteract the effects of each other as they are randomly split.

When we analyze the practical side of financial markets, one would notice the huge amounts of time and resources that are expended to gather informational advantage. Grossman and Stiglitz (1980) suggest that if the information gathering activities of informed traders did not result in returns that are better than those of uninformed traders, then informational efficiency in financial markets would not be possible as each trader would remain uninformed. This would result in very small turnover ratios in the financial markets due to the homogeneous beliefs of all the traders (or market participants), with each trader opting to save costs of information acquisition by staying uninformed. The counterargument to this was the ability of arbitragers and savvy investors to weed out noise traders, retaining the informational efficiency of markets.

If the above counterargument was to hold true, the financial crises that have transpired over the years certainly bring into question the credibility of EMH. Shiller (2003), supporting his work of 1980s, manifests that the S&P Composite Stock Price Index fluctuates wildly around an almost stable trend of the present value of real dividends paid on the index over a period of 131 years. Subsequent to Shiller's work on excess volatility which demonstrated that speculative bubbles can last for a long time, many researchers focused their attention towards long-range dependence. Even after decades of contention, there hasn't been a consensus regarding the validity of EMH in financial markets. The debate about the validity was sparked once again when the Economic Sciences Price Committee of 2013 awarded the recent Nobel Prize in Economics to Eugene Fama and Robert Shiller concurrently, even though the work of the former strongly supports the Efficient Markets model, while the work of the latter explores market inefficiencies.

Adaptive Markets Hypothesis and Its Implications

Prior to the formal statement of AMH, the gradual shift in discussion from market efficiency to inefficiencies in the market led to the development of different concepts. While discussing informational efficiency of infant stock markets that ought to be inefficient, Emerson, Hall and Zalewska-Mitura (1997) float the concept of evolving market efficiency. They provide a method that uses time-varying parameter model to assess the level of market efficiency and gauge the movement towards efficiency. They apply this method on weekly share price data from 1994 to 1996 of four banks listed on Sofia Stock exchange. They find that in the initial stage with poor information dissemination, the market appears to be informationally efficient in the conventional sense; then in the second phase when trading seems to establish, assumption of informational efficiency is strongly rejected; and in the final stage, the market adapts to the trading activities and becomes efficient for two of the four shares considered. Zalewska-Mitura and Hall (1999) provide a formalized framework of the previous method labeling it as Test for Evolving Efficiency (TEE). Daniel and Titman (1999) introduce the term adaptive efficiency referring to the combination of behavioral insights in exploiting pricing anomalies which are dissipated as they get exploited by investors. They consider behavioral bias of investor over-confidence to be the potential explanation of most prominent anomalies. They provide evidence of superior and persistent abnormal returns for portfolio strategies that exploit investor overconfidence.

Using concepts of bounded rationality and satisficing (choices are merely satisfactory, not necessarily optimal), backed and reinforced by natural selection and trial-and-error, Lo (2004) describes AMH as a new version of EMH derived through the application of evolutionary principles to financial markets in which prices reflect as much information as dictated by the combination of economic conditions together with the number and nature of distinct group of market participants[2] in the economy. There are a number of practical implications that AMH offers. The first implication is a dynamic risk-reward relationship that depends upon the preferences of market participants and the particular path followed by market prices over the previous few years. Second, market efficiency is not a steady state, and depends upon the changes in investor population. This signifies variable efficiency without any persistent trend towards higher efficiency. Third, arbitrage opportunities do exist from time to time and diminish as they are exploited by investors, in turn giving rise to new opportunities that are created as a result of changes in market ecology. Finally, non-periodic cyclical profitability of investment strategies suggests that a particular strategy would perform well in certain environment and poorly in another environment. A corollary of this implication is that factors such as size and value might behave as risk factors from time to time, thus yielding superior returns during one period and negative returns in another. If the concept of variable efficiency and non-periodic cyclical profitability as postulated by AMH were indicated to hold true in the market, then it would explain the fascination of market participants with technical and fundamental analysis. It would thus necessitate a focus on active portfolio management (Lo, 2004).

Relevance of Adaptive Markets Hypothesis

The supporters of EMH suggest that because the EMH is not falsifiable, an alternative theory of market efficiency is not meaningful (Fama, 1998; Malkiel, 2003). While discussing the critiques of EMH, Malkiel (2003) mentions financial crises as seemingly irrefutable cases of inefficiency and accepts that assets can be mispriced during bubble periods, but goes on to support EMH, interpreting it as the presence of no arbitrage opportunity. Even if one were to consider EMH as the existence of no arbitrage condition, no arbitrage is a necessary but not a sufficient condition for informational efficiency of markets. Informational efficiency implies the presence of no arbitrage in markets, which do a good job of allocating capital, but the converse is not true due to the limits of arbitrage. Lo (2004) questions the assumption of the ability of arbitrageurs to overcome the irrational behavior of market participants, and indicates that forces of irrationality can be so pervasive that they can oppress and diminish the capacity of arbitrage capital to correct the mispricing. Lo (2004) also admits that AMH is in its nascent stage and is yet to find its place in the discussion of market efficiency at an elementary level. AMH, being qualitative in nature, does not yet offer quantifiable methods to determine the level of informational efficiency of markets. This has led to limited empirical testing of AMH, resulting in a muted discussion about its implications.

[2]Each distinct group of market participant represents a group of investors that behave in a common manner. For example, pension funds, hedge funds, market makers and retail investors (Lo, 2004).

Under the restrictive framework of EMH, financial crises should not occur and cannot be explained, as the assets are always correctly priced due to the ability of asset prices to fully reflect all available information. Shiller (2003) suggests that a static view of market efficiency might lead to incorrect interpretations of informational content of prices. Lo (2004) cites example of dramatic decline in the number of hedge funds that utilized Fixed-Income Relative Value investment strategies after 1998, but then reappeared as the performance of this investment strategy improved. Lo (2004, 2005) cites evidence by Shiller regarding variable efficiency measured through rolling first-order autocorrelation of the S&P Composite Index from January 1871 to April 2003 representing periods in 1950s when the market is more efficient than in the early 1990s. Lo (2005) postulates that convergence to equilibrium (or market efficiency) is neither guaranteed nor likely to occur. This presents a much more flexible view of market efficiency. Through the concept of variable efficiency, AMH presents testable implication of time-varying return predictability dependent on market conditions (such as market crashes, bubbles, economic boom and busts) in which the nature of predictability of stock returns is time-varying. The implication of non-periodic cyclical profitability brings into question the ability of the same investment strategy to be profitable after a period of time even when it is rendered obsolete due to diminished returns previously.

The onset of any financial crisis is preceded by a difference between the risk perception of market participants and the actual risk they undertake. This disparity is caused by financial conditions and innovations that the existing market participants have never encountered, thereby reducing their ability to adapt their behavior accordingly. Lo (2012) suggests that market bubbles are generated due to this potential intermittent disconnect from reality, thereby making the markets adaptive rather than completely efficient or completely irrational. The author also advocates that due to the dynamic nature of risk premiums and volatilities, engaging in tactical asset allocation by taking into consideration the truly adaptive portfolio policies might be favorable. Lo (2012) strives to make sense of the recent financial crisis under the framework of AMH, and describes EMH to be incomplete rather than an outright rejection of the hypothesis. The author also depicts a six decade period[3] (from 1940s—early 2000s) in which volatility was considerably muted and the U.S. financial markets provided a nearly linear log-cumulative-growth curve, thus favoring the buy-and-hold strategy during that period. This suggests prevalence of EMH during the periods in which market conditions are stable and stationary. In contrast, the recent market scenario is much more dynamic and stochastic, resulting in higher volatilities than previously witnessed, thus giving rise to behavioral regularities. Under these conditions of economic climate of uncertainty, EMH becomes less plausible and AMH provides a logically consistent framework for investment (Lo, 2012).

[3]Lo (2012) refers to the six-decade period (1940s—early 2000s) that followed the Great Depression of 1930s as the period of 'Great Modulation'.

Empirical Evidence of Testable Implications Associated with Adaptive Markets Hypothesis

Evolving Efficiency

Just as in the case of EMH, empirical tests preceded the AMH in the form of evolving market efficiency and long-range dependence. Emerson et al. (1997) test evolving market efficiency using weekly data of four banking shares of Bulgarian stock market from 1994 to 1996 through time-varying coefficients in a multi-factor model and GARCH errors. They do not find any evidence of convergence towards efficiency. Zalewska-Mitura and Hall (1999) introduce a Test for Evolving Efficiency (TEE), verified by employing Monte Carlo Simulations, on series from London Stock Exchange (LSE) and Budapest Stock Exchange (BSE) representing developed and developing markets, respectively. The report developed markets (or LSE) to be stable and efficient over time, however, developing markets (or BSE) are reported to be highly sensitive to past shocks. Rockinger and Urga (2000) use time-varying parameter model to test the convergence of Hungarian, Czech, Polish and Russian markets towards efficiency. Covering the period from April 1994 through June 1999, they find Hungarian market to be weak form efficient; Czech and Polish markets to converge towards efficiency over the time period considered; and Russian market to be characterized by a constantly significant level of predictability. Li (2003) combined the time-varying AR model with the TGARCH model and then with the TGARCH-spill-over model to study evolving market efficiency in Shanghai and Shenzhen Stock Exchanges, along with the investigation of possible leverage effect and possible information transmission. The author uses daily data from 1991 to 2001 and finds that over the time period considered, the predictability of returns for the two stock exchanges dies out as the markets become more liquid and regulations are strengthened. Jefferis and Smith (2005) implement TEE using GARCH approach with time-varying parameters on weekly data from 1990s to 2001 for seven stock markets: South Africa, Egypt, Morocco, Nigeria, Zimbabwe, Mauritius and Kenya. They find South African stock markets to be weak form efficient throughout the time period considered, while Egypt, Morocco and Nigeria become weak form efficient towards the end of the period. Stock markets of Kenya and Zimbabwe show no tendency of convergence towards weak form efficiency. Abdmoulah (2010) adopts TEE using GARCH-M (1,1) approach along with state-space time-varying parameters to examine the evolving efficiency of eleven Arab stock markets (Saudi Arabia, Kuwait, Tunisia, Dubai, Egypt, Qatar, Jordan, Abu Dhabi, Bahrain, Morocco and Oman) using daily prices of more than 5 years up to 2009. The author finds all the markets to be weak form and most of the stock markets to experience sub-periods of improvements in efficiency with the exception of Tunisia, Oman and Morocco stock markets which show no converge towards efficiency.

Relative Efficiency

Cajueiro and Tabak (2004a, b, c) in a series of papers test the evolving and relative efficiency of stock markets. Cajueiro and Tabak (2004a) test the evolving efficiency of U.S., Japan and bulk of emerging markets of Latin America and Asia. They calculate Hurst exponent with a time window of four years on data from January 1992 through December 2002. They find on an average a downward trend on the Hurst exponent of all the equity indices for the time period considered, suggesting increased efficiency over the period, with an exception of Brazil, which shows an upward trend. Cajueiro and Tabak (2004b) test the long-range dependence in asset returns for China, Hong Kong and Singapore stock markets. They use the Hurst exponent calculated by classical R/S[4] analysis and find that these markets exhibit long-range dependence. Cajueiro and Tabak (2004c) further test the relative efficiency of thirteen equity indices consisting of eleven emerging markets, U.S. and Japan. They reject the null hypothesis of absence of long-range dependence for all the equity indices based on modified R/S statistic. They also provide efficiency ranking for the equity indices using a rolling sample approach by analyzing Hurst exponent, R/S statistic and modified R/S statistic.

Time-Varying Efficiency

Lim (2007) focuses on non-linear dependence for assessing the relative efficiency of 11 emerging and 2 developed markets from January 1992 through December 2005 using rolling sample portmanteau bicorrelation test statistic over a rolling window of fifty observations. The author shows the portmanteau bicorrelation test statistic to vary over time with stock markets exhibiting long periods of efficiency mixed with short periods of inefficiency. Ito and Sugiyama (2009) examine the degree of time-varying inefficiency of the U.S. stock market using monthly data from January 1955 to February 2006. They calculate first-order autocorrelations by applying sliding window approach to the data and find varying degrees of efficiency through time without any discernable trend of convergence towards efficiency.

Analyzing Practicality of Adaptive Markets Hypothesis

Empirical tests regarding implications of AMH in stock markets giving direct reference to AMH commenced with the work of Todea, Ulici, and Silaghi (2009). They study the profitability of moving average strategies for six Asia-Pacific stock

[4]R/S statistic also called 'Rescaled Range' is a popular way to detect long-range dependence and is calculated by dividing the range of values by the standard deviation.

markets using portmanteau test and bi-correlation test over linear/non-linear correlation and non-correlation windows from 1997 through 2008. They find that the profitability of moving average strategies is not constant over time, but rather episodic. Kim, Shamsuddin, and Lim (2011) provide evidence in favor of time-varying return predictability of US stock market and dependence of return predictability on market conditions using automatic Variance Ratio (VR) test, automatic portmanteau test and generalized spectral test over century-long daily data of Dow Jones Industrial Average (DJIA) index.

Lim, Luo, and Kim (2013) re-examine the time-varying return predictability of three major US stock market indices, namely DJIA index, S&P 500 Composite Price index and NYSE Composite Price index, over the sample period 1969–2008 at daily frequency. They find different US stock indices to exhibit varying degrees of return predictability by using the automatic portmanteau test and wild boot-strapped automatic VR test. They also find a dramatic decrease in the return predictability during the final two decades of the sample period indicating increased efficiency over the second-half of the sample period. Popović, Mugoša, and Đurović (2013) examine the impact of observation period (euphoria and recession), data aggregation level (daily and weekly) and rolling time horizon (window size) on the efficiency of Montenegro equity market by using data of MONEX20 from 2004 to 2011. They find all the three factors to have an impact on the degree of market efficiency, thereby supporting time-varying market efficiency, by using rolling window analysis on first order serial autocorrelation coefficients and on p-value of runs test.

Urquhart and Hudson (2013) test the behavior of independence of the US, UK and Japanese stock markets using linear (autocorrelation, runs and VR) and non-linear (McLeod Li, Engle LM and BDS) tests on more than 50 years of daily data for all the three stock markets with a sub-sample size of five years. On the basis of linear tests, they find the stock markets to go through periods of efficiency and inefficiency, while evidence from non-linear tests indicate continuing time-varying inefficiency. Ghazani and Araghi (2014) study the adaptive behavior of returns in Tehran Stock Exchange using linear (automatic VR and automatic portmanteau) and non-linear (generalized spectral and McLeod Li) tests on data from 1999 to 2013. They find a cyclical pattern of dependency and independency in stock returns, consistent with AMH, using both categories of tests. Hiremath and Kumari (2014) investigate the behavior of returns in the Indian stock market using linear (autocorrelation, runs, VR and multiple VR) and non-linear (McLeod Li, Tsay, ARCH-LM, portmanteau and BDS) tests on data covering a period from 1991 to 2013. They find linear tests to support the notion of cyclical pattern between efficiency and inefficiency, while the results of non-linear tests suggest varying degrees of non-linearity.

Manahov and Hudson (2014) use a special adaptive form of the Strongly Typed Genetic Programming (STGP) based learning algorithm to develop various artificial stock markets populated with traders and apply it to historical data of FTSE 100, S&P 500 and Russell 3000 Index. Based on several econometric techniques including BDS Test, Kaplan Test and Hurst Exponent they find market size and heterogeneous learning styles result in more efficient and adaptable financial market structures. The results are consistent with adaptive behavior of market participants as postulated by AMH suggesting that market efficiency is a dynamic and context-dependent process. Urquhart and McGroarty (2014) examine the performance of four calendar anomalies (day-of-the-week effect, January effect, turn-of-the-month effect[5] and Halloween effect[6]) through subsample and rolling window analysis on daily returns of Dow Jones Industrial Average from 1900 to 2013 using GARCH (1,1) regression and Kruskal–Wallis test. They find the performance of all four calendar anomalies to be time-varying, depending upon the prevalent market conditions.

Conclusion

The above documentation suggests that EMH is a description of an ideal scenario of stock market functionality; however, real world is rarely as ideal. Financial markets are a creation of human beings without any restrictions to the selection of market participants. These market participants might not necessarily be rational, as depicted in the ideal version. Being a by-product of human nature, there are several similarities in the way financial markets behave and evolve as a result of trial-and-error of its participants over a period of time. Just like the evolutionary process of humans, natural selection in the financial market determines the survivors by weeding out financial losers. This process of elimination does not ensure rationality or informational efficiency of markets as new participants keep entering and replacing the decimated ones, leading to dynamic market ecology. The dynamism warrants market efficiency to be variable. Variable efficiency would generate opportunities for non-periodic cyclical profitability by using strategies that examine the inefficiency.

EMH is very abstract in its framework and does not accommodate the possibility of an alternative to informational efficiency in which market inefficiencies can persist. AMH provides a broader context to study the forces behind changes in market ecology that can affect informational efficiency of markets. The framework of AMH accommodates the existence and persistence of mispricing by acknowledging the distinction between risk perception and risk reality, which can be a critical factor for the occurrence of financial crises. Recent evidence relevant to informational efficiency of stock markets provides strong evidence of adaptive

[5]Turn-of-the-month (TOTM) effect is the phenomenon in which rise in stock prices is observed during TOTM interval, i.e. last few and first few days of the month.

[6]Halloween effect is the phenomenon in which the month of May is the best time to divest from stock markets as stocks accumulate significant capital gains only over the six month period from November to April.

behavior of stock returns consistent with the implications of AMH. These studies have emphasized that AMH provides a better financial paradigm than EMH to describe the behavior of stock returns.

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Chapter 20
Investor Sentiment and Investment Decision-Making

When the first primitive man decided to use a bone for a club instead of eating its marrow, that was investment.
Anonymous

Abstract We develop an investor sentiment index that captures the investor behaviour and analyses its suitability in explaining asset prices after augmenting it in multifactor asset pricing models. Seven different proxies including Sensex P/E ratios, dividend premium, modified advances to declines ratio, number of new equity issues, ratio of total equity issues to total equity and debt issues, turnover of BSE and volatility premium have been utilized. The investor sentiment index thus created mimics the movement of Sensex. Investor sentiment finds significance in explaining the returns for most of the portfolio under the different multifactor models. Fama–French three-factor model again lags in explaining the portfolio returns while Carhart four-factor model and residual momentum factor model match in performance for explaining stock returns.

Introduction

There has been a growing discussion on the relationship between investor behaviour and stock returns, over the past years. This view questions the classical theory of rational investors and efficient markets, which leaves hardly any role for behavioural factors (e.g. investor sentiment) in explaining asset prices.

Economists have long recognized the importance of information veracity in valuing risky securities. Market participants concerned about the credibility of information measures may require additional compensation to entice them to hold

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stocks with less transparent information. These same securities are expected to display greater sensitivities to measures of market sentiment (Dave & Turtle, 2012).

Behavioural finance domain that encompasses, the psychological phenomena and its impact on decision-making ability of investors, leads to a discussion regarding impact of investor sentiment. De Long, Shleifer, Summers and Waldmann (1990) present a model that examines impact of the behaviour of irrational investors on asset prices. They discuss the risk generated by noise traders that trade on noise, assuming it to be information that can help them generate higher returns. They theorize that the risk created by noise traders deters rational investors from taking fully offsetting positions to correct mispricing, even in the absence of fundamental risk.

Lee, Shleifer and Thaler (1991) discuss the impact of investor sentiment on discounts of closed-end mutual funds that are disproportionately held by individual investors. They assert that the discounts on closed-end funds are a measure of market-wide individual investor sentiment. Neal and Wheatley (1998) discuss the ability of investor sentiment measures to predict stock returns. They use three popular investor sentiment proxies including closed-end fund discount, odd-lot sales to purchases ratio and net mutual fund redemptions. They find that closed-end fund discount and net mutual fund redemptions induce a size premium.

Fama and French (1993) adopt a time series approach to confirm that portfolios constructed to mimic risk factors related to market, size and value, help in explaining the returns of well-diversified portfolios. Fama and French (1995) attempt to provide a deeper economic foundation for their three-factor asset pricing model by relating the risk factors with the behaviour of earnings. They relate small market capitalization stocks and high book-to-market equity ratio with lower profitability. They argue that this lower profitability drives factor returns and acts as a compensation for risk. Fama and French (1996) concede that momentum effect of Jegadeesh and Titman (1993) is the only anomaly related to CAPM that their three-factor model fails to explain.

Carhart (1997) proposes a four-factor pricing model by adding the momentum factor to the three-factor framework of Fama and French (1993). Fama and French (1998) document the significance of value premium in 13 major markets. The focus then shifted from identification of different factors to exploration of sources of these factors. Barberis, Shleifer, Vishny (1998), and Daniel, Hirshleifer, and Subrahmanyam (1998) develop two different models to explain investor behaviour in order to reconcile the empirical findings of underreaction and overreaction. While Barberis, Shleifer and Vishny (1998) are motivated by conservatism and representativeness heuristic, Daniel, Hirshleifer and Subrahmanyam (1998) mention overconfidence and self-attribution bias to explain underreaction and overreaction. Hong and Stein (1999) develop a model to demonstrate slow information diffusion among the investors, which leads to persistent price trends that benefit momentum traders. Hong, Lim and Stein (2000) report that controlling for firm size, momentum strategies provide superior returns for stocks that have low analyst coverage.

Grundy and Martin (2001) report that the cross-sectional variability in required returns and the reward for bearing industry risk cannot fully explain momentum profits. They also show that momentum strategies have dynamic exposures to market, size and value factors. Jegadeesh and Titman (2001) conclude that behavioural explanations of momentum strategies are more promising, as a risk-based explanation would require momentum profits at any time horizon, even beyond one year.

Baker and Wurgler (2000) relate the share of equity issues in total new equity and debt issues to measures of investor sentiment. They find that this measure is a strong predictor of stock market returns as firms prefer to issue more equity than debt before periods of low market returns, and prefer to issue more debt before periods of high market returns. Fisher and Statman (2000) examine the relationship between stock market returns and the sentiment of three groups of investors, including large-sized, medium-sized and small-sized investors. They find a negative relationship between future stock returns and the sentiment of each of these three groups of investors, and suggest that investor sentiment can be useful in tactical asset allocation.

Fisher and Statman (2003) examine the relationship between consumer confidence and investor sentiment, and the ability of consumer confidence to predict stock market returns. They find a positive relationship between changes in individual investor sentiment and changes in consumer confidence, but no consistent relationship between changes in institutional investor sentiment and changes in consumer confidence. They report that consumer confidence is able to predict stock market returns as there is a negative relationship between the level of consumer confidence and future stocks returns, but a positive relationship between changes in consumer confidence and contemporaneous stock returns as many consumers are also investors. Baker and Stein (2004) suggest market liquidity as an indicator of investor sentiment, where high liquidity is a signal of positive sentiment of irrational investors. They develop a model to explain why an increase in liquidity predicts returns that are abnormally low.

Brown and Cliff (2004) identify direct and indirect sentiment measures as two different types of investor sentiment measures, in which direct sentiment measures are generated through surveys of investor sentiment, while indirect sentiment measures represent different proxies used as indicators of investor sentiment. They find that indirect measures of investor sentiment are related to the direct measures. They document both the sentiment measures to be highly correlated with contemporaneous market returns, but do not find any causal relationship between the sentiment measures and market returns. In contrast to their previous findings, Brown and Cliff (2005) focus on the long-run effects of investor sentiment on stock returns to find that direct measures of investor sentiment predict market returns over the next one to three years. Their findings suggest that the role of investor sentiment should be considered in the asset pricing models.

Baker and Wurgler (2006) use a principal components approach similar to Brown and Cliff (2004) to create an investor sentiment index using different proxies. They find that the when the beginning-of-period investor sentiment index is high (low), subsequent cross section of returns are low (high) for stocks whose valuations are highly subjective and difficult to arbitrage. They perform further tests to reject any classical explanation of their results reflecting compensation for systematic risk. Cornelli, Goldreich and Ljungqvist (2006) highlight a link between sentiment of small investors and post-IPO (Initial Public Offering) prices. They argue that high (low) grey (or pre-IPO) market prices indicate excessive optimism (pessimism) of small investors, and find that high (low) grey market prices to have substantial (slight) correlation with post-IPO prices, thus suggesting an asymmetric relationship. They also find this asymmetric relationship of grey market prices to hold with issue price as well as long-run returns, where high grey market price translates into high issue price and negative long-run returns.

Kumar and Lee (2006) initially show that the trading activities of retail investors are systematically correlated. They successively utilize a direct measure of retail investor sentiment to find a positive relationship between retail investor sentiment and excess returns, with the retail investor sentiment having explanatory power for returns of stocks having high retail concentration. They ultimately show that retail investor sentiment has a much stronger impact on stocks with higher arbitrage costs. Ljungqvist, Nanda and Singh (2006) link the main empirical anomalies related to IPOs with the presence of a particular class of investors exhibiting irrational exuberance. They present a model to strategically take advantage of the market's mispricing of IPOs caused due to the presence of investor sentiment.

Baker and Wurgler (2007) assert that investor sentiment affects stock prices, and discuss bottom-up and top-down approaches to measure investor sentiment. The bottom-up approach uses different psychological biases of individual investors, which when aggregated represents market-wide investor sentiment. The top-down approach traces its effects to market returns to explain which stocks are most likely to be affected by sentiment. They corroborate the findings of Baker and Wurgler (2006) that difficult to value and harder to arbitrage stocks are most affected by sentiment. Tetlock (2007) uses vector autoregressions to show that there is a negative bidirectional relationship between media pessimism and market returns. The author also finds that high or low levels of media pessimism lead to high market trading volume and suggests that measures of media content serve as a proxy for investor sentiment.

Gutierrez Jr. and Prinsky (2007) identify residual momentum to account for overreaction to relative returns, and under reaction to firm-specific news, that generates longer positive profits than the total return momentum. Blitz, Huij, and Martens (2011) extend the work of Grundy and Martin (2001), and Gutierrez Jr. and Prinsky (2007) to show that the time-varying exposures of momentum profits to market, value and size factors of Fama and French (1993) can be reduced by ranking stocks on residual returns instead of total returns.

Data and Methodology

In literature, several proxies have been suggested to reflect investor sentiment. None of them has been uncontroversial. This study utilizes seven different proxies, which have been found to be of significance in other markets in different studies, to reflect investor sentiment. These proxies are measured on a monthly basis. The data for these proxies has been collected from CMIE Prowess Database, Reserve Bank of India (RBI) website and IndiaStat.com website. The data is continually available for each proxy starting from April 2002 till September 2015.

Sentiment Proxies

Sensex P/E ratio (SENSEXPE) represents the Price-to-Equity (P/E) ratio of Sensex, i.e. benchmark index for Indian equities. This ratio is frequently referred by analysts to represent the relative valuation of equities. Computation of this ratio for Sensex, which is considered as the benchmark index for Indian equities, assists in interpreting the valuation of the stock market.

New Equity Issues (NEI) represents the number of firms issuing new equity to investors. Companies are said to issue new equity in periods when the investor sentiment is positive as this leads to better valuations for the company.

Equity Issues to Total Issues (EITI) represents the ratio of total equity issues to sum of total equity issues plus debt issues by companies. Total equity issues are considered as initial plus further public offers by companies. A higher ratio represents better valuation for companies opting to raise money.

This study utilizes a modified of version advances to decline ratio (ADVDEC) commonly referred to as TRIN (Trading Index) or ARMS Index. This ratio is one of the most commonly used technical indicator and has two components. The numerator component represents the ratio of number of stocks that have increased in value over the period to number of stock that have decreased in value over the period. The denominator component represents ratio of volume of stocks that have increased in value over the period to volume of stocks that have decreased in value over the period.

Dividend premium (DIVPREM) represents the valuation premium received by dividend-paying stocks in comparison to the dividend non-paying stocks. Dividend premium has been computed as the log difference of P/B ratio of dividend-paying and non-paying stocks.

Turnover of the stock exchange represents the liquidity that is available in the stock market. Higher liquidity can signal better investor sentiment. Turnover of BSE (TURNOVERBSE) represented by log ratio of the value of stocks traded to the total market capitalization of the stock exchange has been considered in the current study to proxy for the liquidity in the stock market. This series exhibits a trend and therefore has been de-trended over three months.

Volatility premium (VOLPREM) has found significance in some studies as it represents the difference of high volatility and low volatility stocks. Volatility premium has been computed as the log difference of P/B ratios of high volatility stocks and low volatility stocks. These proxies can impact the investor sentiment with a lag.

Two-Stage Principal Component Analysis

These seven proxies can have different timing to reflect a given change in sentiment. In order to take into consideration this relative of the proxies, a two-stage principal component analysis has been used. The first-stage principal component analysis utilizes the seven different proxies along with their one-period lags. The first principal component generated through these 14 variables is referred as the first-stage principal component (FPC). The correlations between FPC and all the 14 variables are computed to ascertain the relative timing of these variables. Each proxy's lag or the original variable, whichever has the higher absolute correlation with FPC has been considered for the second-stage principal component analysis. Turnover of BSE and Volatility premium have very low and insignificant correlations with FPC, and therefore have not been considered for the second stage. The first principal component of the second-stage principal component analysis explains 39% of the sample variance, and has been considered as the investor sentiment index. Equation (20.1) shows the loadings of each component to create the investor sentiment index, where each of the components has first been standardized.

$$\begin{aligned}\mathrm{Sentiment}_t = {} & 0.565\,\mathrm{SENSEXPE}_t + 0.536\,\mathrm{NEI}_t + 0.375\,\mathrm{EITI}_{t-1} \\ & -0.294\,\mathrm{ADVDEC}_{t-1} - 0.408\,\mathrm{DIVPREM}_{t-1}\end{aligned} \tag{20.1}$$

The high correlation of 0.951 between first-stage index and sentiment suggests that there is little information is lost in dropping the nine variables, having low correlations with the first-stage index.

Sentiment Augmented Asset Pricing Models

The creation of investor sentiment index in itself does not communicate much until it plays a role in asset pricing. The effect of sentiment in the asset pricing models can be examined by augmenting the asset pricing models with the investor sentiment index. In this study, the investor sentiment index has been augmented as a factor in three different asset pricing models: Fama–French three-factor model (Eq. (20.2)), Carhart four-factor model (Eq. (20.3)) and Residual momentum factor model (Eq. (20.4)). The asset pricing models would not be useful if the current sentiment is checked for its impact on the portfolio returns, therefore the one-period lag of the sentiment index has been taken as a factor in the asset pricing models.

$$R_p = \alpha + \beta_1 MRP\_500_t + \beta_2 SMB_t + \beta_3 LMH_t + \beta_4 Sentiment_{t-1} + \varepsilon_t \quad (20.2)$$

$$R_p = \alpha + \beta_1 MRP\_500_t + \beta_2 SMB_t + \beta_3 LMH_t + \beta_4 WML_t + \beta_5 Sentiment_{t-1} + \varepsilon_t \quad (20.3)$$

$$R_p = \alpha + \beta_1 MRP\_500_t + \beta_2 SMB_t + \beta_3 LMH_t + \beta_4 RWML_t + \beta_5 Sentiment_{t-1} + \varepsilon_t \quad (20.4)$$

Results and Discussion

Table 20.1 shows the summary statistics and correlations of the indices created and proxies considered in the two-stage principal component analysis. Sentiment represents the final sentiment indicator coming out of the second stage. FPC represents the first-stage index in which fourteen variables consisting of seven original proxies along with their one-period lags have been considered. Proxies suffixed with (–1) reflect the one-period lag of proxies which have been considered to take care of the relative timing to affect investor sentiment. Turnover and Volatility premium have not been considered for second stage principal component analysis due to their low and insignificant correlations in the first-stage principal component analysis. The final sentiment indicator represents five different market proxies, which has been taken to reflect investor sentiment.

Figure 20.1 shows the movement of investor sentiment index and Sensex, in which the investor sentiment index has been aligned to left-axis and Sensex has been aligned to the right-axis. The graph depicts that the investor sentiment index, created through the market proxies, mimics the movements of Sensex. This investor sentiment indicator has now been included in the asset pricing framework to check its significance in the asset pricing models tested previously.

The inclusion of investor sentiment index in the Fama–French three-factor model increases the explanatory power of the model reflected by an increase in the adjusted R-squared values (Table 20.2). The investor sentiment factor is significant in majority of the portfolios.

The inclusion of investor sentiment index in Carhart four-factor model also helps increase the explanatory power of the model (Table 20.3).

The inclusion of investor sentiment index in the residual momentum asset pricing model increases the explanatory power of the model, thereby supporting the notion of investor sentiment impacting asset prices (Table 20.4).

Table 20.1 Descriptive statistics and correlations of investor sentiment proxies

Correlation	Mean	Median	Std. Dev.	Minimum	Maximum	SENTIMENT	FPC	SENSEXPE	NEI	EITI(–1)	ADVDEC (–1)	DIVPREM (–1)	TURNOVERBSE (–1)	VOLPREM
SENTIMENT	0.000	0.0302	1.0034	–2.1813	2.9852	1								
FPC	0.000	–0.1425	1.8671	–4.3088	5.3394	(0.951)*	1							
SENSEXPE	18.700	18.3500	2.6794	11.8800	26.9400	(0.786)*	(0.81)*	1						
NEI	4.129	3.0000	3.6099	0.0000	18.0000	(0.747)*	(0.655)*	(0.467)*	1					
EITI(-1)	0.876	1.0000	0.2682	0.0000	1.0000	(0.523)*	(0.512)*	(0.293)*	(0.256)*	1				
ADVDEC(-1)	0.866	0.7082	0.6194	0.0955	3.4849	(–0.409)*	(–0.267)*	(–0.277)*	–0.158	0.117	1			
DIVPREM(-1)	0.470	0.4967	0.1701	–0.1337	0.8174	(–0.568)*	(–0.603)*	(–0.215)*	(–0.238)*	(–0.206)*	(0.192)*	1		
TURNOVERBSE (-1)	0.000	0.0000	0.0027	–0.0071	0.0104	–0.067	–0.037	–0.082	–0.074	–0.094	–0.058	–0.026	1	
VOLPREM	0.223	0.2028	0.3047	–0.4124	0.8160	–0.057	–0.123	–0.134	–0.049	0.021	–0.006	–0.03	–0.019	1

Source Compiled from Dhankar and Shankar (2019)

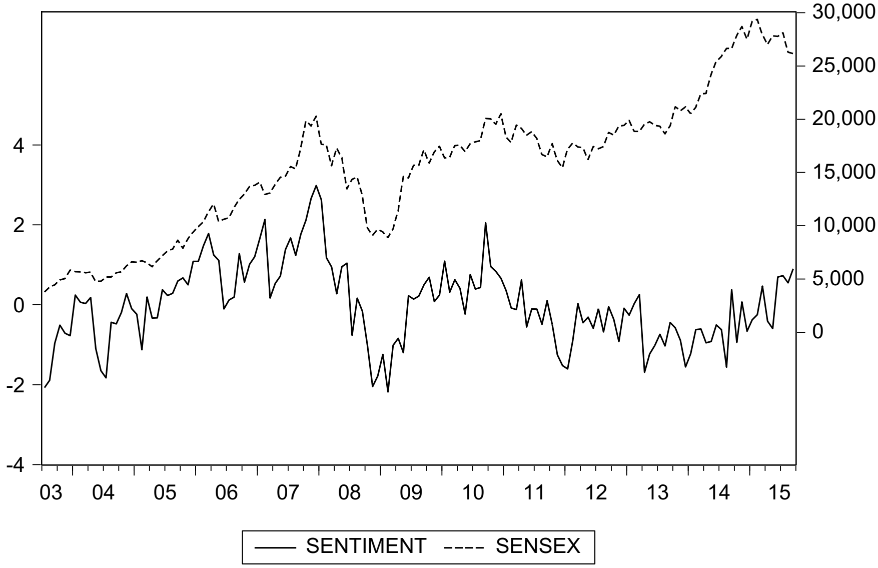

Fig. 20.1 Trend of movements in Sensex and Investor sentiment index from October 2003 to September 2015. *Source* Compiled from Dhankar and Shankar (2019)

Table 20.2 Fama–French three-factor model appended with investor sentiment

Portfolio	Adjusted R-squared	F-statistic	Alpha	MRP_500	SMB	LMH	Sentiment
Bighigh	0.929	(471.758)*	0.005 (2.718)*	1.008 (39.225)*	0.234 (5.663)*	–0.024 (–0.574)	–0.004 (–1.983)*
Bigmedium	0.914	(380.596)*	0.001 (0.311)	1.057 (31.031)*	0.267 (4.878)*	0.457 (8.098)*	–0.005 (–2.098)*
Biglow	0.919	(406.603)*	0.003 (1.028)	1.085 (26.207)*	0.215 (3.229)*	1.172 (17.109)*	–0.003 (–1.065)
Smallhigh	0.893	(299.827)*	0.002 (0.769)	1.082 (25.643)*	1.301 (19.158)*	0.134 (1.912)^	–0.003 (–0.995)
Smallmedium	0.925	(440.955)*	0.002 (0.854)	1.062 (29.472)*	1.095 (18.888)*	0.533 (8.944)*	–0.005 (–2.101)*
Smalllow	0.967	(1058.233)*	0.004 (2.304)*	1.006 (38.774)*	1.320 (31.63)*	0.937 (21.829)*	–0.003 (–1.884)^
Bigwinner	0.878	(258.377)*	0.009 (3.469)*	1.007 (28.359)*	0.391 (6.842)*	0.049 (0.83)	0.000 (–0.016)
BIGLOSER	0.836	(183.289)*	–0.004 (–1.168)	1.146 (20.968)*	0.181 (2.053)*	0.590 (6.524)*	–0.009 (–2.353)*
Smallwinner	0.908	(354.435)*	0.010 (3.484)*	1.021 (26.186)*	1.251 (19.95)*	0.388 (6.021)*	–0.004 (–1.306)
Smallloser	0.925	(441.031)*	–0.004 (–1.327)	1.083 (26.326)*	1.217 (18.394)*	0.935 (13.731)*	–0.005 (–1.749)^

(continued)

Table 20.2 (continued)

Portfolio	Adjusted R-squared	F-statistic	Alpha	MRP_500	SMB	LMH	Sentiment
Bigrwinner	0.918	(401.412)*	0.008 (4.015)*	1.005 (35.542)*	0.328 (7.215)*	0.044 (0.931)	–0.001 (–0.514)
Bigrloser	0.877	(255.48)*	–0.005 (–1.705)^	1.057 (24.335)*	0.202 (2.889)*	0.600 (8.342)*	–0.008 (–2.682)*
Smallrwinner	0.899	(320.867)*	0.012 (4.178)*	0.998 (25.247)*	1.118 (17.576)*	0.405 (6.193)*	–0.006 (–2.227)*
Smallrloser	0.944	(601.577)*	–0.005 (–1.84)^	1.046 (29.805)*	1.276 (22.583)*	0.959 (16.497)*	–0.005 (–2.148)*

Source Compiled from Dhankar and Shankar (2019)

Table 20.3 Carhart four-factor model appended with investor sentiment

Portfolio	Adjusted R-squared	F-statistic	Alpha	MRP_500	SMB	LMH	WML	Sentiment
Bighigh	0.932	(392.36)*	0.006 (3.345)*	0.999 (39.089)*	0.246 (6.013)*	–0.077 (–1.634)	–0.096 (–2.462)*	–0.003 (–1.725)^
Bigmedium	0.922	(340.169)*	0.003 (1.426)	1.037 (31.656)*	0.292 (5.56)*	0.349 (5.801)*	–0.199 (–3.981)*	–0.004 (–1.739)^
Biglow	0.922	(340.178)*	0.005 (1.735)^	1.068 (26.036)*	0.235 (3.577)*	1.083 (14.401)*	–0.163 (–2.605)*	–0.002 (–0.783)
Smallhigh	0.900	(258.668)*	0.005 (1.675)^	1.062 (25.71)*	1.326 (20.058)*	0.022 (0.289)	–0.205 (–3.265)*	–0.002 (–0.649)
Smallmedium	0.927	(361.934)*	0.004 (1.408)	1.051 (29.152)*	1.109 (19.22)*	0.472 (7.138)*	–0.114 (–2.068)*	–0.005 (–1.875)^
Smalllow	0.970	(922.386)*	0.006 (3.314)*	0.992 (39.391)*	1.337 (33.165)*	0.862 (18.668)*	–0.138 (–3.608)*	–0.003 (–1.539)
Bigwinner	0.920	(328.934)*	0.004 (1.715)^	1.045 (35.866)*	0.345 (7.382)*	0.256 (4.783)*	0.380 (8.564)*	–0.002 (–0.997)
Bigloser	0.931	(389.718)*	0.006 (2.162)*	1.070 (29.924)*	0.274 (4.778)*	0.177 (2.7)*	–0.760 (–13.948)*	–0.005 (–2.024)*
Smallwinner	0.927	(362.635)*	0.005 (2.064)*	1.053 (29.892)*	1.212 (21.483)*	0.564 (8.733)*	0.323 (6.018)*	–0.005 (–2.14)*
Smallloser	0.963	(752.658)*	0.003 (1.562)	1.029 (35.401)*	1.283 (27.568)*	0.643 (12.062)*	–0.537 (–12.122)*	–0.002 (–1.105)
Bigrwinner	0.935	(410.672)*	0.005 (2.63)*	1.028 (40.29)*	0.299 (7.327)*	0.171 (3.664)*	0.235 (6.049)*	–0.002 (–1.263)
Bigrloser	0.924	(351.029)*	0.001 (0.54)	1.008 (29.275)*	0.262 (4.76)*	0.331 (5.249)*	–0.494 (–9.417)*	–0.006 (–2.327)*
Smallrwinner	0.903	(266.497)*	0.010 (3.412)*	1.012 (25.733)*	1.100 (17.471)*	0.483 (6.695)*	0.143 (2.386)*	–0.007 (–2.522)*
Smallrloser	0.963	(755.173)*	0.000 (0.241)	1.008 (35.198)*	1.322 (28.827)*	0.752 (14.318)*	–0.380 (–8.703)*	–0.003 (–1.652)

Source Compiled from Dhankar and Shankar (2019)

Table 20.4 Residual momentum factor model appended with investor sentiment

Portfolio	Adjusted R-squared	F-statistic	Alpha	MRP_500	SMB	LMH	RWML	Sentiment
Bighigh	0.931	(385.513)*	0.006 (3.29)*	1.003 (39.175)*	0.233 (5.677)*	–0.082 (–1.589)	–0.104 (–1.927)^	–0.003 (–1.812)^
Bigmedium	0.921	(332.299)*	0.004 (1.729)^	1.045 (31.734)*	0.264 (5.001)*	0.320 (4.816)*	–0.246 (–3.543)*	–0.004 (–1.84)^
Biglow	0.923	(343.832)*	0.007 (2.124)*	1.072 (26.421)*	0.211 (3.251)*	1.036 (12.641)*	–0.245 (–2.868)*	–0.002 (–0.817)
Smallhigh	0.903	(266.465)*	0.007 (2.288)*	1.066 (26.315)*	1.296 (19.995)*	–0.048 (–0.589)	–0.327 (–3.836)*	–0.002 (–0.677)
Smallmedium	0.925	(353.361)*	0.003 (1.215)	1.058 (29.205)*	1.094 (18.871)*	0.488 (6.674)*	–0.082 (–1.07)	–0.005 (–1.991)*
Smalllow	0.970	(918.43)*	0.007 (3.616)*	0.996 (39.726)*	1.317 (32.819)*	0.834 (16.467)*	–0.186 (–3.52)*	–0.003 (–1.619)
Bigwinner	0.911	(292.451)*	0.002 (0.797)	1.031 (33.709)*	0.398 (8.142)*	0.306 (4.957)*	0.464 (7.191)*	–0.002 (–0.697)
Bigloser	0.902	(264.297)*	0.008 (2.553)*	1.102 (25.933)*	0.167 (2.451)*	0.107 (1.243)	–0.871 (–9.727)*	–0.006 (–2.113)*
Smallwinner	0.922	(340.793)*	0.004 (1.384)	1.041 (28.871)*	1.258 (21.804)*	0.605 (8.319)*	0.391 (5.145)*	–0.005 (–1.9)^
Smallloser	0.954	(591.949)*	0.006 (2.252)*	1.050 (32.394)*	1.207 (23.265)*	0.578 (8.836)*	–0.642 (–9.394)*	–0.003 (–1.336)
Bigrwinner	0.940	(449.678)*	0.003 (1.373)	1.023 (42.101)*	0.334 (8.588)*	0.249 (5.071)*	0.370 (7.22)*	–0.002 (–1.279)
Bigrloser	0.930	(379.096)*	0.005 (2.091)*	1.021 (30.929)*	0.191 (3.607)*	0.203 (3.048)*	–0.715 (–10.27)*	–0.006 (–2.565)*
Smallrwinner	0.912	(296.871)*	0.006 (2.247)*	1.016 (27.293)*	1.124 (18.862)*	0.602 (8.016)*	0.356 (4.531)*	–0.007 (–2.795)*
Smallrloser	0.966	(824.371)*	0.004 (1.759)^	1.018 (37.301)*	1.267 (29.005)*	0.648 (11.759)*	–0.560 (–9.728)*	–0.004 (–1.849)^

Source Compiled from Dhankar and Shankar (2019)

Conclusion

Since the stock market is susceptible to behavioural biases, inclusion of an investor sentiment factor seems logical for better performance of the asset pricing models. However, no single factor exists that can be taken to reflect investor sentiment. The investor sentiment created through five different proxies mimics the movements of Sensex, i.e. the benchmark index for Indian equities.

The investor sentiment index is then augmented as a factor in the popular multifactor asset pricing models. Investor sentiment factor finds significance in most of the characteristic portfolios when augmented in the Fama–French three-factor model. This reflects the inability of Fama–French three-factor model to correctly represent inherent risk.

Carhart four-factor model and residual momentum factor model, which has been included in the study as the residual momentum factor has been reported to be superior to total return momentum factor, provide similar results. The investor sentiment factor is significant in fewer of the characteristic portfolios. This can be due to the ability of momentum and residual momentum factor to capture some of the investor sentiment. If this notion is true, the source of momentum factor will be irrational, as opposed to some claims of momentum representing systematic risk that is not priced in the Fama–French three-factor model. The results suggest that investor sentiment is a contrarian predictor of stock market returns.

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