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ASSET PRICING WHEN MARKET SENTIMENTS REGULATE ASSET-RETURNS: EVIDENCES FROM EMERGING MARKETS

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Abstract

After 2003, the growth of equity prices in emerging markets in Asia, Latin America and Europe has been considerably higher in comparison with developed markets and, therefore, these markets have become the focus of attention of investors, the financial press, and researchers. These markets are needed to be studied separately because features of these markets are different from a developed market: on the one hand, they are hypersensitive to investors' sentiments and, on the other, equity returns are predictable by past observations. Unfortunately, common asset pricing models cannot explain such predictability in stock returns. The factor which is responsible for such predictability and hence the nonrandom behavior of the stock return can be accounted for in an asset pricing model. Based on this observation, the present paper proposes a generalization of the conventional asset pricing model. However, the framework would be applicable to all types of markets ranging from strictly efficient to inefficient.

Keywords: Capital Asset Pricing Model, Arbitrage Pricing Theory, emerging markets, market sentiments, Efficient Market Hypothesis

JEL Classifications: G11, G12, G14

1. Introduction

The world economy is moving gradually from a controlled and regulated environment to a liberalized and deregulated system. With this gradual shift in the policy regime worldwide and continuing opening up of economies, a number of new financial markets have emerged which are relatively riskier but at the same time ensure higher returns to investors. Some of these markets, mostly markets in economies like India and China, are growing exponentially and have become the focus of attention of investors, the financial press and researchers. According to Standard & Poor's, the market capitalization of emerging countries has more than doubled over the past decade, growing from less than $2 trillion in 1995 to over $5 trillion in 2006 (Parametric Portfolio Associates (2008)). As a percentage of world market capitalization, developing countries now

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account for more than 12%, and that share is steadily growing. Investors throughout the globe are continually discovering new avenues of investments in these markets. Consequently, it is a challenge to market researchers to develop a model for pricing of securities that would be applicable to an emerging market.

A natural question that might arise is: why does an emerging market need to be studied separately? The answer is inherent in the unique features of those markets. When an economy is relatively autarkic, the business in financial markets is confined to domestic players. Therefore, those markets were not developed enough. When the economies opened up, financial markets grew faster than anyone had forecasted. The markets became hypersensitive to investor sentiments. Unlike a developed market, countervailing forces are less active in emerging markets and, therefore, any common information disclosure fuels herd behavior that leads to a significant upturn or downturn in markets. The stock market crash in India in May 2006 is an example. The principal reason for the crash was the rise in interest rates in the United States. The effect was a reduction in foreign institutional investments (FII) in the relatively riskier emerging markets. FII withdrew from the Indian stock market and the market crashed. The outcome was independent of the fundamentals of Indian firms (see Majumder (2006)).

According to the theory of capital markets, news/information released in the market is the driving force behind an investor's investment decision. However, apart from news/information, an individual investor's investment decision is also guided by collective beliefs, also termed investors' sentiments. Investors' sentiments peak or trough when the market experiences extreme events. The effects gradually reduce with a reduction in volatility and finally reach normal levels with low volatility. Because investors' sentiment is reflected in today's movements in the equity price that subsequently regulate tomorrow's investment decisions, the equity price is expected to have a self-fulfilling trend. Therefore, an investor can expect that if the equity price falls (rises) today, the same trend is to be perceived tomorrow. Exceptions are likely to be fewer in number, because they originate in outcome of counter-cyclical news/information in the equity market. Consequently, it can be argued that the equity price today is an outcome of the combined effect of news/information released in the market and subsequent sentiments cultivated by them. Essentially, any analysis on the equity market remains incomplete if the effect of any one of the above two factors is neglected. Because of this feature of the equity market, it is generally observed that equity prices do adjust to new information, but the adjustment process is not instantaneous. Consequently, underreactions and overreactions by investors are common (see Chopra, Lakonishok and Ritter (1992), Barberis, Shleifer and Vishny (1998)). When investors underreact (overreact) to certain information, the equity price gradually adjusts to its fair value after a certain period. On both occasions, strong autocorrelations are induced in the equity price/return for the transition period when the equity price gradually accelerates towards its fair value. Therefore, investors' sentiment leads all the stocks to move in a particular direction that causes an equity return to be correlated to itself or to any other stock return. This factor is implicit behind the existence of nonrandomness in the equity price (return) which produces market imperfections (Brown (1979)). The effects of that factor are more prominent in an emerging market than a developed market that causes, on the one hand, a greater volatility in the equity return and, on the other, significant autocorrelations (see Chang, Lima and Tabak (2004), Mollah (2007) and Harvey (1995a and 1995b)). Even in a developed market like USA, it can be observed that equity returns are more volatile than implied by equity fundamentals (Shiller (1981); Leroy and Porter (1981)). The excess volatility in the stock returns, as explained by Shiller (1987) and Poterba and Summers (1988) was due to the fact that occasionally investors follow irrational trading rules that induce fads and bubbles for a longer time period. These characteristics of the equity return are even common in an emerging market and also the volatility in equity return is higher in the developing world as compared to the developed world (Parametric Portfolio Associates (2008)).

Against the above backdrop, it is critical to examine whether an emerging market confirms the risk-expected return relationship worked out in well-known asset pricing models of yesteryear. For a perfect capital market with no autocorrelations in the equity returns, the model describing the relationship between the expected return and systematic risk was first introduced by Sharpe (1964) and Lintner (1965). Ever since they invented the Capital Asset Pricing Model (CAPM), economists have systematically studied the theory for pricing an asset traded in a financial market. The scholarly outcome has been the Intertemporal Capital Asset Pricing Model (ICAPM) and Arbitrage Pricing Theory (APT) which are more sophisticated in comparison with the original CAPM (Merton (1973); Ross (1976)). Over the last four decades, investors, bankers and market researchers have used such models to predict asset returns under normal market conditions. The “normal market conditions” essentially means that equity prices are not driven by any sentiment or stocks are not systematically overvalued or undervalued by the market players. In such circumstances, markets act like efficient markets (Fama (1970, 1991 and 1998)). However, an anomaly arises when the assumptions do not apply. Especially for an emerging market, or when the market moves where sentiments dictate, it is imperative to explore the answer to the question: what are the additional factors that determine an investor’s expectation of a stock return? If some news drives market sentiments on a given day, a speculator usually does not expect the stock return to converge to its fair value the next day. Conversely, his expectation also depends on the sensitivity of that stock to the market sentiments. A common asset-pricing model cannot differentiate between the fair value of the return and the investors’ natural expectation of the return. However, there is a difference between the two. The difference would essentially be the influence of the market sentiments on the return of the stock. Most of the time, this influence has nonzero expectation and, therefore, cannot be mixed up with the random term of the model. This factor of the stock return is nonrandom and induces autocorrelations in the stock return. It is a salient factor of the stock return in an emerging market. This might be the rationale of the assumption of significant predictability in the stock returns in an emerging market (Harvey (1995a)).

Classical finance theory had given birth to a rich set of models for determining equilibrium asset returns. However, they left no room for investors’ sentiments. In this theory, most investors are rational and diversify to optimize certain statistical properties of their portfolios. Competition among them leads to an equilibrium, in which an investor’s expectation of the return reflects the fair value of the portfolio. In the present paper, we question the above methodology of forming expectations of the stock return. Ideally, the technology of forming expectations by a rational investor ought to vary with the state of the market. Consequently, we argue that if a market heads towards a crash due to a sudden panic and an investor expects the stock return to quickly converge to its fair value, he does not behave rationally. Therefore, our understanding is that expectations of the stock return would be rationally formed if an investor considers both implicit factors behind the fair return and the play of sentiments in the market. Paradoxically, the existing rational models for asset pricing that began to develop with Sharpe-Lintner CAPM might be a wonderful advancement in this profession, but one could easily understand that these models are not true descriptions of the world around us. Researchers in the present decade worked out a broader framework based upon the psychological behavior of investors (Shiller (2003) and Hirshleifer (2001)). In some of these approaches, security's expected returns are determined by both risks and misvaluations by investors. These behavioral models depend upon experiments that generate psychological biases which may possibly be large in the case of an emerging market. For these markets, abnormal flux in equity returns is merely common that is influenced by occasional exuberance or pessimism by investors. The misevaluations caused by these factors are virtually impossible to estimate. Alternatively, the domain of the standard rational model for asset pricing may be widened by incorporating collective sentiments of investors. Consequently, we propose an alternative approach for asset pricing in the line of the methodologies adopted by Majumder (2006).[2] This approach might be more appropriate for an emerging market.

The rest of the paper is organized as follows. Section 2 illustrates a dilemma (or anomaly) in conventional asset pricing models in case of manipulating them for an emerging market. In this section, it has been analyzed critically that conventional models do not include past returns or past factor scores as alternative explanatory variables, however, equity returns in emerging markets are often found highly correlated to their past values. We have provided a case study on Indian equity market for the period of 1st January, 2003 to 10th March, 2008 to establish our hypothesis. Section 3 provides a generalization of the conventional asset pricing model. Section 4 presents some statistical issues behind solving the model. Section 5 provides empirical analysis using data of 6 large emerging markets, Korea, India, Russia, Greece, Brazil and China. The conclusions are given in section 6.

2. Dilemmas in Asset Pricing: fitting a model having "no memory" using data with "significant memory"

The asset pricing models developed by the stalwarts of the previous century included the objective of designing a common specification of the return-generating process for common financial assets. This class of models presumes that the return on an asset would have two components: a predictable component which is a linear combination of several risk factors and an unpredictable component which is the noise. Among these models CAPM was developed first by Sharpe (1964) and Lintner (1965), in which a single source of risk was assumed. This risk is the systemic risk or the market risk and is measured by the market beta which is the slope of the regression of the return of an asset on the market return. A common interpretation of the market beta is that it measures the sensitivity of the asset's return to the variation in the market return.

Later, Ross (1976) improved on the CAPM by including several risk factors in the model. He developed Arbitrage Pricing Theory (APT) that begins with the assumption that the asset return ($R_{i,t}$) at time t is generated by a linear k-factor model:

$$R_{i,t} = E_i + b_{i1} f_{1,t} + ------ + b_{ik} f_{k,t} + e_{i,t} \quad \text{for } i = 1,\text{-----},n \qquad \text{... (1)}$$

[2] Majumder (2006) developed his model for stock pricing in the context of modeling credit risk.

where E_i is the expected return on asset i conditional on information set I_{t-1} known at the end of period t-1; $f_{j,t}$ is the j th factor score at time t; b_{ij} is the j th factor loading (j=1,----,k), which is constant during the sample period; and e_i represents an idiosyncratic risk specific to asset i. It is assumed that f_js are uncorrelated both with each other and with e_i and that the means of f_j and e_i are zero. Ross has shown that, if the number of securities (n) is sufficiently large and if there are no arbitrage opportunities, there exists numbers $\delta_0, \delta_1, ---, \delta_k$ such that

$$E_i \approx \delta_0 + \delta_1 b_{i1} + ------ + \delta_k b_{ik} \qquad \text{... (2)}$$

where $\approx$ represents "approximately equals" and δ_0 is the riskless rate of return or the return on a zero-beta asset. A common assumption about the residuals is that $e_{i,t} : t = 1, 2, ---$ is a sequence of identically and independently normally distributed random variables having mean zero and a constant variance. However, empirical tests on APT are usually performed with the normality assumption and also without the normality assumption of $e_{i,t}$ (Velu & Zhou (1999)). Under the normality assumption, the equity return in equation (1) will follow a normal distribution, parameters of which are specified by a given factor structure. In this approach, the model is estimated using an ordinary least square/maximum likelihood procedure of estimation. Without the normality assumption, the parameters are estimated using generalized method of moments. Some scholars are more interested to derive and test an asset pricing model without the normality assumption (Kwon (1985)). Our goal, however, cannot be to resolve the debate of whether equity returns are normal. We add another dimension to it by questioning the validity of the distributional assumption itself. The statistical theory reveals that a distributional assumption would be applicable only to a variable which is random. Ideally, randomness implies non-predictability over time. Therefore, if equity returns are random, they ought not to be predictable by any of its past values. In such a scenario, equity prices are expected to have the Markov property. Under the Markov assumption, only the present is relevant for predicting the future and, essentially, how the present evolved from the past is irrelevant. Such a hypothesis is effective for modeling the stock return when the stock market evolves with a special characteristic: all information generated by the market is instantaneously reflected in equity prices. Such a market is called an efficient market. In that market, past returns are presumed to have no memory or predictability power. Ideally, the assumption of market efficiency is a prerequisite before manipulating any asset pricing model, because an asset pricing model assumes that the future return can be forecasted only through present factor scores. Indispensably, past returns or past factor scores would have no role in predicting future returns. In that case, it is expected that residuals of the asset pricing model will possess no autocorrelation. However, on many occasions, reality differs from predictions because market data are generated naturally rather than experimentally and, especially for an emerging market, existence of strong autocorrelations in the residual has become a stylized phenomenon (Harvey (1995a and 1995b); Wright (2001); Chang, Lima and Tabak (2004) and Mollah (2007)). Under such circumstances, the validity of the distributional assumption for the equity return may be questioned.

In practice, equity prices do adjust to new information, but not instantaneously. Consequently, underreactions and overreactions by investors are common. In the case of such underreactions or overreactions, the equity price gradually adjusts to its fair value after a certain period. Gradual price adjustments after undereaction induce a positive autocorrelation, a price reversal caused by overreaction induces a negative autocorrelation in equity returns. Essentially, underreactions and overreactions are results of market sentiments that lead all the stocks to move in a particular direction resulting in an equity return to be correlated with itself or to any other stock return. Then, the question that would be important to market practitioners or researchers is whether common asset pricing models would be able to provide additional information to investors. The answer would necessarily be negative for traders who look for short-term gain by playing on market sentiments. This is so because the model cannot predict the direction and intensity of market sentiments. The second category of investors looks for long-term benefits by basing their decisions on information on equity-fundamentals. There, the dilemma is intractable because it is generally not possible to find equity returns as inputs in models that have not been driven by any sentiments. Essentially, for an equity market where investors' sentiments are prominent, equity returns become predictable, at least partially, by past observations. CAPM and APT cannot explain such predictability in stock returns (Ferson and Korajczyk (1995)). Consequently, it would be misleading to work with these models using input data which have significant predictability. Our hypothesis can be justified empirically by exploring following issues for an emerging market: i) are stock returns predictable over time? ii) if so, which factors do cause predictability?

2.1. Are stock returns predictable over time? - A case study (Indian Capital Market, from 1st January, 2003 to 10th March, 2008)

The Indian capital market is a representative of an emerging market which was relatively less developed before 1990s. However, after 1990s, a series of policy prescriptions, e.g. liberalization of the economy, deregulation of interest rates and globalization, by the Government and the Reserve Bank of India led the market to grow faster than other contemporary markets.

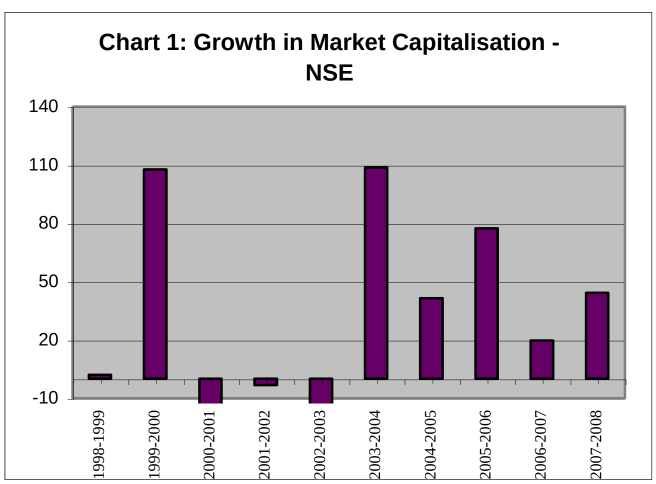


Chart 1 represents the growth over time of the total market capitalisation under National Stock Exchange (NSE) in India in the recent years. It shows a substantial growth over the preceding year of about 50 per cent on average in the last five consecutive financial years.

The mammoth investment growth in recent years has led the Indian capital market to represent itself as the 12^{th} largest in the world in respect of market capitalisation. Consequently, these markets have become the focus of attention of global investors. In such circumstances, the following natural questions arise: do equity returns[3] in the Indian stock market evolve as per the mechanism provided by a common asset pricing model? If not, what are the reasons?

We manipulate an arbitrage pricing model for stocks selected from the NSE market in India based on three risk factors: the return of the market portfolio and two world market indicators (e.g. return on the Nikkei portfolio and the effective Federal Reserve rate). Our sample includes weekly returns[4] of 15 large caps and 15 mid caps equities representing the NSE market in India. The companies are selected from a diversified range of entities considering their market capitalisation and reputation; the sample entities altogether cover a large proportion of total market capitalization. Table I and II below represent the regression results.

The table presents estimates, and p-values of the t-test of regression coefficients of the following regression equation over the period, 1^{st} January 2003 to 10^{th} March 2008,

$$R_t = b_0 + b_1 SP_t + b_2 NK_t + b_3 FED_t + e_t$$

R_t is the weekly rate of return on a equity at time t. SP_t is the weekly return on the S&P CNX 500 index (NSE, India). NK_t and FED_t are the weekly returns on the NIKKEI 225 index (Japan) and the effective Federal Reserve rate respectively. e_t is the random error. SP_t, NK_t and FED_t are centered around the mean. The table also presents generalized Durbin-Watson (D-W) statistics for 1^{st} to 4^{th} order error autocorrelations and R^2 of regressions. The generalised Durbin-Watson (D-W) statistics (d_k) for k th order error autocorrelation (ρ_k) is computed using

$$d_k = \frac{\sum_{t=k+1}^{n} \left(e_t - e_{t-k}\right)^2}{\sum_{t=1}^{n} e_t^2}$$

where n is the number of observations. This statistic has a range of from 0 to 4, with a midpoint 2 and is used to test the null hypothesis (H_0): e_t has no autocorrelation of order k. Such test can be performed with respect to upper and lower critical values, d_U and d_L: if $d_k < d_L$ reject H_0 and an indication of positive autocorrelation; If $(4\text{-}d_L) < d_k < 4$ reject H_0 and an indication of negative autocorrelation; If $d_L < d_k < d_U$ or $(4\text{-}d_U) < d_k < (4 - d_L)$ test is inconclusive;

[3] In the present section, we have performed an asset-specific empirical study, instead of drawing average or portfolio-level empirical results. The reason is that averaging asset returns would essentially smooth out effects of important extreme asset-specific fluctuations which will impede our objective of studying the effect of market sentiments on asset price.

[4] We have considered weekly returns for our empirical analysis because ‘a week’ is not too short and at the same time not too long a time period for computing returns. A relatively longer time period (e.g. ‘a month’) is not selected for calculating returns because those returns will not reflect any major upturn/downturn of the market that occurs within the period. Conversely, returns based on a relatively shorter time period (e.g. ‘a day’) are not considered because those returns are often regulated by the noise.

otherwise H_0 is accepted. In case d_k lies in the indecisive zone, we can use the modified Durbin-Watson (generalized) test under the assumption that d_U is approximately equal to the true significance limit (Theil (1971)). Under modified D-W test, H_0 would be rejected if $d_k < d_U$ or $(4\text{-}d_U) < d_k < 4$. The critical values for D-W (generalized) test for 5% significance level, 3 explanatory variables and 271 observations are d_L = 1.78 and d_U = 1.82. The occurrences of statistically significant D-W statistics under Durbin-Watson (generalized) test are marked in red. Cases under modified Durbin-Watson (generalized) test are marked in violet. The insignificant D-W statistics are marked in light grey.

Table I: Regressions of the equity return on the market return and selected other world market indicators

Company Name	OLS Estimates					Generalised D-W statistics for				
		b_0	b_1	b_2	b_3	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	R^2
Large Caps										
ABB Ltd.	♦ Coefficients	0.86	0.88	-0.07	-0.05	2.11	2.13	2.33	1.93	0.31
	♦ p-values	0.11	0.00	0.51	0.74					
Associated Cement Co Ltd.	♦ Coefficients	0.22	0.90	0.00	-0.03	2.04	1.71	2.12	1.99	0.37
	♦ p-values	0.65	0.00	0.93	0.78					
Bharti Airtel Ltd.	♦ Coefficients	1.67	0.75	0.18	-0.27	2.03	2.20	2.17	1.96	0.26
	♦ p-values	0.00	0.00	0.13	0.10					
Bharat Petroleum Corp Ltd.	♦ Coefficients	0.02	1.03	0.15	-0.12	2.35	2.16	1.89	2.12	0.36
	♦ p-values	0.96	0.00	0.22	0.47					
Dabur India Ltd.	♦ Coefficients	0.69	0.75	0.14	-0.25	2.28	2.01	2.16	2.00	0.12
	♦ p-values	0.44	0.00	0.43	0.31					
Grasim Industries Ltd.	♦ Coefficients	0.68	0.97	-0.01	-0.13	2.18	1.73	2.21	1.92	0.42
	♦ p-values	0.16	0.00	0.84	0.33					
HCL Technologies Ltd.	♦ Coefficients	0.65	0.79	0.34	-0.30	2.23	2.43	1.70	2.11	0.10
	♦ p-values	0.57	0.00	0.16	0.34					
HDFC Ltd.	♦ Coefficients	0.01	0.88	-0.00	0.06	2.63	2.08	2.01	2.07	0.34
	♦ p-values	0.97	0.00	0.96	0.62					
ICICI Bank Ltd.	♦ Coefficients	0.17	0.98	0.14	-0.01	2.52	1.94	2.15	2.10	0.40
	♦ p-values	0.74	0.00	0.19	0.91					
ONGC	♦ Coefficients	0.41	1.10	-0.01	-0.19	2.34	2.01	1.84	1.98	0.42

	♦ p-values	0.44	0.00	0.88	0.02					
Punjab National Bank	♦ Coefficients	0.96	1.18	0.22	-0.29	2.04	2.64	2.24	1.94	0.17
	♦ p-values	0.41	0.00	0.37	0.37					
Reliance Industries Ltd.	♦ Coefficients	-0.28	0.91	0.07	0.16	2.03	1.94	2.05	2.23	0.47
	♦ p-values	0.50	0.00	0.36	0.15					
Tata Steel Ltd.	♦ Coefficients	0.03	1.16	0.27	-0.03	2.24	1.93	2.13	1.86	0.39
	♦ p-values	0.95	0.00	0.04	0.83					
WIPRO Ltd.	♦ Coefficients	-1.79	0.96	-0.21	0.22	2.05	2.01	1.98	2.08	0.10
	♦ p-values	0.11	0.00	0.36	0.46					
Hindalco Industries Ltd.	♦ Coefficients	0.05	1.27	0.24	-0.12	2.62	2.57	1.52	2.22	0.11
	♦ p-values	0.98	0.00	0.49	0.80					
Mid Caps										
Andhra Bank	♦ Coefficients	0.65	1.35	0.00	-0.28	2.35	2.32	1.85	1.93	0.27
	♦ p-values	0.49	0.00	0.99	0.28					
Aventis Pharma Ltd.	♦ Coefficients	1.45	0.60	0.12	-0.44	2.04	2.27	2.19	1.80	0.25
	♦ p-values	0.00	0.00	0.23	0.00					
Bank Of Baroda	♦ Coefficients	0.05	1.47	-0.09	-0.10	2.22	1.87	2.10	2.18	0.45
	♦ p-values	0.93	0.00	0.48	0.57					
Bank Of India	♦ Coefficients	-0.48	1.59	-0.11	0.12	2.30	1.88	1.97	2.11	0.44
	♦ p-values	0.51	0.00	0.45	0.55					
Bharat Electronics Ltd.	♦ Coefficients	0.60	0.98	0.01	-0.13	2.25	2.05	1.97	1.98	0.33
	♦ p-values	0.30	0.00	0.92	0.41					
Bharat Forge Co Ltd.	♦ Coefficients	1.46	1.01	-0.14	-0.42	2.25	2.22	1.85	2.17	0.42
	♦ p-values	0.00	0.00	0.15	0.00					
Bongaigaon Refinery Ltd.	♦ Coefficients	0.72	1.61	-0.28	-0.36	2.24	1.97	1.78	1.91	0.42
	♦ p-values	0.33	0.00	0.07	0.08					
I-FLEX Solutions Ltd.	♦ Coefficients	-1.14	0.81	0.10	0.22	2.19	2.04	1.91	1.94	0.15
	♦ p-values	0.18	0.00	0.57	0.35					
Ingersoll-Rand India Ltd.	♦ Coefficients	-.033	0.77	-0.05	-0.00	2.46	1.88	1.89	1.87	0.20
	♦ p-values	0.59	0.00	0.65	0.98					
Punjab	♦ Coefficients	-0.26	0.68	0.12	0.02	2.19	2.19	1.98	1.65	0.18

Tractors Ltd.	♦ p-values	0.68	0.00	0.36	0.90					
RAYMOND Ltd.	♦ Coefficients	0.83	0.96	-0.10	-0.31	2.25	2.24	2.03	1.89	0.33
	♦ p-values	0.14	0.00	0.36	0.04					
Reliance Capital Ltd.	♦ Coefficients	-0.20	1.52	-0.08	0.15	2.07	2.01	1.81	2.12	0.41
	♦ p-values	0.78	0.00	0.61	0.47					
SYNDICATE BANK	♦ Coefficients	0.34	1.51	-0.07	-0.18	2.15	1.81	2.28	1.87	0.44
	♦ p-values	0.62	0.00	0.63	0.35					
Union Bank Of India	♦ Coefficients	0.73	1.52	1.13	-0.26	2.32	2.40	1.99	2.09	0.24
	♦ p-values	0.52	0.00	0.58	0.41					
Vijaya Bank	♦ Coefficients	0.84	1.26	-0.18	-0.31	1.95	1.82	2.34	2.10	0.36
	♦ p-values	0.21	0.00	0.18	0.10					

Table I shows a wide variation in the estimates of regression coefficients, their p-values and Durbin-Watson (generalized) statistics among companies. However, following similarities among them are observed. The market beta (b_1) is high on the positive side and significant for all sampled stocks. However, betas for Nikkei index (b_2) and FED rate (b_3) possess higher p-values[5] (greater than 0.1) for most of the stocks, which imply insignificance of those betas. Therefore, we can infer that stock returns in the Indian equity market are predictable, highly by the market return, but not so predictable by other world market indicators. The result is consistent with other findings that the emerging market returns are generally influenced by local rather than global information variables (Harvey (1995a)). Beside these, for almost all cases, Durbin-Watson (generalized) test indicates that atleast one of 1^{st} to 4^{th} order error autocorrelations are significantly different from zero. We find, however, no uniformity among stocks in the order of the error autocorreclation to be significant. Upon these consequences, it is interesting to observe that if the error autocorreclation at some specified lag is found significant for a particular stock, there is no reason to infer that the same is to be true for another stock. Our above observations may lead following inferences: for almost all stocks, along with the market return, one or more lagged equity returns may have a significant predictability power. However, in the case of a particular stock, the order of the significant lag and the degree of its predictability is a further empirical issue to investigate. In this scenario, we can expect that addition of a suitable lagged variable as an additional explanatory variable may develop an empirical model providing a better fit to the data, which, however, does not have enough theoretical justifications.

The predictability of the equity return by lagged returns, as we have explained earlier, might be the outcome of the play of sentiments in the market. If our hypothesis is true, then such predictability will necessarily increase when the market passes through a high volatile state. In such scenario, the future becomes increasingly uncertain and so it seems difficult for investors to

[5] Generally, one rejects the null hypothesis if the p-value is smaller than or equal to the significance level.

forecast tomorrow's equity return. In such a state of the market, it is natural that investors' decisions would be influenced by exuberance or pessimism. Consequently, our basic presumption, "market sentiments is a major driving force behind over time predictability of a stock return", can be tested by comparing the predictability power of lagged returns in the high volatile state of the market with their overall predictability. For identifying the high volatile time period, we have plotted below weekly returns on S&P CNX 500 index for the time period from 1st January 2003 to10th March 2008 (chart 2).

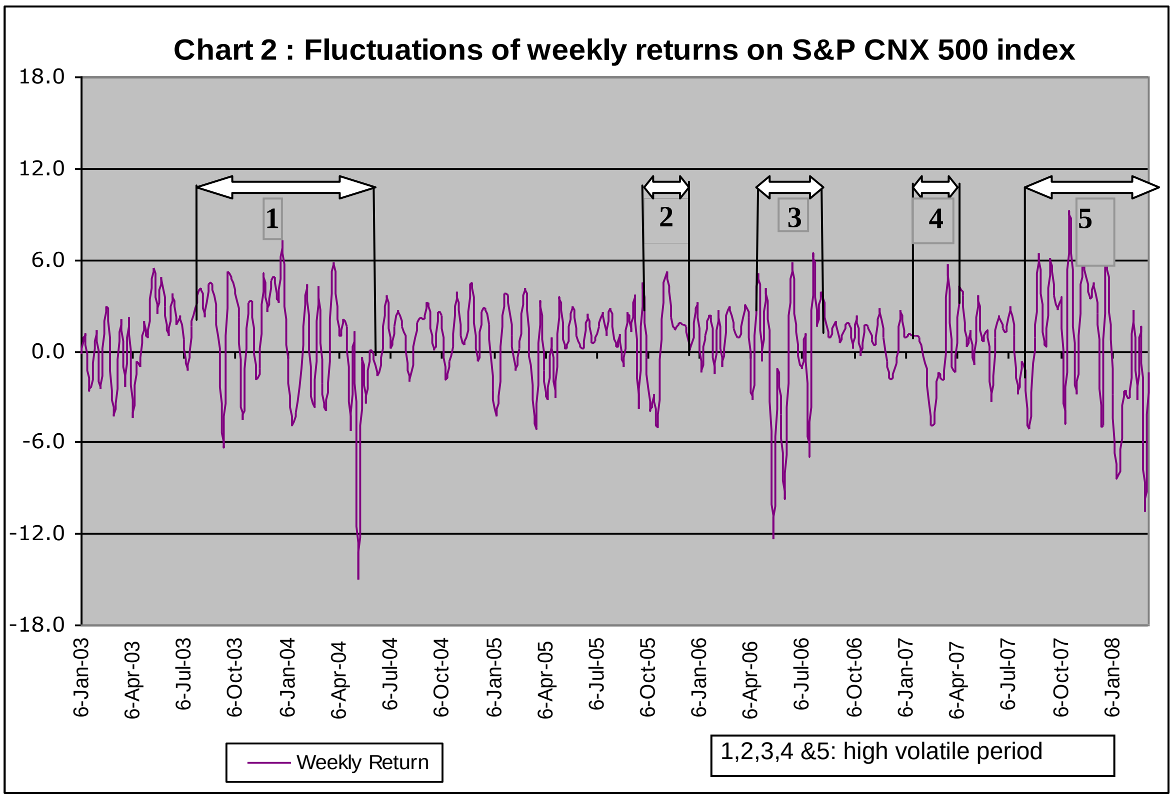


Chart 2 has identified five extreme/stress scenarios, marked by 1, 2,3, 4 and 5. The proximate causes of high volatility in those time period are: **1:** 28/07/2003 to 31/05/2004, an uncertainity in foreign institutional investments and panic due to post-election uncertainties; **2:** 12/09/2005 to 14/11/2005, the effects of the Demat/IPO scam; **3:** 27/03/2006 to 14/08/2006, petroleum price movements and intensification of conflict in the Middle East; **4:** 19/02/2007 to 16/04/2007, uncertain effects on the economy/markets of the tax reform in the Budget proposal 2007-08; **5:** 13/08/2007 to 10/03/2008, spillover effects of subprime crisis in USA, increase of domestic commodity inflation and oil price inflation.

The table presents estimates, and p-values of the t test of regression coefficients of the same regression equation as in table I for the same sampled companies, only for different set of returns. The table also presents generalized Durbin-Watson (D-W) statistics for 1st to 4th order error autocorrelations and R^2 of regressions. Only high volatile time periods are included (i.e. scenarios 1, 2, 3, 4 and 5 marked in the chart 2).. These critical values (d_U and d_L) of the D-W test for 5% significance level, 3 explanatory variables and 116 observations are d_L = 1.64 and d_U = 1.75. Accordingly, the generalized D-W test would detect non-zero autocorrelation if $d_k < d_L$ or $(4\text{-}d_L) < d_k < 4$. Such cases are marked in red. In case d_k lies in the inconclusive zone, we can use the modified Durbin-Watson (generalized) test (Theil (1971)). Under the modified D-W test, ρ_k would be significant if $d_k < d_U$ or $(4\text{-}d_U) < d_k < 4$. Such cases are marked in violet. The insignificant D-W statistics are marked in light grey.

Table II: Regressions of the equity return on the market return and selected other world market indicators for the high volatile state of the market

Company Name	OLS Estimates									
		b_0	b_1	b_2	b_3	Generalised D-W statistics for $\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	R^2
Large Caps										
ABB Ltd.	♦ Coefficients	0.96	0.89	-0.12	-0.21	2.45	2.00	2.19	1.78	0.46
	♦ p-values	0.23	0.00	0.40	0.33					
Associated Cement Co Ltd.	♦ Coefficients	0.37	0.87	0.05	-0.19	2.27	1.54	2.04	2.07	0.44
	♦ p-values	0.67	0.00	0.77	0.43					
Bharti Airtel Ltd.	♦ Coefficients	1.97	0.75	0.33	-0.38	2.23	2.29	2.21	1.82	0.39
	♦ p-values	0.04	0.00	0.07	0.15					
Bharat Petroleum Corp Ltd.	♦ Coefficients	-0.01	1.07	0.04	0.03	2.41	2.28	1.80	2.10	0.45
	♦ p-values	0.99	0.00	0.85	0.92					
Dabur India Ltd.	♦ Coefficients	0.31	0.86	-0.30	-07	2.58	1.66	2.42	1.98	0.33
	♦ p-values	0.75	0.00	0.10	0.79					
Grasim Industries Ltd.	♦ Coefficients	1.23	0.99	0.04	-0.28	2.37	1.60	2.30	2.03	0.51
	♦ p-values	0.15	0.00	0.80	0.22					
HCL Technologies Ltd.	♦ Coefficients	1.84	0.73	0.58	-0.69	2.22	2.46	1.68	2.12	0.11
	♦ p-values	0.45	0.02	0.21	0.30					
HDFC Ltd.	♦ Coefficients	0.14	0.88	-0.05	0.05	2.62	2.03	2.69	2.01	0.45
	♦ p-values	0.86	0.00	0.72	0.83					
ICICI Bank Ltd.	♦ Coefficients	0.40	1.00	0.23	-0.06	2.50	1.94	2.21	2.25	0.50
	♦ p-values	0.67	0.00	0.18	0.80					
ONGC	♦ Coefficients	0.12	1.18	-0.05	0.01	2.32	2.18	1.79	2.18	0.61

	♦ p-values	0.89	0.00	0.76	0.98					
Punjab National Bank	♦ Coefficients	0.13	1.05	0.51	-0.04	2.13	2.80	2.26	2.20	0.16
	♦ p-values	0.96	0.00	0.26	0.95					
Reliance Industries Ltd.	♦ Coefficients	-0.44	0.94	-0.02	0.31	2.40	1.73	1.95	2.27	0.65
	♦ p-values	0.46	0.00	0.84	0.06					
Tata Steel Ltd.	♦ Coefficients	0.12	1.12	0.30	0.05	2.39	2.05	2.20	1.72	0.51
	♦ p-values	0.91	0.00	0.12	0.85					
WIPRO Ltd.	♦ Coefficients	0.93	0.69	0.14	-0.31	2.27	2.45	1.78	2.26	0.35
	♦ p-values	0.29	0.00	0.41	0.20					
Hindalco Industries Ltd.	♦ Coefficients	-0.22	1.33	0.55	0.04	2.62	2.58	1.45	2.26	0.12
	♦ p-values	0.95	0.00	0.42	0.97					
Mid Caps										
Andhra Bank	♦ Coefficients	-0.34	1.32	0.14	0.03	2.44	2.48	1.80	2.05	0.28
	♦ p-values	0.86	0.00	0.68	0.96					
Aventis Pharma Ltd.	♦ Coefficients	1.66	0.58	0.16	-0.56	2.19	2.01	2.36	1.68	0.34
	♦ p-values	0.04	0.00	029	0.01					
Bank Of Baroda	♦ Coefficients	-0.80	1.35	0.05	0.16	2.25	1.77	1.99	2.26	0.58
	♦ p-values	0.42	0.00	0.78	0.55					
Bank Of India	♦ Coefficients	-1.05	1.51	-0.12	0.24	2.40	1.98	1.87	2.30	0.52
	♦ p-values	0.38	0.00	0.60	0.47					
Bharat Electronics Ltd.	♦ Coefficients	-0.44	1.04	0.08	-0.04	2.60	2.26	1.91	1.83	0.47
	♦ p-values	0.65	0.00	0.68	0.88					
Bharat Forge Co Ltd.	♦ Coefficients	0.76	1.04	-0.14	-0.27	2.52	2.15	1.70	2.24	0.53
	♦ p-values	0.35	0.00	0.36	0.23					
Bongaigaon Refinery Ltd.	♦ Coefficients	-0.04	1.72	-0.55	-0.08	2.32	1.98	1.71	1.96	0.54
	♦ p-values	0.97	0.00	0.2	0.82					
I-FLEX Solutions Ltd.	♦ Coefficients	-3.21	0.91	0.02	0.54	2.06	2.33	1.70	2.04	0.21
	♦ p-values	0.04	0.00	0.95	0.20					
Ingersoll-Rand India Ltd.	♦ Coefficients	-0.55	0.79	-0.09	-0.19	2.53	1.56	1.88	2.00	0.35
	♦ p-values	0.54	0.00	0.58	0.45					
Punjab	♦ Coefficients	0.53	0.76	0.06	-0.19	2.00	2.32	1.79	1.48	0.28

Tractors Ltd.	♦ p-values	0.62	0.00	0.76	0.52					
RAYMOND Ltd.	♦ Coefficients	0.36	1.01	-0.13	-0.15	2.27	2.38	2.02	1.95	0.39
	♦ p-values	0.73	0.00	0.51	0.59					
Reliance Capital Ltd.	♦ Coefficients	-0.08	1.56	0.06	0.41	2.36	2.24	1.67	2.26	0.51
	♦ p-values	0.96	0.00	0.80	0.91					
SYNDICATE BANK	♦ Coefficients	-0.22	1.52	-0.08	-0.06	2.39	1.61	2.36	1.81	0.54
	♦ p-values	0.84	0.00	0.72	0.85					
Union Bank Of India	♦ Coefficients	-0.17	1.45	0.41	-0.05	2.36	2.49	1.97	2.17	0.25
	♦ p-values	0.94	0.00	0.35	0.94					
Vijaya Bank	♦ Coefficients	0.51	1.25	-0.20	-0.23	1.10	1.67	2.12	2.05	0.49
	♦ p-values	0.62	0.00	0.30	0.42					

Our sample includes altogether stocks of 30 companies. For each company, D-W (generalized) statistics are computed for testing significance of 1st to 4th order error autocorrelations. The total number of D-W (generalized) statistics computed for the whole sample is 120. On these 120 occasions, the number of cases where the D-W test detects non-zero autocorrelations is 46 in table I, and for table II, this number is 64. We find that for each row in the table II, the number of statistically significant D-W (generalized) statistics is at least two on almost all occasions. Besides, it can be observed that the values of D-W (generalized) statistics in table II are largely divergent, being dispersed from the number "2" either on the higher or on the lower side, whereas those values in table I are relatively centered around "2". Ordinarily, the value of D-W (generalized) statistics dispersed from the number "2" indicates strong autocorrelation in the error. The findings lead to some interesting inferences: the occasions where D-W (generalized) statistics are statistically significant are not infrequent both in table I and II, which indicate, in general, a non-zero predictability of one or more lagged equity returns to regress an equity return both in the normal state of the market and in the high volatile state. Additionally, error autocorrelations are significantly different from zero in greater number of occasions in the table II as compared to those of the table I. This significance would either be in the higher side or in the lower side: the value of D-W statistic greater than the upper critical bound indicates negative autocorrelation in the error and the value less than the lower critical bound indicates positive autocorrelation in it. The frequency of occurrences and the relative values of both the positive and negative autocorrelations in the error are relatively greater in the table II as compared to those in the table I. These observations are consistent with our hypothesis that autocorrelations in the error ought to be higher in the high volatile state of the market as compared to that of the normal state. Such autocorrelations manifest the predictability power of lagged returns to express an equity return which is often greater in the high volatile state of the market as compared with its overall predictability.

3. The Asset Pricing Model – A Generalisation

The capital market is composed of a continuum of investors who purchase or sell financial assets in the form of equities. We assume that the market is frictionless. However, it is influenced by the collective sentiments of investors. Investors are assumed to have homogeneous beliefs about the returns of each asset. The beliefs are governed by several factors. These factors are of two kinds: one set of factors is correlated with fundamentals and the other set of factors is uncorrelated with them. Ideally, effects of fundamentals on the stock return cause a systematic change in it. This would essentially be the long-term component of the stock return. This component is influenced by factors like the financial health of the firm, implicit market risk and the economy's position in the business cycle etc. The financial health of a firm can be assessed by some parameters like the firm size, the leverage, earnings-to-price ratios, book-to-market equity ratios etc. In contrast, nonfundamentals would essentially be the transitory component of the stock return which is influenced by factors like investors' sentiments and noise. In the short run, the market sentiment influences all the stocks in a specific direction, either upward or downward. The resulting stock returns depart from their fair values. Consequently, the short-run expectation of the return of a stock depends, with other factors, on the market sentiments. However, in the long run, the market reaches its normal position where the effects of sentiments are zero and, therefore, the expectation would be consistent with the fundamentals.

3.1. The Equity Return

The return based on the firm's equity prices at time t, R_t^E, can be broadly decomposed into two parts: the part that is consistent with equity fundamentals (R_t^{Ex}) and the part that is unexplained by fundamentals (R_t^{UEx}). It can be assumed that R_t^{Ex} is governed by the factor, F_t, which is composed of the linear combination of all factors correlated to fundamentals. Similarly, R_t^{UEx} may be assumed to be governed by the factor, M_t, which is composed of the linear combination of all factors uncorrelated to fundamentals. If factors, F_t and M_t, are linearly related to form R_t^E, we can write:

$$R_t^E = (1-\alpha)F_t + \alpha M_t \quad \text{... (3)}$$

where α is the relative weight to the factor M_t. Further, M_t may be thought as a linear combination of the effects of two factors: the market sentiment (S_t) and a random component ($e^/$). Therefore,

$$M_t = \beta S_t + (1-\beta)e^/ \quad \text{...(4)}$$

where β is the relative weight to the factor S_t. Using equation (4), equation (3) can be rewritten as:

$$R_t^E = (1-\alpha)F_t + \eta S_t + e \quad \text{... (5)}$$

where $\eta = \alpha.\beta$ and $e = \alpha(1\text{-}\beta)e^/$. Representing the equation (5) in terms of betas, we get:

$$\beta_{R,S} = 1-\alpha\ \beta_{F,S} + \eta\beta_{S,S}$$

where $\beta_{I,S} = \dfrac{\text{Covariance}\ \ I,S}{\text{Variance}\ \ S}$ gives the sensitivity of the factor I (I = R/F) to the market sentiment, S_t. By definition, the factor S_t is uncorrelated to that of F_t. Therefore,

$$\eta = \beta_{R,S}$$

In the equation (5), $1-\alpha\ F_t$ is essentially the part of the equity return that is consistent with fundamentals, therefore, an alternative representation of equation (5) in terms of R_t^{Ex}, S_t and e would be:

$$R_t^E = R_t^{Ex} + \beta_{R,S}S_t + e \qquad \text{... (6)}$$

Because R_t^{Ex} is consistent with fundamentals, R_t^{Ex} is the explainable part of the stock return by an efficient asset pricing model. However, S_t is not observable from the market. We can estimate S_t from the observed return on the market portfolio (R_t^M).

3.2. The Market Return

Similar to a conventional asset pricing model, we assume that there exists a well-diversified portfolio, called the market portfolio, which is the optimal portfolio for at least one utility-maximising investor. Because of the diversified nature of that portfolio, the nonsystemic risks of each asset sums up net to zero. The only risk that exists in the market portfolio is the systemic risk. Therefore, the return of such a portfolio is regulated by those factors which fuel systemic risk. These factors may be of two types: one linked to fundamentals and others not so linked. Here, unlike the equity of a single firm, fundamentals are more economy-specific than firm-specific. For a given factor structure, we can divide the return of the market portfolio (R_t^M) into two parts: the part consistent with fundamentals (R_t^{Mx}) and the part unexplained by fundamentals (R_t^{UMx}):

$$R_t^M = R_t^{Mx} + R_t^{UMx} \qquad \text{... (7)}$$

R_t^{Mx} is influenced by the elements like the growth of macro variables, external shocks and any upturn/downturn of domestic/or international markets. Macro variables like inflation, growth and interest rates etc. have an influence on the market return due to the fact that when the economy is on the upturn/downturn, the condition applies to all firms; external shocks, e.g. a rise in the interest rate in the USA, may have a spillover effect on the emerging economy and hence an emerging market; any upturn/downturn in returns of market portfolios of other markets have an influence on R_t^{Mx} because it is expected to correlate with other markets. Therefore,

$$R_t^{Mx} = \beta_I I_t + \beta_Z Z_t + \beta_A R_t^A \qquad \text{... (8)}$$

where I_t is a suitable macroeconomic indicator, Z_t is a external variable that has influence on the domestic market and R_t^A is an another domestic/or international market return. Betas are the factor loading. All factors are are centered around the mean.

Conversely, the components of R_t^{UMx} include investors' sentiment (S_t) and noise (e^M). Investors' sentiment collectively generates underreactions or overreactions to certain information. Consequently, the market return departs from its fair value. In course of time it reverts to its original position. Therefore,

$$R_t^{UMx} = S_t + e^M \qquad \text{... (9)}$$

Using equations (8) and (9), equation (7) can be rewritten as below:

$$R_t^M = S_t + \beta_I I_t + \beta_Z Z_t + \beta_A R_t^A + e^M \qquad \text{... (10)}$$

The market sentiment, S_t, is unobservable. At the same time, it can be defined as the nonrandom departure of the market return from its fair value. This part of the market return is explained by the exuberance or pessimism by investors to certain information. Consequently, any autocorrelation that is observed in the market return is the result of possible bullish/bearish responses by investors to market information.

3.3. Modeling Expectation of the Equity Return

Using equations (6) and (10), and because of the fact that e and e^M has zero expectations, R_t^{Ex} can be solved as below:

$$R_t^{Ex} = E\left[\ R_t^E - \beta_{E,\chi}\chi_t\right] \qquad \text{... (11)}$$

where $\chi_t = R_t^M - \beta_I I_t + \beta_Z Z_t + \beta_A R_t^A$, and E(.) is the expectation operator. As per our notations, R_t^{Ex} is the part of the equity return consistent with fundamentals and which, therefore, can be explained by an efficient asset pricing model. Unlike the traditional approach, R_t^{Ex} is not the simple expectation of the equity return, but it is the expectation of the equity return where effects of market sentiments on a particular stock have been eliminated.

Equation (11) reveals that if a hypothetical equity market is formed with the equity return as $R_t^{EH} = R_t^E - \beta_{E,\chi}\chi_t$ and all other parameters are identical to the existing equity market, then such a market would be an efficient market because, in that market, equities are not systematically overvalued or undervalued by market players and prices are consistent with fundamentals. The above market may be used efficiently as an input in any common bond or stock or option pricing model. For an example, we develop below a four-factor asset pricing model which is a modification of the Fama and French (1993) model.

An example

We assume that equity returns in the hypothetical equity market are governed by three classes of factors: firm-specific factors, market-specific factors, and economic indicators. The firm-specific factors, e.g. firm size, leverage, earnings-to-price ratios, and book-to-market equity ratios etc., are responsible for the cross-sectional variation in the stock returns. Accordingly, we can follow the Fama and French (1992, 1993 & 1995) model where they posit a theoretical justification of 1) the relationship between the firm size and the expected stock returns which should be negative and 2) the relationship between book-to-market equity (BE/ME) and the expected stock returns which should be positive. For validating the model, they used two variables, SMB and HML, where SMB is the difference between the return on a portfolio of smaller stocks and portfolio of bigger stocks and HML is the difference between the return on a portfolio of high BE/ME stocks and the return on a portfolio of low BE/ME stocks.

The market-specific factors, e.g. hike/fall in oil prices, political uncertainties etc., affect the overall demand/supply conditions of the market and hence change equity prices/returns of all firms in the market. We can assume that all such factors are summarized in the market index. The macroeconomic indicators, e.g. overall industrial production, are also implicit behind a change in the equity return because, as indicated earlier, the position of the economy on the cycle impacts on all firms in the market. On the basis of the above analysis, we can write our model:

$$R_t^{EH} = \beta_{H0} + \beta_{H1} R_t^{MH} + \beta_{H2} SMB_t^H + \beta_{H3} HML_t^H + \beta_{H4} IIP_t + e^H \qquad \text{... (12)}$$

where R_t^{MH} is the return at time t on the market portfolio of the new hypothetical stock market, IIP_t is the industrial production index and e^H is the noise. Unlike the return on the original market portfolio R_t^M , R_t^{MH} cannot be estimated directly from the historical values of the market index. However, the same can be derived:

$$R_t^{MH} = \sum_i w_i R_t^{EH_i} \qquad \text{... (13)}$$

where w_i is the weight attached to the ith stock in the market portfolio. One can choose w_i in the same way as it is in the original market portfolio (i.e. $R_t^M = \sum_i w_i R_t^{E_i}$) .

Equation (12) is similar to a four-factor arbitrage-pricing model; the only difference is that the present model is based on a transformed market where effects of market sentiments are isolated from equity prices. Essentially, our model is a generalization of the four-factor arbitrage-pricing model applicable to an inefficient market. The model facilitates the isolation of the long run expectation of the equity return E^L from the short run expectation E^S . In the long run, the effects of the market sentiments are zero; therefore, the expectation of the stock return would essentially be:

$$E^L\left(R_t^E\right) = E\left(R_t^{EH}\right) = \beta_{H0} + \beta_{H1} R_t^{MH} + \beta_{H2} SMB_t^H + \beta_{H3} HML_t^H + \beta_{H4} IIP_t \qquad \text{... (14)}$$

On the other hand, in the short run, the expectation of return would be governed by, with other factors, market sentiments and may be assessed from the following equation:

$$E^S\ R_t^E\ = E\ R_t^{EH}\ + \beta_{E,\chi} E\ \chi_t\ = \beta_{H0} + \beta_{H1} R_t^{MH} + \beta_{H2} SMB_t^H + \beta_{H3} HML_t^H + \beta_3 IIP_t + \beta_{E,\chi} E\ \chi_t \qquad \text{... (15)}$$

If the underlying market is efficient, then equity prices instantaneously adjust to new information. In such a case, unenthusiastic or overenthusiastic responses to information, if any, would occur randomly. Consequently, the long-run and the short-run expectation of the equity return would be identical and, therefore, our model would be transformed to the common four-factor arbitrage-pricing model.

3.4. The Market Risk

Traditionally, the market risk faced by an individual stock is measured by the beta which estimates the sensitivity of the return of the stock to the market return. The beta is an important factor in explaining the asset return in a common asset-pricing model. However, when the market return is driven by investors' sentiments, the value of the beta would be biased due to those sentiments. Such a beta cannot be an input to explain the expected stock return. The rationale behind the argument is that a conventional asset pricing model was developed to estimate the fair value of the return and, naturally, investors' sentiments cannot be a factor to explain the fair value. Market risk must be a factor, but that risk ought not to be driven by any sentiments. The dilemma is intractable for an emerging market, because for those markets it is not possible to find equity prices that have not been driven by any sentiments. Consequently, any assessment of beta must be biased by market sentiments. Therefore, it is worthwhile isolating an explicit market risk, that is, the risk generated from market sentiments, from an implicit market risk, that is the risk of adverse movements of the market return when there is no play of sentiments. The former type of market risk originates when any news in the market fuels investors' sentiments collectively and lead all the stocks in a particular direction. Such risk is represented in our model by $\beta_{E,\chi}$. The latter type of market risk is the risk in an efficient market that is akin to the market risk depicted in the Capital Asset Pricing model. In the present model, it is denoted by β_{H1}.

4. Solving the Model - Some Statistical Issues

An alternative representation of equation (10) would be:

$$R_t^M = S_t + R_t^{Mx} + e^M \qquad \text{... (16)}$$

Equation (16) indicates that the difference between the market return, R_t^M, and estimated fair return, R_t^{Mx}, is the market sentiment mixed with noise:

$$R_t^M - R_t^{Mx} = S_t + e^M$$

or

$$E\ R_t^M - R_t^{Mx}\ = S_t \qquad \text{... (17)}$$

where E(.) is the expectation operator. Equation (17) reveals that an unbiased estimator of the market sentiment (S_t) is $R_t^M - R_t^{Mx}$. Therefore, without loss of generality, we can use $R_t^M - R_t^{Mx}$ in place of χ_t in equation (11). Finally, estimation of our model is translated to solving system of simultaneous equations as stated in the Model II of Table III.

5. Empirical Findings

The methods developed in the previous pages are now applied using sectoral portfolio returns from different emerging markets. Our empirical study includes six large emerging stock markets throughout the globe. These stock markets are KRX market in Korea, NSE market in India, RTS market in Russia, Athens stock market in Greece, Bovespa market in Brazil and China's A share market. We have considered available sectoral indexes compiled by above emerging market exchanges. In the case of China, we have considered MSCI indexes for different sectors. The sample includes 30 sectoral portfolio returns which are regressed on market returns and other selected indicators. The data on weekend returns for these portfolios and also on the selected indicators has been downloaded from the Bloomberg system. Both conventional arbitrage-pricing model and the modified arbitrage-pricing model developed by us are estimated and a comparative result is presented in tables III and IV. The above two models are compared in respect of beta parameters and the residual volatility.

Conventional arbitrage-pricing model is estimated by regressing the equity return R_t^E on the market return and selected other indicators. We have chosen Nekkei 225 index NK_t and Dow Jones Industrial Average DOW_t as suitable indicators because they have an influence on emerging markets returns. In estimating modified arbitrage-pricing model described in the preceding section, we may follow two steps procedure: **Step 1**: market return R_t^M is regressed on selected indicators. We have chosen FED rate in USA FED_t, returns on Nekkei 225 index NK_t and Dow Jones Industrial Average DOW_t as suitable indicators for emerging markets. The selected market portfolios are: KRX 100 index in Korea, S&P CNX 500 index in India, RTS index in Russia, ASE general index in Greece, BOVESPA index in Brazil and China A's stock index. **Step 2**: we regress the transformed equity return R_t^{EH} on the transformed market return R_t^{MH} and selected other indicators. Similar to the case of original arbitrage-pricing model, Nekkei 225 index NK_t and Dow Jones Industrial Average DOW_t are chosen as suitable indicators for emerging markets.

Our sample includes weekly returns on sectoral portfolios for Greece, China, India and Brazil for the period of 1st January 2003 to 10th March 2008. The total number of observations for each of these countries is 271. However, for Russia data on sectoral portfolios is available for the period, 14th January 2005 to 10th March 2008, indicating overall 165 observations. For Korea, our sample period is 1st February 2004 to 16th May 2008 indicating overall 219 observations.

The Table III presents a comparative picture of estimates and p-values of regression coefficients of following two models: the conventional arbitrage-pricing model (i.e. model I) and the modified arbitrage-pricing model (i.e. model II).

Model I:

$$R_t^E = b_0 + b_1 R_t^M + b_2 NK_t + b_3 DOW_t + e_t$$

Model II:

$$R_t^M = \beta_0 + R_t^{Mx} + e_t^M$$

$$R_t^{Mx} = \beta_I NK_t + \beta_F FED_t + \beta_D DOW_t$$

$$\chi_t = R_t^M - R_t^{Mx}$$

$$R_t^{EH} = R_t^E - \beta_{E,\chi} \chi_t$$

$$R_t^{MH} = \sum_i w_i R_t^{EHi}$$

$$R_t^{EH} = b_0 + b_1 R_t^{MH} + b_2 NK_t + b_3 DOW_t + e_t^H$$

where β_is and b_is are factor loading. w_i is the weight attached to the i th entity in the transformed market portfolio. Because such portfolio is not available in the market, we construct it using our sample data. In the present paper, we follow equal weighted approach in forming R_t^{MH}. Therefore, w_i =1/n where n is the number of sampled portfolios for a country.

Table III: Simultaneous estimation of 3 factor arbitrage-pricing model and 'modified' arbitrage-pricing model using returns on emerging markets' sectoral portfolios

Sectoral Portfolios (Sector : name)		Model I				Model II			
		b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3
Korea									
Auto: KRX Auto	♦ Coefficients	-0.16	0.78	0.07	-0.03	-0.03	1.11	-0.20	0.11
	♦ p-values	0.30	0.00	0.42	0.82	0.84	0.00	0.05	0.24
Semiconductor: KRX Semiconductor	♦ Coefficients	-0.03	1.12	0.20	-0.33	-0.08	1.28	0.04	-0.11
	♦ p-values	0.84	0.00	0.03	0.00	0.53	0.00	0.66	0.20
Health care: KRX Health care	♦ Coefficients	0.42	0.75	0.10	-0.39	-0.07	1.40	-0.39	-0.29
	♦ p-values	0.05	0.00	0.39	0.01	0.68	0.00	0.01	0.02
Bank: KRX Bank	♦ Coefficients	-0.05	1.07	-0.07	0.07	0.12	0.44	0.34	0.35
	♦ p-values	0.77	0.00	0.43	0.53	0.45	0.00	0.01	0.00
IT: KRX IT	♦ Coefficients	-0.07	1.05	0.05	-0.30	0.06	0.78	0.20	-0.06
	♦ p-values	0.58	0.00	0.47	0.00	0.61	0.00	0.01	0.45
India									
IT: CNX-IT	♦ Coefficients	-1.25	1.22	-0.18	-0.60	-1.37	4.81	-1.18	-1.41
	♦ p-values	0.15	0.00	0.67	0.30	0.00	0.00	0.00	0.00

Bank: Bank NIFTY	♦ Coefficients	-0.02	1.09	0.01	0.16	0.39	0.18	0.40	0.56
	♦ p-values	0.92	0.00	0.89	0.15	0.02	0.00	0.00	0.00
MIDCAP: CNX MIDCAP	♦ Coefficients	0.08	1.03	-0.04	-0.04	0.51	-0.02	0.39	0.40
	♦ p-values	0.28	0.00	0.28	0.46	0.00	0.35	0.00	0.00
LARGE CAP: S&P CNX NIFTY	♦ Coefficients	-0.02	0.92	0.03	0.08	0.47	0.03	0.40	0.45
	♦ p-values	0.72	0.00	0.11	0.01	0.00	0.03	0.00	0.00
Russia									
OIL & GAS: RTS_oil & gas	♦ Coefficients	-0.25	1.11	-0.02	-0.08	0.95	-0.39	0.56	0.61
	♦ p-values	0.00	0.00	0.69	0.14	0.00	0.00	0.00	0.00
Telecom: RTS_Telecom	♦ Coefficients	0.15	0.65	-0.05	0.09	-0.33	1.46	-0.27	-0.08
	♦ p-values	0.42	0.00	0.61	0.45	0.08	0.00	0.00	0.49
Metal & Mining: RTS_Metals & Mining	♦ Coefficients	0.21	0.82	0.08	-0.03	0.34	0.50	0.25	0.21
	♦ p-values	0.19	0.00	0.30	0.77	0.08	0.01	0.01	0.09
LARGE CAP: RTS_Industrial	♦ Coefficients	0.64	0.36	-0.02	-0.11	-0.61	1.92	-0.51	-0.59
	♦ p-values	0.00	0.00	0.85	0.41	0.00	0.00	0.00	0.00
Financial: RTS_financial	♦ Coefficients	0.49	0.87	0.11	-0.07	-0.36	1.50	-0.03	-0.15
	♦ p-values	0.04	0.00	0.35	0.66	0.18	0.00	0.79	0.37
Greece									
Bank: FTSE/ATHEX banks	♦ Coefficients	0.04	1.29	-0.08	0.02	0.23	-0.20	0.32	0.64
	♦ p-values	0.60	0.00	0.03	0.72	0.00	0.01	0.00	0.00
Telecom: FTSE/ATHEX telecom	♦ Coefficients	-0.02	0.82	-0.01	-0.02	0.19	0.16	0.16	0.26
	♦ p-values	0.90	0.00	0.81	0.79	0.14	0.17	0.02	0.01
Insurance: FTSE/ATHEX insurance	♦ Coefficients	-0.21	1.41	-0.15	-0.07	-0.41	2.90	-0.57	-0.61
	♦ p-values	0.37	0.00	0.19	0.65	0.00	0.00	0.00	0.00
Small CAP: FTSE/ASE small cap 80	♦ Coefficients	-0.06	0.96	0.08	-0.02	-0.05	1.21	0.00	-0.09
	♦ p-values	0.67	0.00	0.26	0.79	0.67	0.00	1.00	0.29
OIL & GAS: FTSE/ATHEX oil & gas	♦ Coefficients	-0.03	0.76	0.15	-0.16	0.03	0.93	0.09	-0.21
	♦ p-values	0.86	0.00	0.06	0.14	0.82	0.00	0.24	0.06
Brazil									
Electric Energy :BOVESPA Electric Energy	♦ Coefficients	0.03	1.00	-0.02	-0.24	-0.52	2.68	-0.28	-1.30
	♦ p-values	0.82	0.00	0.74	0.03	0.00	0.00	0.00	0.00

LARGE CAP: Brazil IBX	♦ Coefficients	0.12	0.85	0.05	0.10	0.47	-0.03	0.28	1.04
	♦ p-values	0.02	0.00	0.04	0.02	0.00	0.79	0.00	0.00
Corporate Governance: Brazil Corp Gov	♦ Coefficients	0.16	0.76	0.11	0.16	0.18	0.75	0.16	0.39
	♦ p-values	0.04	0.00	0.00	0.01	0.04	0.00	0.00	0.00
Telecom: Brazil Telecom	♦ Coefficients	-0.28	0.94	-0.10	0.13	-0.13	1.59	-0.16	-0.12
	♦ p-values	0.02	0.00	0.06	0.14	0.28	0.00	0.01	0.46
China									
Energy: China(A) Energy	♦ Coefficients	0.08	0.92	-0.03	0.00	-0.05	1.11	-0.08	0.12
	♦ p-values	0.62	0.00	0.70	0.97	0.72	0.00	0.26	0.24
Materials: China(A) Materials	♦ Coefficients	0.09	1.08	0.00	-0.04	0.11	0.76	0.05	0.01
	♦ p-values	0.31	0.00	0.99	0.54	0.30	0.00	0.27	0.83
Large Cap: China(A) Industrial	♦ Coefficients	0.01	1.01	-0.02	-0.08	0.15	0.67	0.04	-0.03
	♦ p-values	0.84	0.00	0.52	0.12	0.06	0.00	0.35	0.54
Health Care: China(A) Health Care	♦ Coefficients	-0.05	0.95	0.01	-0.16	0.02	0.98	-0.01	-0.07
	♦ p-values	0.71	0.00	0.84	0.11	0.91	0.00	0.94	0.51
Financial: China(A) Financials	♦ Coefficients	0.00	0.99	0.00	0.29	0.19	0.49	0.09	0.31
	♦ p-values	0.99	0.00	0.97	0.01	0.26	0.00	0.26	0.01
IT: China(A) Information Technology	♦ Coefficients	-0.10	0.92	0.14	-0.46	0.06	0.93	0.12	-0.37
	♦ p-values	0.50	0.00	0.07	0.00	0.73	0.00	0.11	0.00
Telecom: China(A) Telecom	♦ Coefficients	0.26	0.64	0.09	-0.25	-0.47	2.06	-0.22	0.02
	♦ p-values	0.29	0.00	0.41	0.16	0.03	0.00	0.03	0.88

Results presented in table III indicate that for both model I and II, the market beta (b_1) is high in the positive side and significant for all sampled portfolios. However, in the case of model I, betas for Nikkei index (b_2) and Dow Jones Industrial Average (b_3) possess higher p-values (greater than 0.1) for majority of entities, which imply insignificance of those betas. Only in the case of Brazil, t-test indicates that b_2 and b_3 are significantly different from zero for almost all sampled portfolios for both model I and II. The outcome suggests that Brazil's Bovespa stock market is correlated to the world market. However, the same is not applicable for other emerging markets. It can be observed that there are a large number of entities, for which both b_2 and b_3 are statistically insignificant in fitting model I, however, in many occasions, either one of these betas or both becomes statistically significant in model II. Examples of the cases where both of the betas become significantly different from zero in fitting of model II are: KRX Bank in Korea;

CNX IT, Bank Nifty, CNX midcap and S&P CNX NIFTY in India; RTS_oil & gas, RTS_Metals & Mining and RTS_Industrial in Russia; FTSE/ATHEX banks, FTSE/ATHEX telecom, FTSE/ATHEX insurance and FTSE/ATHEX oil & gas in Greece; BOVESPA electric energy in Brazil. These observations may lead us to infer that the predictability by world market indicators increases when we manipulate the 'modified' arbitrage-pricing model (i.e. model II) for the same portfolio from emerging markets. Therefore, the transformed market has a greater correlation to the world market than the original equity market. Following table represents differences between the short run and the long run expectations and residual volatility in respect of model I and II.

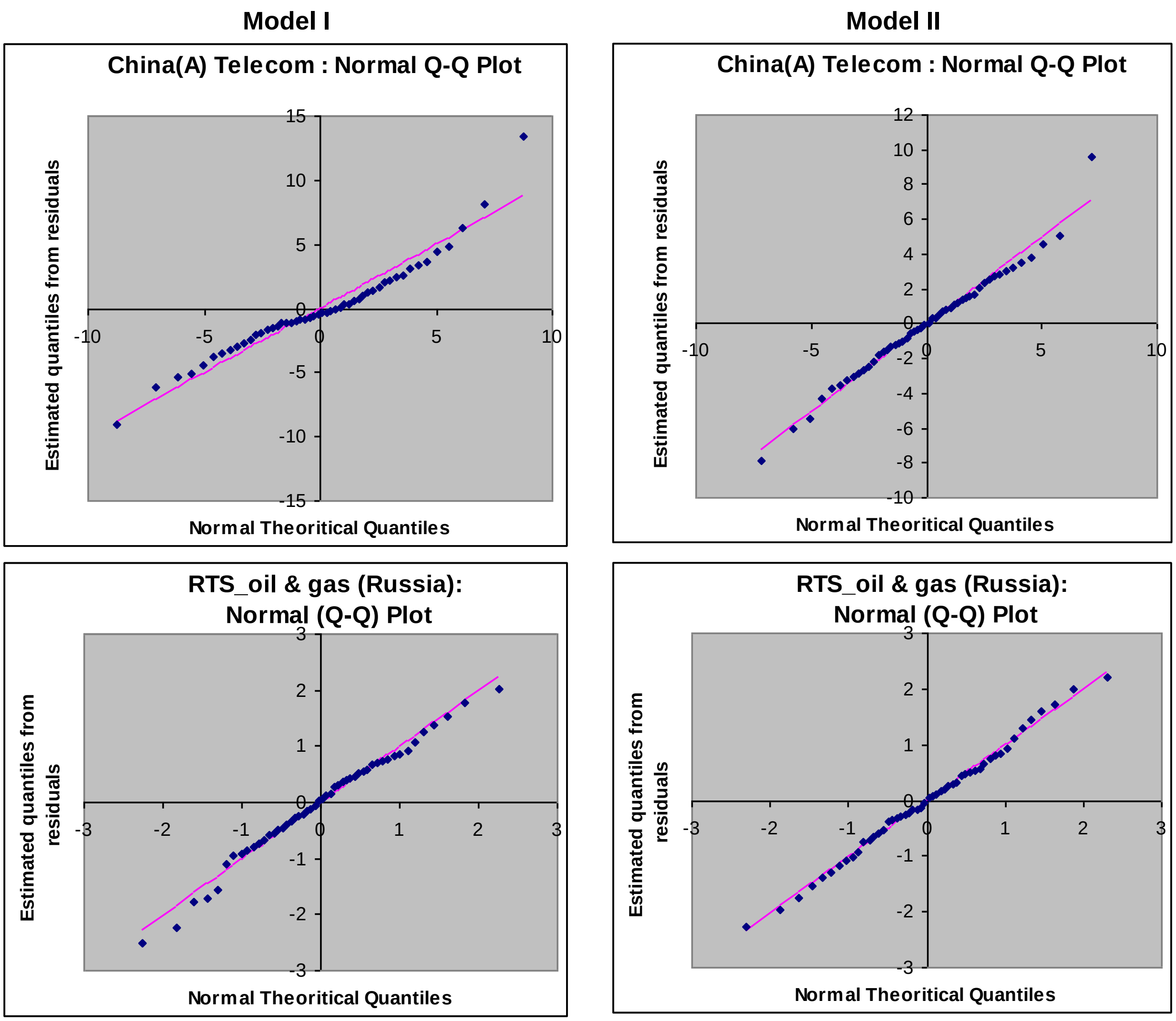
Table IV: Selected statistics in estimating model I and II

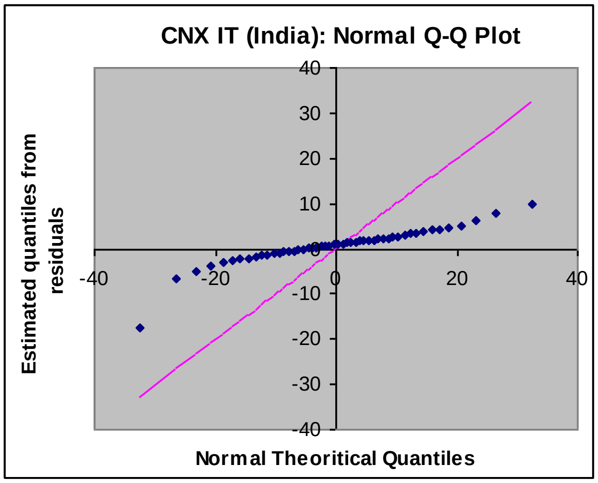
Countries	Absolute difference (average) between the short run and the long run expectations	Average residual volatility in Model I	Average residual volatility in Model II
1. Korrea	0.043	5.6	4.1
2. India	0.212	51.3	4.1
3. Russia	0.254	4.8	3.6
4. Greece	0.022	6.5	4.0
5. Brazil	0.095	2.8	2.0
6. China	0.044	5.5	4.8

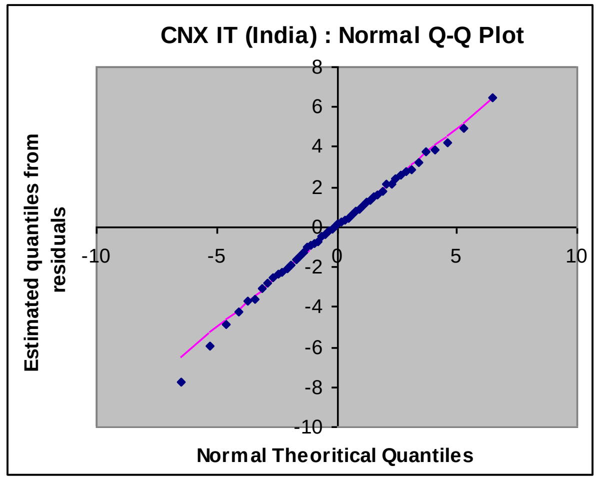
Table IV has recorded a significant difference between the short run and the long run expectations of the portfolio return for India, Russia and Brazil. However, this difference is comparatively less for countries like Greece, China and Korea. We have already argued this difference reflects the intensity of collective investors' sentiments to drive the equity price. Therefore, equity markets in India, Russia and Brazil are more sensitive to investors' sentiments. Table IV also produces some interesting results in respect of portfolio's residual volatility. In preceding sections, we have already mentioned that equity returns are frequently governed by excess volatility; excess volatility is in the sense that equity returns are more volatile than implied by equity fundamentals. However, it is interesting to observe that for all countries average residual volatility is significantly greater in model I as compared to model II. The additional residual volatility, as we have explained earlier, might be due to effects of investors' sentiments on equity returns. Those effects are primarily isolated from the original equity return in application of model II. Therefore in that model, market sentiments cannot induce additional volatility in residuals. Thus, in view of lower residual volatility, model II exhibits a superior performance as compared to model I.

It might be of further interest to researchers/ or practitioners if residuals of the model I or II produce a better fit to the normal distribution. The issue may be addressed by a Normal Quantile-Quantile (or Q-Q) plot for residuals which is formed by plotting estimated quantiles from residuals against theoretical quantiles from a normal distribution. For an example, we have drawn normal Q-Q plot for China-A Telecom, RTS oil and gas and CNX IT portfolio in India.

Chart 3: Normal Quantile-Quantile (Q-Q) plots for residuals







It can be observed from chart 3 that points on the Q-Q plot are closer to the straight line for model II as compared with model I. Normal Q-Q plot for other portfolios would likely produce a similar result. Therefore, residuals in the 'modified' arbitrage-pricing model (i.e. model II) are expected to be normally distributed, even though residuals in the conventional arbitrage-pricing model (i.e. model I) do not follow a normal distribution.

6. Conclusion

Existing asset pricing models effectively predict asset returns for given levels of risks and are useful information to an investor in the case of selecting his portfolio or a banker in the case of monitoring the financial health of a company. Over last four decades, investors, bankers, and market researchers have used such models to predict asset returns under normal market conditions. Normal market conditions prevail when the market is least governed by investors' sentiments. A problem arises when such conditions are not applicable to a capital market. Especially in an emerging market, it will be expected that market sentiment is a major driving force behind equity price movements and, generally, it is the implicit factor behind predictability in stock returns over time. Our empirical study for India has suggested that on many occasions weekly stock returns are significantly predictable by own past observations and such predictability is aggravated in a highly volatile market scenario. CAPM and APT cannot explain such predictability. These models are based on the assumption that the asset return is a randomly generated process following certain basic distributional principles. However, such an assumption is neither valid for an emerging market, nor can a conventional asset pricing model be manipulated for these markets. When the equity market is perfect and there exists no autocorrelation in the equity return, an investor's rational decision would essentially be based on information in the market at present. Consequently, in principle, past returns do not guide the decision making by a rational investor. But when equity returns are found predictable by past observations, a class of traders emerges in the equity market who observes today's market sentiments and predicts the trend in the equity price tomorrow. Their investment decision is largely guided by investors' collective beliefs or market sentiment. Indisputably, an emerging market belongs to the this category, in which the total investor base can be classified broadly into two kinds: one, the investors who look for short-term gain by playing on the market sentiment and, the other, the investors who look for long-term benefits by basing their decisions on the information on equity-fundamentals. However, conventional asset pricing models in their present form are not useful to both types of investors. The dilemma is intractable for the first category of investors because conventional asset pricing models cannot forecast the short-term equity return regulated by the market sentiment. These models are not useful for the second category of investors because it is generally not possible to find equity returns as inputs in models that have not been driven by any sentiments. In such circumstances, the existing class of asset pricing models may be viewed as normative approaches. Those theories presume equity prices are determined by fundamentals and market sentiment has a transitory role to play. In contrast, the model developed in the present paper proposes the following: equity price changes due to investors' sentiments (collective) can be isolated from original equity price movements (or returns). The residual part is the portion of the equity price (or return) that is governed only by equity-fundamentals and the noise. Therefore, if a hypothetical stock market is constructed using prices (or returns) as that of the residual part, and all other parameters are identical to the original equity market, then such a market must be an efficient market. In that market, investors' sentiments cannot induce investors to systematically overvalue or undervalue a stock and, therefore, apart from the noise, the equity price (or return) is governed only by its fundamental value. In this connection, our empirical study has established the following: i) residual volatility is considerably lower for the modified asset pricing model as compared to the conventional model, ii) in general, residuals in the modified asset pricing model are normally distributed, even though residuals in the conventional model do not follow a normal distribution and iii) the transformed market has a greater correlation to the world market than the original equity market. Transformed returns comprising the hypothetical market meet the prerequisites of applying an asset-pricing model and, therefore, any conventional asset pricing model could be efficiently manipulated for those returns.

Our model has advantages over a conventional asset-pricing model in that we have introduced the concept of the short-run and the long-run expectations of the equity return. The short run expectation of the return of the equity depends, with other factors, on market sentiments. However, in the long run, the market reaches its normal position where effects of sentiments are zero and, therefore, the expectation would be consistent with the fundamentals. The empirical analysis provided by us for emerging markets has recorded a significant difference between the short run and the long run expectations of the equity return. This difference reflects the intensity of collective investors’ sentiments to drive the equity price. The absolute value of the above difference is expected to abate with a gradual progress of the emerging market towards a developed market. The recent trend indicates that global players, namely mutual fund agencies, hedge fund corporations, large banks and corporates, are choosing emerging markets for their new investments and also for reallocating their old investments resulting in the market growing even faster. With this accelerating trend in activities and involvements by major investment players, the equity market would likely generate a number of countervailing forces that diminish the effect of investors’ sentiments on equity prices. The outcome would be that the equity market would become more stable and hence the differences between the short run and the long run expectations of the equity return would be reduced. Market practitioners and researchers would be interested in the rationale for separating the two different kinds of expectations of the equity return. Each kind of expectation possesses distinct advantages. The short-run expectation of return will benefit decision making by traders who look for short-term gains by playing on market sentiments. On the other hand, the long run expectation assesses the fair value of the return which will useful for estimating the cost of capital for firms and evaluating the moderate/or long term performance of managed portfolios. Additionally, both types of expectations can be inputs in the policymaking by a risk manager of an institution and the market regulator. In sum, the model presented in this paper is a generalization of the conventional asset pricing model which has advantages akin to the earlier model. However, it would be applicable to all types of markets ranging from an efficient to an inefficient type. Therefore, our model will widen the scope of asset pricing models.

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