Asset Pricing Model for Inefficient Markets: empirical evidence from the Indian market

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Abstract

In the last decade, the efficient market hypothesis and its validity for emerging markets grew as a fertile topic of debate in Finance. However, the dilemma of market efficiency still remains intractable. It is more likely that any literature review in respect of market efficiency would produce contradictory results: for a single paper producing empirical evidence supporting the market efficiency, we can perhaps find a contradictory paper which empirically establishes market inefficiency. Paradoxically, popular models in finance developed in 1970s or 1980s were based on the assumption that the market under consideration was efficient. The conventional bond or stock or option pricing models are common examples of this type. In an alternative approach, we have worked out a model which incorporates market sentiments in the domain of the standard rational model of asset pricing. Our model would be well applicable for a 'less than' efficient market and, therefore may be the useful input in investors' policies.

JEL Classification: G12, G14

Key Words: Capital Asset Pricing Model, Arbitrage Pricing Theory, Efficient market hypothesis

* The views expressed in this paper are of the author and not of the organization to which he belongs.

I. Introduction

Beginning with Sharpe (1964) and Lintner (1965), economists have systematically studied the asset pricing theory or, precisely, the portfolio choice theory of a consumer. Sharpe (1964) and Lintner (1965) introduced the Capital Asset Pricing Model (CAPM) to investigate the relationship between the expected return and the systematic risk. From the day CAPM was developed, it was regarded as one of the primary models to price an equity or a bond portfolio. However, economists of the later generation worked out an Intertemporal Capital Asset Pricing Model (ICAPM) and Arbitrage Pricing Theory (APT) which are more sophisticated in comparison with the original CAPM (e.g. Merton, 1973; Ross, 1976). These models and also models for pricing options as developed by Black and Scholes (1973) effectively predict asset returns for given levels of risks which 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 used such models to predict asset returns in normal market conditions. The "normal market condition" essentially means 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 (e.g. Fama, 1970; Fama, 1991; Fama, 1998). But, an anomaly arises when such conditions are not applicable for a capital market.

Although theories for the pricing of a bond or a stock or an option were considered by economists as an enormous breakthrough in the history of finance, their inventors believed financial markets evolve with some special characteristics: market prices adjust to new information without delay and, as a result, no arbitrage opportunities exist that would allow investors to achieve above-average returns without accepting above-average risk. This hypothesis is associated with the view that price movements approximate those of a random walk. If new information develops randomly, then so will market prices, making the market unpredictable apart from its long-run uptrend. Under such a backdrop, the Geometric Brownian Motion (GBM) process, also called a lognormal growth process, had gained wide acceptance as a valid model for the growth in the price of a stock over time. Most economists in the 1970s and 1980s considered the GBM process or its ancestor, the efficient market hypothesis, the leading principle to understand the basic nature of a financial market and therefore were critical inputs in various asset-pricing models. Black-Scholes option pricing model is a common example of the above type of models. Conversely, CAPM, or its any modified versions, depend on identifying a "market portfolio" that is mean-variance efficient. Practically, such a portfolio could be any index of an efficient capital market. Thus a tradition grew according to which it was legitimate to consider any market index as a proxy of such a portfolio. However, prior to the use of the model, the question of the validity of the applicability of efficient market hypothesis to the market under consideration was hardly addressed. Even if such a question is addressed, any literature review in respect of market efficiency would likely to produce contradictory results: for a single paper producing empirical evidences supporting the market efficiency, we can perhaps find a contradictory paper which empirically establishes market inefficiency. For an example, Chan, Gup & Pan (1997), Rubinstein (2001), Malkiel (2003 & 2005) and many others provided empirical evidences in favour of market efficiency. Conversely, we can provide references of studies by Fama and French (1988), Poterba and Summers (1988), Lo and MacKinlay (1988), Cutler, Poterba and Summers (1989), Jegadeesh (1990) whose findings are indicative of a market inefficiency. These studies are based on statistical tests for market efficiency which can be broadly classified into two categories: one, 'event studies' that examine market reactions after major economic events and two, exploring overtime predictability in equity returns. When the outcomes of these tests are indicative of market inefficiency, application of common asset pricing models might result in significant flaws in an institution's policies. This is so because a common model for pricing stocks or bonds or options is based on the assumption that asset prices follow a martingale process over short horizons as systematic short-run changes in fundamental values is negligible with unpredictable information arrival.

Over the past 20 years, several scholars documented overtime predictability in stock returns in different set of markets. For developed markets, we can quote an example of Blandon (2007), Jegadeesh and Titman (1993), Gregoriou, Hunter and Wu (2009), Avramov, Chordia, and Goyal (2006), Pesaran and Timmermann (1995), Kramer (1998) who empirically established the existence of autocorrelation in equity returns for daily, weekly and monthly returns. Chen, Su, Huang (2008) observed positive autocorrelation in US stock market even in shorter horizon returns than the daily returns. Similar results for emerging markets were observed by Chang, Lima and Tabak (2004), Mollah (2007) and Harvey (1995a and 1995b). Empirical results by these authors established that in many occasions past returns contain additional information about expected stock returns. In those circumstances, it is expected that an unconditional or a conditional autoregressive process performs better compared to a standard APT model. This might be the motivation of Conrad and Kaul (1988), LeBaron (1992) and Koutmos (1997) to model a stock-return as a suitable autoregressive process. However, many scholars observed that return autocorrelations are sample dependent and may exhibit sign reversals (e.g. Chan, 1993, p. 1223; Knif, Pynnonen & Luoma, 1996, p. 60; McKenzie and Faff, 2005). In this case, a researcher may be more interested in finding suitable time lags or exploring time-varying specification of coefficients. Upon these consequences the problems of searching an appropriate asset pricing model may boil down to selecting suitable factors and/or lagged returns which can efficiently generate the process for expected return. Basics of the asset pricing theory, however, accepted the market return as an explanatory variable (e.g. Sharpe, 1964 and Lintner, 1965). With the market return the researcher would be tempted to include one or more lagged returns because lagged returns occasionally show greater predictability than any other macro variables. The combination of the market return and the lagged returns might develop an empirical model providing a better fit to the equity data. However, critics may question about theoretical justifications of this kind of models.

The autocorrelations in equity returns might be an outcome of the scenario when an individual investor’s investment decision is atleast partially guided by investors’ sentiments (e.g. Barberis, Shleifer & Vishny, 1998; Majumder, 2006). We generally observe that 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. 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 (e.g. Chopra, Lakonishok and

Ritter, 1992; Barberis, Shleifer and Vishny, 1998). 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 underreaction 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. In addition to the above, the occasional exuberance or pessimism by investors to certain information leads the stock return to be more volatile. Even in a developed market like USA, it can be observed that equity returns are more volatile than implied by equity fundamentals (e.g. Shiller, 1981; Leroy and Porter, 1981; Shiller, 1987). These characteristics of the equity return are even common in an emerging market like India and also the volatility in equity return is higher in the developing world as compared to the developed world (see Parametric Portfolio Associates, 2008). These are the common evidence of inefficiencies in emerging markets as well as developed markets.

Against the above backdrop, the question that has gained importance to market practitioners or researchers is whether the bond or stock pricing models invented in the 1970s and 1980s were able to provide additional information to investors. The answer would necessary be negative for traders who look for the short-term gain by playing on market sentiment. This is so because the model cannot predict the direction and intensity of the market sentiment. The second category of investors looks for long-term benefits by basing their decisions on information on firms' financial health. In this case, the dilemma is intractable because it is generally not possible to find equity prices, as inputs in models, that have not been driven by any sentiment. In such circumstances an alternative approach for modeling expected return might be a suitable autoregressive model as adopted by Conrad and Kaul (1988), LeBaron (1992) and Koutmos (1997). Here the dilemma is two fold: 1) such models are based on empirical properties of the data and hence they are sample/situation specific and 2) in some occasions, lagged returns cannot explain a major portion of the variation in returns. We can quote from Conrad and Kaul (1988) that variation through time in short-horizon expected returns is 26% of the return variance for the smaller portfolios and 1% for the larger portfolios. In such circumstances, we propose an alternative approach for asset pricing in the line of the methodologies adopted by Majumder (2006)[i]: equity price changes due to investors' sentiments (collective) can be modeled and isolated from original equity price movements (or returns). The residual part is the portion of the equity price (or return) that is governed by the factors which caused a systematic change in it. Such prices (or returns) would correspond to a hypothetical efficient stock market and can be used as an effective input in the bond or stock pricing formula. The approach will widen the scope of asset-pricing models ranging from a strict efficient market to an inefficient market. The rest of the paper is organized as follows. Section II describes the model. Section III provides empirical findings. Policy implications of the model are given in Section IV, and Section V concludes.

II. The Model

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, the behavior of investors is governed by market sentiments. As an example, post-election uncertainty or uncertainty in policies of newly elected governments often induces a panic among investors which subsequently may lead to a major downfall in equity prices. The stock market crash in India on 17th May 2004 was an example (e.g. Majumder, 2006). It was the biggest ever fall at that time in a single day's trading in the Indian equity market which was occurred due to the panic that the newly elected government could halt economic reforms. The outcome, however, was independent of the fundamentals of Indian firms. Thus, any upturn/downturn in equity prices might be a consequence of any of the hundreds of unforeseen events such as frauds or war or droughts or hikes/fall in oil prices etc. These events are not predictable. All the same, influencing market sentiment they change overall supply/demand conditions and consequently disrupt the stability of markets. While it is impossible to predict ex-ante all of these events causing stock price movements, the common approach to develop an asset pricing model accepted by earlier generation economists include selecting firm-specific and macroeconomic factors which have an influence on general decisions of an investor. These factors are of two kinds: one set of factors is correlated with equity fundamentals

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

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 systematic 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. These factors are responsible for cross sectional variation in the stock returns. In contrast, nonfundamentals would essentially be the transitory component of the stock return which is influenced by factors like market 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. In course of time it reverts to its original position. Therefore, 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 fundamentals.

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}), the part that is unexplained by fundamentals (R_t^{UEx}):

$$R_t^E = R_t^{Ex} + R_t^{UEx} \tag{1}$$

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 market sentiments, S_t, and the noise (e). Market sentiments are unobservable. However we developed an approach to quantify the effects of market sentiments through modelling returns of the market portfolio which is presented in the next section. If the factors, F_t and S_t are linearly related to form R_t^E, we can write:

$$R_t^E = (1-\alpha)F_t + \alpha S_t + e \tag{2}$$

where α is the relative weight to the factor S_t. Any change in equity price is observable from the market. However, the influence of either F or S on the equity price cannot be separated directly. We can segregate the effect of F and S from the equity price under certain reasonable assumptions: factors F and S can be viewed as two assets which form a portfolio E. Consequently, equation (2) can be represented in terms of betas:

$$\beta_{E,S} = (1-\alpha)\beta_{F,S} + \alpha\beta_{S,S} \tag{3}$$

where $\beta_{I,S} = \dfrac{\text{Covariance}(I,S)}{\text{Variance}(S)}$ gives the sensitivity of the returns on asset I (I=E/F/S) to asset S. By definition, the factor S_t is uncorrelated to that of F_t and e. Therefore,

$$\alpha = \beta_{E,S} \tag{4}$$

A. The Market sentiments

Our model is based on the basics of isolating effects of non-fundamentals from the equity return. The residual part of which is the component of the equity return governed by the factors which caused a systematic change in it. Therefore, this part can be taken as an input in an asset pricing model. Non-fundamentals would essentially be investors' sentiments. However, effects of investors' sentiments are not observable from the market and also never clearly defined in Economics literature. 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. We are experienced, in the one extreme, investors' sentiments render into a panic which may lead a sharp downturn in the market index. In the other extreme, positive sentiments may cause a significant rise in the market index. Therefore, the initial step in modeling market sentiments might be based on the assumption that effects of market sentiment are properly summarized into a diversified market portfolio. However, it is not necessarily implied that sentiments are only factors behind any ups or downs of market returns. Movements in the market return are essentially due to the combined effects of market fundamentals and collective investors' sentiments. Consequently, it is not difficult to a researcher to segregate the above two effects by fitting a linear model.

We can go back to the basics of asset pricing theory that indicate the market portfolio is a well-diversified portfolio, which is the optimal portfolio for at least one utility-maximising investor. Because of the diversified nature of that portfolio, the nonsystematic risks of each asset sums up net to zero. The only risk that exists in the market portfolio is the systematic risk. Therefore, the return of such a portfolio is regulated by those factors which fuel systematic 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 market fundamentals (R_t^{Mx}) and the part unexplained by fundamentals (R_t^{UMx}):

$$R_t^M = R_t^{Mx} + R_t^{UMx} \tag{5}$$

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. 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,

$$R_t^{UMx} = S_t + e^M \tag{6}$$

Using equations (6), equation (5) can be rewritten as below:

$$R_t^M = S_t + R_t^{Mx} + e^M \tag{7}$$

The market sentiment, S_t, is unobservable. At the same time, it can be defined as the stationary 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. R_t^{Mx} is the fair value of market return and when this part is estimated by fitting a standard model for predicting market return (see Appendix) we also can get an estimate of S_t. An alternative representation of equation (7) would be

$$E\left(R_t^M - R_t^{Mx}\right) = S_t \tag{8}$$

where E(.) is the expectation operator. Equation (8) reveals that an unbiased estimator of the market sentiment (S_t) is $\left(R_t^M - R_t^{Mx}\right)$.

B. The systematic Component

The systematic component of the equity return (R_t^{Ex}) would essentially be the part of the return which is consistent with equity fundamentals. In the equation (2), this part is $(1-\alpha)F_t$. Using equations (2), (4) and (8) R_t^{Ex} can be solved as below:

$$R_t^{Ex} = E\left(R_t^E - \beta_{E,(M\text{-}Mx)}\left(R_t^M - R_t^{Mx}\right)\right) \tag{9}$$

where 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 (9) reveals that if a hypothetical equity market is formed with the equity return as $R_t^{EH} = \left(R_t^E - \beta_{E,(M\text{-}Mx)}\left(R_t^M - R_t^{Mx}\right)\right)$ 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 pricing model.

Let us assume that $\psi\left(F_1, F_2, ----, F_N\right)$ is a general asset pricing model for a common bond or stock where ($F_1, F_2, ----, F_N$) is the set of factors influencing the value of the underlying asset. In this case, common factors are market returns, interest rates, exchange rates, oil price inflation etc. In the present model, ψ is applied on the transformed returns comprising the hypothetical market. The model facilitates to isolate the long run expectation of the asset return $\left(E^L\right)$ from the short run expectation $\left(E^S\right)$. In the long run, the effects of the market sentiments are zero; therefore, the expectation of the asset return would essentially be:

$$E^L\left(R_t^E\right) = E\left(R_t^{EH}\right) = \psi\left(F_1, F_2, ----, F_N\right) \tag{10}$$

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:

$$E^S\left(R_t^E\right) = E\left(R_t^{EH}\right) + \beta_{E,(M\text{-}Mx)} E\left(\left(R_t^M - R_t^{Mx}\right)\right) = \psi\left(F_1, F_2, ----, F_N\right) + \beta_{E,(M\text{-}Mx)}\alpha_M \tag{11}$$

where the intercept $\left(\alpha_M\right)$ of regressing the market return on select factors as shown in the appendix gives an estimate of $E\left(R_t^M - R_t^{Mx}\right)$. 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 a common asset pricing model.

C. The adjustments, when factors F and S are not uncorrelated

News/information released in the market is the driving force behind any systematic or unsystematic changes in the equity return. Unsystematic changes occur due to effects of investors' sentiments on equity prices. Upon these consequences one may argue that occasionally factor F, which is consistent with equity fundamentals, might be correlated to factor S, which is driven by investors' sentiments. In such situation, $\beta_{F,S}$ in equation (3) would be nonzero. We can estimate $\beta_{F,S}$ by the iterative procedure described below. Equation (3) gives an estimate of α in terms of betas:

$$\alpha = \frac{\beta_{E,S} - \beta_{F,S}}{1 - \beta_{F,S}} \tag{12}$$

Using the value of α, the return on the asset F can be evaluated from equation (2) as below:

$$F_t = E\left(\frac{(1 - \beta_{F,S})R_t^E - (\beta_{E,S} - \beta_{F,S})S_t}{(1 - \beta_{E,S})} \right) \tag{13}$$

Let us denote the value of F_t and $\beta_{F,S}$ in the (i-1)th iteration is $F_t(i-1)$ and $\beta_{F,S}(i-1)$ respectively. Based on the equation (13), we can compute the i th approximation of F_t as follows:

$$F_t(i) = \frac{(1 - \beta_{F,S}(i-1))R_t^E - (\beta_{E,S} - \beta_{F,S}(i-1))S_t}{(1 - \beta_{E,S})} \tag{14}$$

Using the above equation, the set of values of $F_t(i)$ can be calculated for t = 1,2,…,n. Accordingly, the i th approximation of $\beta_{F,S}$ would be,

$$\beta_{F,S}(i) = \frac{\text{Covariance}(F(i), S)}{\text{Variance}(S)} \tag{15}$$

The first approximation of $\beta_{F,S}$ might be $\beta_{F,S}(1) = 0$. Using equation (14) and (15) it is possible to generate a series of appoximations for $\beta_{F,S}$. The process converges if $|\beta_{F,S}(i) - \beta_{F,S}(i-1)| < \varepsilon$. Accordingly, we can obtain a desired degree of accuracy by considering a smaller ε.

III. Empirical Findings

Prior to manipulating any asset pricing model for predicting equity returns, it is worthwhile to examine whether the capital market is informationally efficient. One effective way to test this might be through investigating serial correlation properties of equity returns. Such test is also useful to examine existence of investors' sentiment in the equity market. In the present paper, the test is performed on daily portfolio returns in the similar line of Jegadeesh (1990). The particular cross-sectional regression model used in the empirical tests is

$$R_{i,t} - \overline{R}_{i,t} = a_{0t} + \sum_{j=1}^{6} a_{jt} R_{i,t-j} + u_{i,t} \tag{16}$$

where $R_{i,t}$ is the return on the portfolio i in day t, $\overline{R}_{i,t}$ is the mean daily return and $u_{i,t}$ is the random error. a_{it}'s are regression coefficients. For our empirical estimation, six sectoral portfolios are selected which are compiled by the NSE exchange of India. These portfolios are: S&P CNX Nifty (P1), CNX Nifty Junior (P2), S&P CNX Defty (P3), Bank Nifty (P4), CNX Midcap (P5) and CNX Infrastructure (P6)[ii]. Parameter estimation and the test statistics are obtained separately for the original equity market and the hypothetical equity market constructed using our model. Empirical results based on original equity market are compared with results based on hypothetical equity market. Additionally, in account of exploring the performances of our model in different stress scenarios, we have historically simulated two scenarios based on the daily return volatility. These scenarios are: low to medium volatile scenario and high volatile scenario. The tests are conducted using daily returns over the period January, 2003 to March, 2009. Results are presented in the table 1 and 2.

[ii] Details of these portfolios are available in the NSE-India site: www.nse-india.com. Daily portfolio price data are obtained from the above site.

Table 1: Cross Sectional Regression Estimates for the Original Market

	Portfolios	$\hat{a}_0$	$\hat{a}_1$	$\hat{a}_2$	$\hat{a}_3$	$\hat{a}_4$	$\hat{a}_5$	$\hat{a}_6$	R^2
Low to Medium Volatile Scenario	P1	0.162* (3.89)	0.079* (2.26)	-.086* (-2.42)	0.062 (1.75)	-0.063 (-1.75)	-0.067 (-1.89)	-0.038 (-1.06)	0.025
	P2	0.191* (4.09)	0.144* (4.09)	-.086* (-2.42)	0.038 (1.05)	-0.056 (-1.58)	-0.051 (-1.41)	0.002 (0.04)	0.032
	P3	0.171* (3.77)	0.095* (2.69)	-.071* (-1.99)	0.080* (2.24)	-0.066 (-1.86)	-0.042 (-1.18)	-0.031 (-0.86)	0.023
	P4	0.194* (3.10)	0.086* (2.46)	-0.015 (-0.42)	0.036 (1.01)	-.073* (-2.04)	-.076* (-2.12)	-0.022 (-0.61)	0.022
	P5	0.167* (4.13)	0.202* (5.77)	-.114* (-3.17)	0.101* (2.78)	-0.036 (-0.99)	-0.017 (-0.48)	-0.031 (-0.88)	0.050
	P6	0.193* (3.41)	0.102* (2.63)	-0.074 (-1.88)	0.061 (1.56)	-.098* (-2.49)	-0.014 (-0.37)	0.005 (0.15)	0.025
High Volatile Scenario	P1	-0.023 (-0.28)	0.079* (2.15)	-0.055 (-1.51)	0.006 (0.16)	-0.016 (-0.42)	0.003 (0.09)	-0.063 (-1.72)	0.013
	P2	-0.053 (-0.56)	0.176* (4.81)	-0.067 (-1.80)	0.031 (0.83)	-0.038 (-1.03)	-0.003 (-0.07)	-0.042 (-1.14)	0.034
	P3	-0.049 (-0.55)	0.096* (2.63)	-0.031 (-0.85)	0.021 (0.57)	-0.018 (-0.49)	0.016 (0.43)	-.082* (-2.24)	0.016
	P4	-0.044 (-0.43)	0.152* (4.17)	-.082* (-2.22)	0,019 (0.51)	-0.049 (-1.32)	-0.035 (-0.96)	-0.081 (-2.21)	0.038
	P5	-0.037 (-0.47)	0.233* (6.37)	-.099* (-2.64)	0.064 (1.70)	-0.022 (-0.60)	-0.001 (-0.03)	-0.016 (-0.44)	0.055
	P6	-0.136 (-1.20)	0.099* (2.46)	-.080* (-2.01)	0.020 (0.50)	-0.021 (-0.51)	0.001 (0.03)	-.103* (-2.58)	0.025

* Indicates the corresponding coefficient is statistically significant at 5% level of significance

Table 2: Cross Sectional Regression Estimates for the Hypothetical Market

	Portfolios	$\hat{a}_0$	$\hat{a}_1$	$\hat{a}_2$	$\hat{a}_3$	$\hat{a}_4$	$\hat{a}_5$	$\hat{a}_6$	R^2
Low to Medium Volatile Scenario	P1	-.019* (-2.19)	0.159* (4.53)	-0.030 (-0.86)	0.073* (2.06)	-0.063 (-1.76)	0.001 (0.04)	0.026 (0.74)	0.032
	P2	0.020 (0.96)	0.042 (1.19)	-0.059 (-1.70)	-0.041 (-1.18)	0.023 (0.67)	-.078 (-1.98)	0.022 (0.63)	0.013
	P3	-0.013 (-1.01)	0.048 (1.37)	0.014 (0.39)	-0.027 (-0.79)	-.089* (-2.52)	0.070 (1.97)	0.011 (0.31)	0.015
	P4	-0.026 (-0.69)	0.053 (1.51)	-0.004 (-0.13)	-0.023 (-0.65)	0.001 (0.00)	-0.050 (-1.41)	-0.008 (-0.23)	0.006
	P5	0.036 (1.95)	0.127* (3.63)	-0.016 (-0.46)	0.067 (1.89)	-0.017 (-0.47)	0.012 (0.34)	-.099* (-2.78)	0.029
	P6	0.023 (0.94)	0.045 (1.16)	-0.008 (-0.23)	0.016 (0.42)	-0.044 (-1.14)	0.055 (1.44)	0.041 (1.07)	0.009
High Volatile Scenario	P1	0.016 (0.99)	0.037 (1.01)	-0.046 (-1.28)	0.004 (0.11)	-0.059 (-1.62)	-0.065 (-1.78)	-0.034 (-0.94)	0.013
	P2	-0.019 (-0.64)	0.036 (0.99)	-0.056 (-1.55)	-0.002 (-0.06)	-0.067 (-1.83)	-0.057 (-1.58)	0.016 (0.45)	0.013
	P3	-0.012 (-0.55)	-0.100 (2.01)	-0.022 (-0.60)	0.005 (0.42)	-0.052 (-1.41)	0.006 (0.18)	-0.055 (-1.51)	0.017
	P4	-0.001 (-0.03)	0.121* (3.32)	-0.024 (-0.65)	-0.028 (-0.77)	0.020 (0.54)	-0.019 (-0.53)	0.015 (0.41)	0.016
	P5	-0.012 (-0.46)	0.053 (1.45)	-0.051 (-1.41)	-0.012 (-0.35)	-0.009 (-0.25)	-.092* (-2.52)	-0.008 (-0.23)	0.014
	P6	0.030 (0.97)	-0.053 (-1.32)	-0.003 (-0.09)	-0.023 (-0.56)	-0.004 (-0.11)	-0.038 (-0.95)	-0.029 (-0.74)	0.005

* Indicates the corresponding coefficient is statistically significant at 5% level of significance

where $\hat{a}_i$ is the estimate of the i th regression coefficient (i= 0,1,2,3,4,5 and 6). t-statistics for testing the statistical significance of the regression coefficient is given in the paranthesis. Table 1 shows that coefficients for one day lagged return are positive and statistically significant for all sampled portfolios in low to medium volatile scenarios and also in high volatile scenario. Moreover, the coefficient, a_1, is bigger in absolute magnitude than the rest. The results indicate positive first order autocorrelation for returns in the original equity market. In addition to this, table 1 indicates one or more higher order autocorrelations are different from zero for almost all portfolios. However, the average R^2 of the daily cross-sectional regressions is 0.032; i.e., on average the lagged returns considered here can explain 3.2 percent of the cross-sectional variation in individual security returns. Our results are consistent with the findings of earlier authors (see Kramer, 1998; Blandon, 2007). Contrarily, table 2 indicates that for almost all occations, coefficients for lagged returns are not statistically significant for both the scenarios resulting a very low R^2 of regression. Therefore, in general, stock returns in the hypothetical market are not autocorrelated. The results can be verified further by presenting F-statistics under the hypothesis that all slope coefficients are jointly equal to zero.

Table 3: F-Statistics for testing joint significance of all slope coefficients

Portfolios	**Original Market**		**Hypothetical Market**	
	Low to Medium Volatile Scenario	**High Volatile Scenario**	**Low to Medium Volatile Scenario**	**High Volatile Scenario**
P1	3.45*	1.57	4.43*	1.60
P2	4.30*	4.41*	1.76	1.60
P3	3.23*	2.12*	2.08	2.09
P4	3.01*	4.91*	0.81	2.04
P5	7.12*	7.21*	3.96*	1.80
P6	2.78*	2.67*	1.01	0.56

* Indicates the F-Statistics is statistically significant at 5% level of significance

Table 3 indicates that for the original market almost all F statistics are statistically significant at 5% significant level indicating all slope coefficients are not jointly equal to zero. However, results are opposite for the hypothetical market where most of the F statistics are statistically insignificant. The results indicate that the original equity market returns are autocorrelated for at least one lag, however the hypothetical market returns are not so autocorrelated.

IV. An optimal allocation of resources - Policy Implications of the model

We can quote from Lady Windermere's Fan by Oscar Wilde, "What is a cynic? A man who knows the price of everything, and the value of nothing". The observations by the great novelist is appropriate as well for a modern investor who evaluates the value of his investments by using any conventional asset pricing model and subsequently encounters mispricing. Paradoxically, CAPM, APT and their presently available variants might be wonderful advancements in this profession, but one could easily understand that they are not true descriptions of the world around us. These models are based on the basics that past returns do not have memory or predictability power, which is empirically an untenable assumption (see Gregoriou, Hunter and Wu (2009); Mollah (2007); Avramov, Chordia, and Goyal (2006)). Thus a modern investor may not become skeptic when he encounters mispricing. While exploring the causes of this mispricing, Bird, Menzies and Rimmer (2010) asserted that the foundation for this mispricing well encapsulated by the words, irrational exuberance, which reflect a period when emotions take over and valuation plays at best a limited role in determining equity prices. Valuation by any existing model would likely produce a suboptimal risk-return relationship which may guide an investor to adopt wrong policies for his new investments or for reallocating his old investments. Such investment strategies, collectively, may also affect the real economy by disrupting the optimal allocation of resources. Conversely, our model provides a direction of incorporating market sentiments in the domain of the standard rational model of asset pricing. The process of transforming the original market to a hypothetical efficient market, described in the preceding section, will smooth out, at least partially, the abnormal volatility and large autocorrelations often found in the asset return data without changing properties of the original asset pricing model. The outcome might be a superior alternative to a conventional model which can be applicable for all sets of markets ranging from an emerging to a developed one. Major policy implications of this generalization of standard asset pricing models inherent in its greater applicability, some of which are specified below:

i) About six decades ago the economist John Maynard Keynes warned investors by declaring, "The market can stay irrational longer than you can stay solvent"[iii]. The observation by the great economist is equally applicable for a modern investor. Nonetheless, our model will provide a quantitative support to an investor's policies for his new investments or for reallocating his old investments even when the market is irrational. The quant would also be useful in monitoring off performances of his existing portfolios.

ii) The model facilitates to compute the long run expectation and the short run expectation of the asset return separately. The short-run expectation will guide 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 be 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 as well as the market regulator.

iii) Large asset price bubbles have the potential to cause severe economic damage. This might be the cause of growing interest in governments (typically through their central banks) playing a more interventionist role in controlling asset price bubbles. The foremost task, however, might be detection of the bubble. Our model computes the difference between the short-run and the long run expectations of asset return, which can be manipulated in detecting bubbles in those returns.

iv) After the global financial crisis of yesteryear, achieving financial stability has been considered as a broader objective in policymaking by the central bank in many countries. In this regard, an optimal risk-return relationship, as an outcome of our model, will assure the efficient allocation of resources promoting greater stability in the financial system.

[iii] This quote is drawn from Finkelstein (2006)

V. Conclusion

A generation ago, the efficient market hypothesis was widely accepted by financial economists as a principle to explain the price behavior in a financial market. It was, therefore, the theoretical basis for much of the financial market researches during the 1970s and the 1980s. Among the theories developed at that time, bond, stock and option pricing theories were the leading examples which presumed that the underlying market is informationally efficient. These theories are based on the assumption that asset prices follow a martingale process over short horizon as systematic short-run changes in fundamental values is negligible with unpredictable information arrival. However, these assumptions are not applicable for most of the equity market in the today's world because it became a stylized phenomenon that daily, weekly and monthly equity returns are over time predictable. In such circumstances, the conventional asset pricing models might be considered as one extreme representation of the reality. Alternatively, the researcher may select a suitable autoregressive model for the equity return which, however, might be the other extreme representation of the reality. This model is applicable when the variation through time in short-horizon expected returns is the leading component of the return variance. Above two approaches are based on mutually conflicting hypothesis and, therefore, each of them is the partial representation of the reality.

The present paper 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. However, the market sentiment is unobservable. At the same time, it can be defined as the stationary 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 might be the result of possible bullish/bearish responses by investors to market information. Against this backdrop, our paper makes following contributions to the conventional economics literature: first, we propose that equity price changes due to investors' sentiments (collective) can be modeled and 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. Second, our approach will facilitate to segregate the short-run expectation of the equity return from the long-run expectation. 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. In this connection, our empirical study for Indian equity market has established the following: original equity market returns are autocorrelated for at least one lag, however the hypothetical market returns are, in general, not so autocorrelated. Therefore, transformed returns comprising the hypothetical market meet the prerequisites of applying an asset-pricing model and, therefore, any conventional bond or stock pricing model could be efficiently manipulated for those returns. The approach will widen the scope of asset-pricing models ranging from a strict efficient market to an inefficient market.

Appendix: Modeling predictable component of the of the market return

Dynamics of stock market returns can be modeled efficiently by an ICAPM based approach pioneered by Merton (1973) and Campbell (1993). Some variants of this class of models provide superior in-sample and out-of-sample forecasts (see Guo and Savickas 2006). Adopting Campbell's (1993) results that the conditional excess stock market return, $E\left(R_t^M\right) - r_t^f$, is a linear function of its conditional variance, $\sigma^2_{M,t-1}$, and its conditional covariance with the discount rate shock, $\sigma_{M,DR,t-1}$, our model is translated to:

$$E\left(R_t^M\right) - r_t^f = \alpha_M + \gamma_1 \sigma^2_{M,t-1} + \gamma_2 \sigma_{M,DR,t-1} \quad \text{(A1)}$$

where α_M is the slope of the regression, γ_1 and γ_2 are regression coefficients. r_t^f is the risk free rate of return. According to Merton (1980) and Andersen et al. (2003) realized stock market variance $\left(\sigma^2_{M,t-1}\right)$ is the sum of squared daily excess stock market returns in a specified time period. $\sigma_{M,DR,t-1}$ may be computed by the approach adopted by Guo and Savickas (2006): at first, we can calculate the daily idiosyncratic shock to i th stock using Capital Asset Pricing Model (CAPM):

$$e_{i,t} = R_t^i - \alpha - \beta R_t^M \tag{A2}$$

where R_t^i is the return on the i th stock. The discount rate shock is the weighted average of all e_i s, the weight for the i th stock is the proportion of market capitalization of the i stock to the total market capitalization. Using the relation $\sigma_{M,DR,t} = \beta_{M,DR,t}\sigma_{DR,t}^2$, where $\beta_{M,DR,t}$ is the loading of stock market returns on the discount rate shock and $\sigma_{DR,t}^2$ is conditional variance of the discount rate shock, we can rewrite equation (A1) as:

$$R_t^M - r_t^f = \alpha_M + \gamma_1\sigma_{M,t-1}^2 + \gamma_2\beta_{M,DR,t-1}\sigma_{DR,t-1}^2 + e_t^{M*} \tag{A3}$$

where e_t^{M*} is the residual of the regression; $E\left(e_t^{M*}\right) = 0$. For simplicity, we assume that $\beta_{M,DR,t}\left(\approx \beta_{M,DR}\right)$ is constant across time. In equation (A3), $\sigma_{M,t}^2$ and $\sigma_{DR,t}^2$ are estimated as the variance of daily excess stock market returns and conditional variance of the discount rate shock respectively which are computed based on a stipulated time period. In an alternative approach, we can fit a GARCH (1,1)-type model for estimating $\sigma_{M,t}^2$ and $\sigma_{DR,t}^2$:

$$\sigma_{M,t}^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\sigma_{M,t-1}^2 \tag{A4}$$

$$\sigma_{DR,t}^2 = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2\sigma_{DR,t-1}^2 \tag{A5}$$

A common interpretation of the intercept, α_M, is that α_M is the deviation of the average market return from its fair value $\left(R_t^{Mx}\right)$. When this deviation is zero the regression model presented in equation (A3) will converge to standard ICAPM model for predicting market return. In that case, estimated fair return would be

$$R_t^{Mx} = r_t^f + \gamma_1\sigma_{M,t-1}^2 + \gamma_2\beta_{M,DR,t-1}\sigma_{DR,t-1}^2 \tag{A6}$$

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