Multi-Index Conditional Investment Performance Measure: An Empirical Analysis

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Abstract

The present study seeks to examine the mutual fund performance of the open-ended selected equity schemes of UTI based on multi-index measures as well as conditional multi-index measure. It is observed from the analysis that multi-index measure is able to capture the beta and alpha effects on market adjusted basis and the estimated coefficients is a better representative as compared to the single index measure. When time lagged (lagged at 1 month, 2 months, quarterly and yearly) multi-index measures are applied then the estimated coefficients (alpha & beta) which are market adjusted and time adjusted look more representative than the multi-index measure (without lagged effect). Finally, when we extended the time lagged multi-index measure on a conditional way (conditional on public information variables) then we observe that conditional multi-index lagged measure provides much more representative results in all respects as compared to the all measures after conditioning public information effects.

Keywords: Single Index Measure, Multi-Index Measure, Conditional Multi-Index Measure, Stock Selection, Asset Class Exposures

JEL Classification: G12, C13, C22

1. Introduction

The evaluation of investment performance has long been a topic of considerable interest to financial economists. Generally, the investment performance concerns with three dimensions namely successful prediction of security prices, efficient estimation of market movement and minimisation of diversifiable risk. The above activities can be achieved in a better way if fund managers provide right information with regard to mutual funds as well as asset class exposures. Generally, low level of information provided by the fund managers combined with inadequate methods of evaluating risk turn aside investors from correctly assessing the risk-adjusted returns of their holdings in the asset class in the stock market. Some of the past studies have reported that fund managers don't provide periodical information with regard to fund exposures to the principal risk factors and none of them provides a really strong measure of risk. Therefore, the impact of the relative performance measures as compared to the performance of investments in traditional asset classes need to be examined. Although, performance appraisal of mutual fund is a difficult task due to the existence of various biases as well as by their unclear nature and multifaceted strategies involved in the portfolio operation. Some of the authors have pointed out that (Asness et al 2000, Brooks & Kat 2002 etc) alternative investment like mutual funds is illiquid in nature because the NAV is estimated by the fund managers which could due to the lack of market transparency, take advantage of this flexibility and manipulation of prices so as to smoothen the fund performance. Therefore, returns performance provided by the mutual fund managers are biased as well as the risk metrics explain an unrealistic pattern of returns. Hence, any unrealistic assumption on the stochastic process on returns leads to face the risk of a type I error.

Finally, the persistence of non-linear effects in the portfolio exposure to risk factors, non-linear exposure of single assets to different risk factors come against the assumption of linearity of returns. Although, the model developers have adopted various strategies to enhance the ability of linear factor-based models to analyze fund returns. The much more realistic approach consists of identifying factors that capture the non-linearity of these funds returns. Alternatively, we are searching for new factors that are themselves non-linear with respect

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to the traditional risk factors. The use of time-lags as market risk-adjustment factors is a solution to the above issues. Side by side, conditional market-adjusted estimates provide better and meaningful coefficients than the single index measure. These, approaches lead us to a linear specification of the measure. This, in addition, accommodates other issues encountered in practice. Therefore, to address these problems we introduce three multi-index models – an asset class factor model, a time-lagged asset class factor model and a conditional asset class factor model. Finally, the study has shown the comparison of results among different schemes and their market-adjusted, time-lagged adjusted and conditional market-adjusted effects on returns and their impact on the estimated coefficients.

The remaining of the study is prepared as follows: Section.1 reviews the existing literature. Section.2 describes the objectives of the study. Section.3 deals with the data and study period. Section.4 explains about the methodology Section.5 presents the empirical results and analysis. Finally, section.6 recommends concluding remarks.

2. Objective of the Study

It is well known that Multi-Index measure provides better performance estimates as compared to the single index performance measure. Moreover, multi-index conditional measure also provides improved performance estimates than the traditional multi-index measure. Now, the main objectives of the paper are as under:

1. To examine the stock-selection performance based on five models
2. To estimate market-adjusted and time-lagged adjusted coefficients
3. To estimate conditional market-adjusted coefficients
4. To observe whether lagged effect exists in the portfolio management strategy
5. To detect whether lagged effect brings valuable information when evaluating portfolio performance

3. Data and Study Period

An attempt is made to analyse managers' performances of sampled open-ended mutual fund schemes and comment on the adequacy of their performances by attributing it to the stock-selection, market-adjusted and time-lagged adjusted risk, return and asset class exposures. Therefore, we obtain monthly closing net asset values (NAV) of 30 equity mutual fund schemes of Unit Trust of India (UTI) and subsequently, monthly return series of the schemes is computed from the NAV. Primarily, the study considers all the open-ended equity mutual fund schemes but considers those, which are at least in existence for three years in mutual fund operation. It is also believed that some of the schemes have stopped their operation during the study period are also taken into consideration. Hence, the study is not free from survivorship bias. However, some of the authors have addressed that there is no consensus as to the magnitude and significance of this bias and suggested that its impact is very negligible and / or statistically insignificant (see Grinblatt & Titman 1989a, Brown et al 1992, Brown & Goetzmann 1995 and Romacho & Cortez 2006 etc). The information of NAV obtained from the secondary sources like the website of AMFI (www.amfiindia.com) and other sources which provide mutual fund data. The respective sources are crossed checked with other sources to ensure validity of the data and observed that there were no differences. As, the sample schemes are having greater equity exposure hence, the study uses BSE and NSE indexes as benchmarks. The monthly information with regard to monthly closing indexes value is obtained from the website of Bombay Stock Exchange (www.bseindia.org) and National Stock Exchange (www.nseindia.org). The study uses a set of public information variables, which are generally used by the previous studies for predicting security returns and risk with the change of time with more accuracy. This study exclusively uses a set of relevant publicly available information which is expected to produce the estimated coefficients with more accuracy under the assumption that risk and expected returns are time variant with the change of the economy. The one month lagged information variables are monthly 91-day Treasury bill yields (TB) of Govt. of India obtained from the website of Reserve Bank of India (RBI) that carry a fixed rate of return and enjoy a high rate of liquidity and safety since they are backed by the Government, monthly Rupee-dollar exchange rates (EX) obtained from the website of www.xrates.com, monthly Inflation rate (FL) obtained from the Centre of Statistical Organisation, monthly dividend yield (BY) of the BSE Sensex obtained from the website of Bombay Stock Exchange and monthly dividend yield of NSE index (NY) obtained from NSE website. Finally, a period of thirteen calendar years (1st January 2001 – December 2013) are taken into consideration, which is long enough to have seen a variety of ups and downs in the stock market and recent enough to reflect upon the complete picture about mutual fund performance.

4. Methodology

According to Sharpe (1992) the traditional view of asset allocation assumes that an investor assigns assets among many funds, each of which holds a number of securities. A sponsor is concerned in the investor's exposures to the key asset classes. All these are a function of (i) the monies put in each scheme and (ii) the exposure of each scheme to the different asset classes or indexes. The exposure of a scheme to diverse asset classes is determined by (1) the monies that the particular scheme put in different securities and (2) the exposures of the securities to the asset classes. Now, it is possible to establish the scheme's exposures from the analysis of the portfolio of securities held. In fact, inspection of proposed models 1 and 2 immediately suggests that the estimated slope coefficients from a multiple regression analysis could be interpreted as the fund's historic exposures to the asset class returns. To predict the scheme's exposures one can use regression analysis for a scheme's returns as dependent variable and the return of selected indexes as explanatory variables representing investment styles. For the purpose of stock selection of single index measure which is used by Jensen (1968) does not provide better estimates. But, it is assumed that introduction of multi-index measure provides better performance estimates as compared to the single index measure.

Unlike the method used in previous studies by Sharpe (1988) and by Elton et. al. (1993), the normalization of estimated coefficients (constrained such as to get the sum of coefficients equal to 1 or, equivalently to 100%) cannot be justified when lagged variables are used in the regression. On the other hand, we are conscious of the fact that the non-normalization of coefficients has its own limits. However, in our view, the aim of both types of analysis – constrained and unconstrained – is to infer the pattern of the manager's style rather than assigning a metric to the stakes he or she acquires on different markets.

The intention of this paper is to have a break up between systematic and unsystematic risk of mutual fund schemes keeping away from a priori the selection of index problem. It is proved that traditional single index measure cannot provide a distinction between these two types of scheme exposures. The single index measure is based on the assumption of capital asset pricing model (CAPM) framework where the risk premium of a mutual fund scheme i (excess return of mutual fund scheme i over the risk free rate) is a linear function of the systematic risk (beta) of the scheme and market risk premium. In fact, the single index measure relies on the estimated coefficients from the following regression:

$$R_{it} = \alpha_i + \beta_i(R_{mt}) + e_{it} \qquad \textbf{(Model 1)}$$

Where, R_{it} is the excess return of the i^{th} mutual fund scheme at time period t, R_{mt} is the excess return on the market portfolio at time period t, β_i is the index of systematic risk of scheme i, α_i is the alpha coefficient and e_{it} is the random error term of the scheme i at time period t that has zero mean and constant standard deviation with the following properties: $E(e_{it}) = 0$, $Var(e_{it}) = \sigma^2 e_{it}$ and $Cov(e_{it}, e_{ij}) = 0$.

Alternatively, the multi-index regression model (Elton, Gruber, Das & Hlavka'1993) is as under:

$$R_{it} = \alpha_i + \beta_{BSE}R_{BSE,t} + \beta_{NSE}R_{NSE,t} + e_{it} \qquad \textbf{(Model 2)}$$

Where, Where, R_{it} is the excess return of the i^{th} mutual fund scheme at time period t, $R_{BSE,t}$ is the excess return on BSE sensex at time period t, $R_{NSE,t}$ is the excess return on NSE sensex at time period t β_i is the market coefficients of i^{th} scheme on BSE and NSE, α_i is the alpha coefficient and e_{it} is the random error term of the scheme i at time period t that has zero mean and constant standard deviation with the following properties: $E(e_{it}) = 0$, $Var(e_{it}) = \sigma^2 e_{it}$ and $Cov(e_{it}, e_{ij}) = 0$.

Here, model 2 implies the decomposition of the scheme's performance across two types of indexes namely Bombay stock exchange (BSE) and National stock exchange (NSE). Although, the above model is a specific case of a multiple linear regression analysis of a factor model. It inherently assumes that the return and risk of a scheme can be divided in two components, one is explained jointly by market factors that influence returns of the schemes of similar type and the other remains unexplained which consists of a constant component plus a random error term with zero mean and a constant variance.

It is observed from model 2 that the scheme's return doesn't adjust on a timely basis that does not necessarily accommodate our previous considerations related to the valuation of mutual fund scheme. In order to relax this assumption and capture market-timing effects, we further introduce lagged market effects as explanatory variables for the current mutual fund performance. It is assumed that this assumption is more rational if we account for the fact that return series of the mutual fund scheme is conditional from the net asset value (NAV) calculation, which is supposed of netting out the returns. Therefore, we offer an extension of model 2, which considers additional lagged effects:

$$R_{i,t} = \alpha_i + \sum_{k=0}^{n} \beta_{t-k,BSE}\; R_{t-k,BSE} + \sum_{k=0}^{n} \beta_{t-k,NSE}\; R_{t-k,NSE} + e_{it}$$

(Model 3)

Where, the notations as above are as under and furthermore:

$\beta_{t-k,BSE}$ is the beta coefficient corresponding to the lagged market index BSE at time t-k, $\beta_{t-k,NSE}$ is the beta coefficient corresponding to the lagged market index NSE at time t-k, $R_{t-k,BSE}$ is the lagged market return of BSE at time t-k, $R_{t-k,NSE}$ is the lagged market return of NSE at time t-k, n is the number of lagged months and t & k are the time indexes with months t = 1......,n....,T and k = 0......,n respectively.

From model 3 we expect to estimate significant coefficients for 1 month, 2 months and 3 months (quarter) time lags. The results obtained from model 3 are corrected for heteroskedasticity and autocorrelation problems using White's (1980) correction test.

It is easy to understand that model 2 and model 3 are superior to single index model. Here, model 2 only provides market adjusted betas and alphas, whereas model 3 estimates both market adjusted as well as time adjusted coefficients. More specifically, the beta coefficient of model 2 captures only the benchmark effects whereas, beta and alpha coefficients of model 3 capture benchmark effects as well as time-lagged adjusted market effects.

Although, the above models implicitly assume that risk and expected return is constant overtime and these measures don't take into consideration the fact that risk and expected returns vary with the change of the state of the economy and as such these measures are likely to be untrustworthy. The main drawbacks of the above measures are that they cannot capture the dynamic behaviour of the market returns. It is possible if some relevant publicly available information which is considered as more informative is incorporated in the single index model. Therefore, Ferson & Schadt (1996) proposed an alternative approach to address these problems.

According to the conditional version of the CAPM, the return of a mutual fund scheme i can be written as follows:

$$R_{it} = \beta_{i,BSE}(A_{t-1})R_{BSE,t} + e_{it} \qquad (4a)$$

With $$E(e_{it} / A_{t-1}) = 0 \qquad (4b)$$

And $$E(e_{it}\, R_{BSE,t} / A_{t-1}) = 0 \qquad (4c)$$

Where, R_{it} is the excess return of mutual fund scheme i between the time period t and t-1, $R_{BSE,t}$ is the excess return of the benchmark index over the risk free asset and A_{t-1} denotes a vector of instruments for the information available at time period t-1. The beta of the regression equation $\beta_{i,BSE}(A_{t-1})$ is the conditional market beta of excess return of the mutual fund scheme i at time period t-1 that depends on the information vector A_{t-1}. Thus, beta varies over time due to certain number of factors. The conditional market beta of excess return of the mutual fund scheme i can be defined as follows:

$$\beta_{it-1} = Cov(R_{it}, R_{BSE,t}/A_{t-1}) / Var(R_{BSE,t}/A_{t-1}) \qquad (4d)$$

The equation 4a does not provide the alpha term because it uses information variables A_{t-1} when the latter is null. The error term in the above regression equation is independent as per equation 4b that leads to the assumption of efficient market hypothesis (EMH) and equation 4c tells that the $\beta_{i,BSE}(A_{t-1})$ is the conditional regression coefficient. Then, beta can be approximated of a mutual fund scheme i through a linear function by using a development from Taylor series following Shanken (1990) as under:

$$\beta_{im}(A_{t-1}) = b_{oi} + B'_i a_{t-1} \qquad (5)$$

The elements of vector B_i are the response coefficients of the conditional beta with respect to the information variables A_{t-1}. a_{t-1} denotes a vector of the differentials of A_{t-1} from the unconditional means that can be written as follows:

$$a_{t-1} = A_{t-1} - E(A_{t-1}) \qquad (6)$$

Now, it is possible to formulate a conditional measure of managed portfolio return by combining the above equations as under:

$$R_{it} = b_{oi}R_{BSE,t} + B'_i(a_{t-1})R_{BSE,t} + e_{it} \quad (7)$$

Where, $E(e_{it} / A_{t-1}) = E(e_{it}R_{BSE,t} / A_{t-1}) = 0$ (8)

The stochastic factor of the above measure is a linear function of the market return in excess of the risk free rate (R_f). Where, the coefficients of the above measure are conditional on public information A_{t-1}.

The traditional unconditional measures don't draw a distinction between the skill in using public information, which is available to everybody and a manager's specific stock picking ability. The conditional approach allows these to be separated. Therefore, to evaluate stock-selection performance the empirically developed model incorporates the term α_{ci} and the measure is as under:

$$R_{it} = \alpha_{ci} + b_{0i}R_{BSE,t} + B'(a_{t-1}R_{BSE,t}) + e_{it} \quad (9)$$

Where, α_{ci} implies the average conditional differentials between the excess return of i[th] mutual fund scheme and the excess return of a vibrant reference strategy. $B'(a_{t-1}R_{BSE,t})$ controls public information effect.

At the beginning it is very much important to determine what kind of information variables are to be used. This is almost same as using explanatory variables. This study uses a set of one month lagged publicly available information. Now, by_{t-1}, ny_{t-1}, tb_{t-1}, fl_{t-1} and ex_{t-1} represent the differentials compared to the average of the variables BY_{t-1}, NY_{t-1}, TB_{t-1}, FL_{t-1} and EX_{t-1} that can be written as follows:

$by_{t-1}=BY_{t-1}-E(BY_t)$, $ny_{t-1}=NY_{t-1}-E(NY_t)$, $tbt_{-1}=TB_{t-1}-E(TB_t)$, $fl_{t-1}=FL_{t-1}-E(FL_t)$ and $ex_{t-1}=EX_{t-1}-E(EX_t)$ (10)

Then, the relationship can be written as under:

$$a_{t-1}\begin{bmatrix} by_{t-1} \\ tb_{t-1} \\ fl_{t-1} \\ ex_{t-1} \\ ny_{t-1} \end{bmatrix} \text{ and } B_i\begin{bmatrix} b_{1i} \\ b_{2i} \\ b_{3i} \\ b_{4i} \\ b_{5i} \end{bmatrix} \quad (11)$$

Hence, the conditional beta is the function of a set of information vector. The conditional beta can be interpreted by using the approach of Rosenberg & Mckibben (1973) and Rosenberg & Marathe (1975) as under:

$$b_i = b_0 + b_{1i}by_{t-1} + b_{2i}tb_{t-1} + b_{3i}fl_{t-1} + b_{4i}ex_{t-1} + b_{5i}ny_{t-1} + e_{it} \quad (12)$$

Hence, the conditional single index measure can be formulated as under:

$$R_{it} = \alpha_{ci}+b_{0i}R_{BSE,t}+b_{1i}dy_{t-1}R_{BSE,t}+b_{2i}tb_{t-1}R_{BSE,t}+b_{3i}fl_{t-1}R_{BSE,t}+b_{4i}ex_{t-1}R_{BSE,t}+b_{5i}ny_{t-1}R_{BSE,t}+e_{it} \quad (13)$$

Where, α_{ci} represents the difference between a scheme's excess return and the excess return to the particular combination of market index and the set of information variables that replicate the scheme's time varying risk exposure. The term b_{0i} represents the conditional beta or in other words, it can only be viewed as the separate influence of the market after taking into consideration the influence of public information variables. The coefficients b_1, b_2, b_3, b_4 and b_5 measure the variations of the conditional beta to the lagged information variables.

It is well known that better estimation of the beta allows for better estimation of the alpha. Therefore, the value of alpha also follows conditional process. Thus, the relationship depicted by the conditional alpha can be written as follows:

$$\alpha_{ci} = \phi_i(a_{t-1}) \quad (14)$$

Now, the alpha coefficient can be written by taking into consideration the information variables, which is made up of four components as under:

$$\alpha_{ci}=\phi_{0i}+\phi_{1i}by_{t-1}+\phi_{2i}tb_{t-1}+\phi_{3i}fl_{t-1}+\phi_{4i}ex_{t-1}+\phi_{5i}ny_{t-1}$$

$$\text{with} \quad \phi_i = \begin{bmatrix} \phi_{1i} \\ \phi_{2i} \\ \phi_{3i} \\ \phi_{4i} \\ \phi_{5i} \end{bmatrix} \quad (15)$$

Finally, the conditional single index measure can be formulated as under:

$$R_{it} = \phi_{0i}+\phi_{1i}by_{t-1}+\phi_{2i}tb_{t-1}+\phi_{3i}fl_{t-1}+\phi_{4i}ex_{t-1}+\phi_{5i}ny_{t-1}+b_{0i}R_{index,t}+b_{1i}by_{t-1}R_{index,t}+b_{2i}tb_{t-1}R_{index,t}+b_{3i}fl_{t-1}R_{index,t}+b_{4i}ex_{t-1}R_{index,t}+b_{5i}ny_{t-1}R_{index,t}+e_{it}$$

(Model 16)

Here, ϕ_{1i}, ϕ_{2i}, ϕ_{3i}, ϕ_{4i} and ϕ_{5i} measure the variations in conditional alpha compared to the dividend yields (BSE & NSE), the return on the T-bills, change in rupee-dollar exchange rate and change in inflation rates. The coefficients of model 16 are estimated through regression equation from the time series data. The heterocedasticity and multicolinearity problems in the regression model are corrected through proper test.

It is expected that conditional single index model provides better forecast than the traditional single index model. But if we decompose the scheme's performance across two types of indexes under conditional framework then we can examine the risk exposures in a better way. In fact, this is a conditional multiple linear regression analysis. Let us consider the following multi-index conditional regression model:

$$R_{it}=\phi_{0i}+\phi_{1i}by_{t-1}+\phi_{2i}tb_{t-1}+\phi_{3i}fl_{t-1}+\phi_{4i}ex_{t-1}+\phi_{5i}ny_{t-1}+b_{0i}R_{BSE,t}+b_{1i}by_{t-1}R_{BSE,t}+b_{2i}tb_{t-1}R_{BSE,t}+b_{3i}fl_{t-1}R_{BSE,t}+b_{4i}ex_{t-1}R_{BSE,t}+b_{5i}ny_{t-1}R_{BSE,t}+\lambda_{0i}R_{NSE,t}+\lambda_{1i}by_{t-1}R_{NSE,t}+\lambda_{2i}tb_{t-1}R_{NSE,t}+\lambda_{3i}fl_{t-1}R_{NSE,t}+\lambda_{4i}ex_{t-1}R_{NSE,t}+\lambda_{5i}ny_{t-1}R_{NSE,t}+e_{it}$$ **(Model 17)**

It is assumed that model 16 and model 17 provide better estimates than model 1, model 2 and model 3. In other words model 16 and model 17 provide conditional estimates as compared to the above stated models. Moreover, the problems of heterocedasticity, autocorrelation and multicolinearity are corrected through appropriate test.

The monthly rate of return of each mutual fund schemes and the market index (BSE Sensex & NSE Sensex) are computed as follows:

$$R_{i,t} = \log \frac{NAV_{i,t}}{NAV_{i,t-1}} \qquad (18)$$

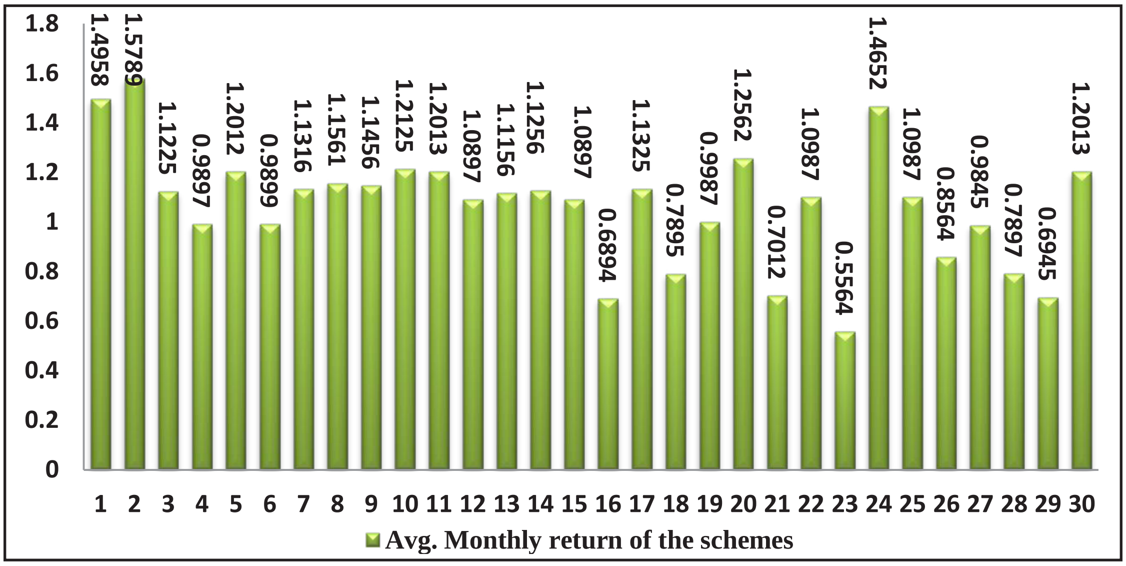
$$R_{m,t} = \log \frac{Market\ Index_t}{\text{Market Index}_{t-1}} \qquad (19)$$

Where, R_{it} is the logarithm return of the i^{th} mutual fund scheme at the end of time (month) t. $NAV_{i,t}$ is the net asset value of the i^{th} mutual fund scheme at time (month) t and $NAV_{i,t-1}$ is the net asset value of the i^{th} mutual fund scheme at the end of the previous time (month) period 't-1'. Similarly, R_{mt} is the logarithm return of the market.

To observe the pattern of the time series data Jarque-Bera test of normality is applied. Similarly, the unit root problem is corrected through DF test.

5. Result and Analysis

The study analyses the monthly return series of the schemes. Here, the monthly graphical representation of the average return of the schemes is given. It is observed that the return of the schemes is different. Time-drift is observed in the return series and also market-timing effect is also present in the return series.



Graph 1: Average Monthly Return of the Schemes

Table 1 represents the summary statistic for monthly return series of the equity mutual fund schemes. The computed J-B statistic of the individual return series of the schemes is far from zero (J-B>0) which confirms rejection of null hypothesis of a normal distribution.

Table 1: Descriptive Statistic of the Mutual Fund Schemes

Sl.No	OB	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB
1	65	1.4958	0.6701	13.3500	-14.0121	5.8891	-0.558	0.968	5.9109
2	65	1.5789	1.3213	52.3209	-20.2547	8.8335	2.501	16.841	835.8981
3	89	1.1225	0.0864	16.1046	-17.1508	4.5089	0.360	7.364	203.0197
4	76	0.9897	0.6015	13.6451	-3.6353	3.2047	2.389	7.134	233.4569
5	76	1.2012	0.4910	12.7231	-2.1568	2.8753	2.432	6.892	225.3342
6	76	0.9899	0.3854	25.0245	-18.3584	5.1323	1.312	12.545	520.1643
7	76	1.1316	0.3213	10.9112	-2.6485	2.5642	2.570	6.342	211.0285
8	76	1.1561	0.6528	14.7562	-28.3245	5.4556	-2.327	17.421	1029.6447
9	76	1.1456	0.7012	10.0125	-2.6567	2.1236	1.542	3.592	70.9761
10	76	1.2125	0.7856	8.1226	-2.5678	2.0523	2.125	5.345	147.6665
11	100	1.2013	0.3123	15.2133	-0.7745	2.7562	3.102	10.312	603.4457
12	100	1.0897	0.5085	7.4012	-3.7562	1.8452	0.845	1.754	24.7192
13	100	1.1156	0.6023	10.5213	-1.7012	1.7321	2.413	9.845	500.8929
14	100	1.1256	0.6548	12.1325	-2.8412	2.4521	2.589	9.365	477.1455
15	100	1.0897	0.8015	6.4257	-7.5053	2.0895	-0.520	4.128	75.5083
16	100	0.6894	0.5684	9.5023	-6.3023	2.1045	0.450	4.615	92.1176
17	100	1.1325	0.7546	7.3045	-4.7452	1.5756	1.204	5.256	139.2667
18	100	0.7895	0.5023	7.6078	-15.2107	3.2789	-2.495	13.512	864.4760
19	100	0.9987	0.7785	4.4012	-0.2012	0.8012	1.754	2.812	84.2225
20	100	1.2562	0.7125	7.7145	-1.7956	1.4526	1.845	5.256	171.8402
21	100	0.7012	0.7456	5.5678	-11.7527	2.2546	-3.062	14.323	1011.0488
22	100	1.0987	0.7426	9.3065	-4.1023	1.6854	1.798	7.586	293.6609
23	100	0.5564	0.7546	11.7223	-7.7027	3.4145	0.337	5.145	112.1888
24	100	1.4652	0.5987	30.0231	-9.2652	5.1123	4.425	20.450	2068.8542
25	100	1.0987	0.6886	16.8745	-10.0268	3.0456	1.742	18.680	1504.5027
26	100	0.8564	0.5895	4.6122	-10.3014	2.0345	-3.721	21.302	2121.4940
27	100	0.9845	0.8125	25.0123	-21.7845	3.1254	1.025	29.837	3726.8711
28	100	0.7897	0.4645	12.7589	-10.3215	2.6712	2.023	16.102	1148.5188
29	100	0.6945	0.5421	4.8452	-2.2023	1.0402	1.211	4.203	98.0471
30	100	1.2013	0.7896	5.8562	-3.0845	1.4562	1.102	4.201	93.7751

Note: The name of the schemes is given in Table. 7

Similarly, Table 2 shows the summary statistic of the independent variables namely market indexes (BSE & NSE) R_m, dividend yields (BY & NY), 91-day Treasury bill rate (TB), inflation rate (FL) and Rupee-Dollar exchange rate (EX). The computed J-B statistic of the independent variables is different from zero which indicates rejection of null hypothesis of a normal distribution.

Table 2: Descriptive Statistic of the Independent Variables

Name	OB	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB
R_{BSE}	156	1.4496	0.9457	49.94	-30.24	9.07	0.578	6.366	75.9978
R_{NSE}	156	1.2617	1.0372	28.066	-26.410	7.3746	-0.238	1.639	13.5128
BY	156	1.5794	1.5266	2.52	0.85	0.42	0.329	-0.963	96.83

Name	OB	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB
NY	156	0.8047	-0.7143	67.164	-46.902	11.642	1.314	8.412	235.274
TB	156	0.3739	0.6024	59.19	-39.65	9.17	0.531	15.644	965.995
FL	156	2.4207	2.5333	5.60	-2.10	1.35	-0.716	1.337	28.9872
EX	156	0.2019	0.5393	7.16	-6.80	2.22	0.545	2.291	1.1447

The empirical work based on time series data assumes that the underlying time series is stationary that means its mean, variance and auto-covariance (at various lags) remain the same. Table 3 presents the summary statistic of time-series returns data of 30 schemes. It is observed that the computed absolute tau statistic ($|\tau|$) of 13 time series return data exceeds the DF critical absolute tau values at 5% significance level which indicates rejection of null hypothesis that means the time series of 13 schemes are stationary.

It is assumed that the nature of disturbances of any regression model is homoscedastic that means they all have the same variances. Practically, it has not so happened or in other words their nature is heteroscedactic. White's (1980) general heteroscedasticity test is applied to examine the problem. Here, Table 3 also presents the test statistic of heteroscedasticity and shows that the computed chi-square values of the regressions are lower than the critical chi-square values at 5% level of significance and hence, it may be said to have non existence of such problem.

Table 3: Unit root & Heteroscedasticity Tests of the Return Series of the Schemes

Sl.No	Estimated Coefficient	Standard Error	Tau Statistic	DF Statistic	χ^2	Table Value (5% level)
1	0.323	0.131	2.4656	-2.89	3.295	19.6751
2	-0.267	0.132	-2.0227	-2.89	3.762	19.6751
3	0.276	0.111	2.4865	-2.89	3.762	19.6751
4	0.412	0.112	3.6786	-2.89	9.732	19.6751
5	0.374	0.123	3.0407	-2.89	2.798	19.6751
6	-0.213	0.113	-1.8850	-2.89	8.176	19.6751
7	0.311	0.131	2.3740	-2.89	5.456	19.6751
8	0.079	0.125	0.6320	-2.89	6.236	19.6751
9	0.656	0.111	5.9099	-2.89	6.566	19.6751
10	0.542	0.124	4.3710	-2.89	14.982	19.6751
11	0.489	0.132	3.7045	-2.89	16.218	19.6751
12	0.597	0.078	7.6538	-2.89	9.123	19.6751
13	0.756	0.103	7.3398	-2.89	9.254	19.6751
14	0.512	0.099	5.1717	-2.89	9.254	19.6751
15	0.625	0.096	6.5104	-2.89	8.345	19.6751
16	0.412	0.097	4.2474	-2.89	7.231	19.6751
17	-0.118	0.115	-1.0261	-2.89	5.235	19.6751
18	0.110	0.121	0.9091	-2.89	16.264	19.6751
19	0.321	0.110	2.9182	-2.89	13.542	19.6751
20	0.212	0.087	2.4368	-2.89	7.492	19.6751
21	0.256	0.110	2.3273	-2.89	5.496	19.6751
22	0.348	0.124	2.8065	-2.89	5.566	19.6751
23	0.375	0.103	3.6408	-2.89	18.102	19.6751
24	0.212	0.101	2.0990	-2.89	18.102	19.6751
25	0.113	0.112	1.0089	-2.89	13.456	19.6751
26	0.217	0.115	1.8870	-2.89	8.287	19.6751

Sl.No	Estimated Coefficient	Standard Error	Tau Statistic	DF Statistic	χ^2	Table Value (5% level)
27	0.010	0.132	0.0758	-2.89	4.898	19.6751
28	0.101	0.102	0.9902	-2.89	15.542	19.6751
29	0.498	0.089	5.5955	-2.89	8.262	19.6751
30	-0.016	0.113	-0.1416	-2.89	7.221	19.6751

Table 4 reports Pearson Correlation Matrix, which reveals that the highest simple correlation coefficient between independent variables (return on BSE & return on NSE) is 0.7952. According to Gujrati (2004) and Hair *et al.* (2011) the simple correlation not exceeding 0.90 between the independent variables should not be considered harmful. On the other hand, R^2 value higher that 0.800 is considered to be harmful because of the presence of multicolinearity problem. It is examined that the computed values of R^2 of the schemes' are lower than 0.800, which necessarily proves non-existence of multicolinearity problems between the independent variables. VIF is another popular measure to test multicolinearity. The value of VIF higher than ten (10) is likely to cause a multicolinearity problem. Here, the values range between 1.0578 and 1.9756 (i,e. less than 10) that means the absence of multicolinearity problem. Tolerance may also be used as a measure of examining multicolinearity problem. The tolerance value is more than 0.20 may be considered that the explanatory variables in the regression model being free from the problem of multicolinearity. Here, the computed tolerance value ranges between 0.508 and 0.955 which clearly indicates the fact that the regression models are free from the problems of multicolinearity of the explanatory variables.

Table 4: Test of Multicollinearity (Pearson Correlation Matrix)

Variable	R_{BSE}	R_{NSE}	*BY*	*NY*	*TB*	*FL*	*EX*
$\mathbf{R_{BSE}}$	1.000						
$\mathbf{R_{NSE}}$	0.7952	1.000					
BY	0.1728	0.1727	1.000				
NY	-0.6536	-0.6655	0.8093	1.000			
TB	-0.2266	-0.2181	-0.2423	0.0956	1.000		
FL	-0.1709	-0.1720	-0.0294	-0.0994	0.2532	1.000	
EX	0.0923	0.0898	0.1712	0.1753	0.2485	-0.2171	1.000

Table 5 presents the estimated coefficients based on single index as well multi-index measures. It is observed from the table that significant alpha value is higher when considering NSE index (19) as compared to the BSE (17) index based on single-index measure. Moreover, the risk exposure in NSE is lesser as compared to the BSE market. Hence, the investors like to invest in NSE market rather than BSE because of lucrative returns and lower degree of risk. It is straightforward to note that the model 2 is more representative than the model 1 because the risk of exposures in two types of markets are lower than the risk exposures when compared to model 1. Here, the investors can get the opportunity to invest in two types of markets and the managers also have the choice to select stock from both the markets. It is found that 21 schemes have provided significant selectivity performances based on multi-index measure. Although, the alpha and beta are market adjusted and the schemes' returns are not adjusted on a timely basis. In order to estimate market-adjusted and time-adjusted returns the study uses lagged market effects as explanatory variables for the current portfolio performance.

We have extended the model 2 and formulated model 3 by introducing different time lags like 1 month, 2 months, quarterly (3 months) and yearly (11 months) for estimating market adjusted as well time adjusted coefficients in different markets. No doubt, model 2 is superior to model 1 but model 3 is even superior than model 2 because it estimates market adjusted as well as time adjusted coefficients. It is observed that model 3 in all cases is more representative than the model 2. The estimated alpha values of the schemes have been improved in all versions of model 3. Here, the managers are more efficient to select stocks when different lags are used. In model 3 the beta coefficients also contain both market adjusted effects and time-lagged adjusted market effects. The lag effect provides additional information to the investors and the investment managers about risk exposures in different asset classes (markets) when evaluating portfolio performance. If we observe the computed R^2 value we can find that the values have improved in all versions of model 3 as compared to model 2 that indicates that the sample is represented optimally by model 3. The R^2 value can be interpreted as being recognizable to the schemes' style and the remaining is attributable to selection of stocks. Therefore, deviation of returns occurred mainly for style itself which arises from selection of specific stocks within one or more asset classes, alternation among classes, or both. Hence, Model 3 with all relevant lags (1 month, 2 months, quarterly and yearly) is a better representative than the model 1 and model 2.

Table 5: Estimated Coefficients of the Schemes

Sl. No	*Model 1 (Index BSE)*		*Model 1 (Index NSE)*		**Model 2 (Multi-Index no lags)**			
	α	β	α	β	α	β_{BSE}	β_{NSE}	R^2
1	1.322	0.512*	0.840	0.567*	0.865*	-0.197	0.749*	0.432
2	0.721	0.554*	0.862	0.626*	0.900	-0.304	0.907	0.412
3	0.792	0.201*	1.360*	-0.163*	0.945*	0.032	0.037	0.475
4	0.990*	0.078*	1.045*	-0.046	1.093*	0.054	-0.090	0.398
5	0.436	0.069	1.293*	-0.061	1.165*	0.076	-0.054	0.412
6	1.281	0.004	0.901	0.041	0.283	0.138	0.130	0.532
7	0.996*	0.054	1.054*	-0.020	1.037*	0.014	-0.014	0.512
8	0.977	0.120	1.347*	-0.175	1.166*	-0.041	0.035	0.546
9	1.212*	0.076*	1.196*	-0.041	1.176*	0.036	-0.040	0.412
10	1.175*	0.054	1.259*	-0.048	1.228*	0.023	-0.027	0.477
11	1.312*	-0.007	1.366*	-0.077*	1.392*	-0.015	-0.076	0.465
12	1.156*	0.026	1.028*	0.008	1.112	-0.016	-0.021	0.489
13	1.170*	0.045*	1.078*	0.021	1.156*	0.003	-0.027	0.562
14	0.707	0.109*	1.097*	0.016	1.170*	-0.069	0.034	0.523
15	1.100*	0.067*	1.032*	-0.015	1.182*	-0.053	-0.031	0.542
16	0.792	0.052	0.530*	0.066*	0.726	-0.068*	0.004	0.598
17	0.448	-0.014	1.044	-0.011	1.135*	-0.028	-0.024	0.489
18	0.029	0.004	0.230	-0.044	0.047	-0.001	0.062	0.475
19	1.024*	-0.015	0.982*	-0.009	0.987*	-0.004	-0.004	0.398
20	1.331*	0.011	1.206*	0.010	1.239*	-0.012	0.000	0.345
21	0.564	-0.015	0.632	0.041	0.575	-0.039	0.081*	0.412
22	1.130*	0.012	1.073	-0.005	0.011	-0.001*	0.000	0.526
23	0.723	0.025	0.537	-0.027	0.654	-0.105*	0.023	0.601
24	1.432*	0.105	1.408*	0.015	1.331*	0.014	0.030	0.584
25	1.049*	0.047	1.063*	0.021	1.078*	-0.038	0.039	0.545
26	0.826*	-0.006	0.781	-0.013	0.710*	0.011	0.017	0.576
27	0.861	0.037	0.862	0.024	0.973*	0.001	-0.039	0.523
28	0.804*	0.051	0.734*	0.035	0.809*	-0.021	0.002	0.486
29	0.007*	0.001*	0.624	-0.004	0.621	0.011	-0.010	0.412
30	1.103*	0.002	1.182*	0.005	1.219*	-0.006	-0.009	0.438

* Significance at 5% level

Table 6: Estimated Coefficients based on Multi-Index Lagged Model

Sl. No	Model 3 (Lags 1 Month)					Model 3 (Lags 1 Month, 2 Months)						
	α	$\beta_{t, BSE}$	$\beta_{t, NSE}$	$\beta_{t-1,BSE}$	$\beta_{t-1,NSE}$	α	$\beta_{t, BSE}$	$\beta_{t, NSE}$	$\beta_{t-1, BSE}$	$\beta_{t-1, NSE}$	$\beta_{t-2, BSE}$	$\beta_{t-2, NSE}$
1	0.530	-0.078	0.624*	0.068	0.091	0.698*	-0.116	0.663*	0.246	-0.085	-0.180	0.372
2	0.582	-0.291	0.905	-0.031	0.019	0.782*	-0.291	0.907	0.135	-0.144	0.007	0.184
3	0.578	0.152	0.054	-0.276	0.302	0.553	0.133	0.078	-0.372	0.403	-0.189	0.214
4	0.464	0.124	-0.037	-0.030	0.089	0.621*	0.111	-0.032	0.040	0.001	0.311	-0.272
5	0.954*	0.144	-0.080	0.106	-0.061	0.991*	0.148	-0.091	0.228	-0.198	0.349	-0.355
6	0.903*	0.145	-0.155	0.130	-0.096	0.916*	0.153	-0.169	0.218	-0.194	0.229	-0.235
7	0.915*	0.256	-0.193	-0.222	0.216	0.910*	0.251	-0.195	-0.129	0.107	0.324	-0.307
8	0.769*	0.137	-0.004	-0.439	0.499	0.899*	0.146	-0.002	-0.499	0.579	-0.298	0.231
9	0.966*	0.148	-0.083	0.017	0.006	0.941*	0.157	-0.098	0.081	-0.066	0.166	-0.160
10	1.018*	0.202	-0.144	-0.182	0.210	0.962*	0.183	-0.126	-0.200	0.221	0.072	-0.030
11	1.239*	0.242	-0.256	0.116	-0.130	1.255*	0.243	-0.258	0.138	-0.153	0.038	-0.045
12	1.000*	0.333	-0.318	0.210	-0.197	0.963*	0.335	-0.329	0.234	-0.225	0.111	-0.096
13	1.026*	0.319	-0.268	-0.088	0.079	0.974*	0.316	-0.264	-0.115	0.103	0.023	0.004
14	0.888*	0.962*	-0.859*	0.442	-0.372	0.829*	0.958*	-0.858*	0.474	-0.421	0.341	-0.275
15	0.935*	0.606*	-0.552*	0.286	-0.285	0.870*	0.597	-0.537*	0.138	-0.182	-0.137	0.176
16	0.535*	0.111	-0.082	0.377	-0.337	0.440	0.099	-0.067	0.321	-0.294	0.199	-0.107
17	1.098*	0.016	-0.042	0.371	-0.393	1.019*	0.009	-0.027	0.229	-0.241	-0.337	0.355
18	0.237	0.079	-0.084	0.431	-0.471	0.098	0.062	-0.056	0.218	-0.253	-0.329	0.399
19	0.991*	0.019	-0.035	0.012	-0.015	0.950*	0.019	-0.033	-0.031	0.033	-0.128	0.129
20	1.183*	-0.035	-0.268	0.279	-0.007	1.196*	-0.035	-0.274	0.286	-0.028	0.021	-0.002
21	0.690*	0.000	-0.364	0.348	-0.005	0.683*	-0.008	-0.476	0.450	-0.298	0.297	0.022
22	1.022*	0.014	-0.131	0.141	-0.020	0.936*	0.014	-0.128	0.138	0.020	-0.043	0.033
23	0.877*	-0.012	-0.211	0.223	-0.013	0.142	-0.061	0.035	0.083	0.028	0.085	0.056
24	1.176*	0.456	-0.389	0.862	-0.713	1.160*	0.459	-0.417	1.207	-1.115	1.458*	-1.330*
25	0.973*	0.117	-0.100	0.730	-0.651	0.795*	0.101	-0.075	0.556	-0.481	-0.101	0.204
26	0.737*	0.011	-0.010	-0.212	0.205	0.724*	0.011	-0.007	-0.263	0.265	-0.206	0.191
27	0.750	0.249	-0.243	1.015	-0.898	0.619*	0.240	-0.241	1.084	-1.002	0.731	-0.589
28	0.680*	0.652*	-0.609*	0.446	-0.429	0.552*	0.641*	-0.594*	0.356	-0.347	0.070	0.016
29	0.545*	0.143	-0.104	0.063	-0.046	0.536*	0.142	-0.102	0.039	-0.018	-0.082	0.079
30	1.212*	-0.005	-0.009	-0.009	0.010	1.252*	-0.002	-0.017	-0.005	0.013	-0.038	0.013

Table 6: (Continue)

R^2 (1 month lagged multi-index model)												
1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*
0.436	0.420	0.490	0.401	0.415	0.535	0.516	0.548	0.420	0.492	0.671	0.492	0.568
14	**15**	**16**	**17**	18	19	20	21	22	23	24	25	26
0.532	0.548	0.499	0.491	0.479	0.401	0.351	0.422	0.531	0.606	0.591	0.548	0.579
27	**28**	**29**	**30**									
0.536	0.490	0.419	0.445									

Table 6. (Continue)

R^2 (1 month & 2 months lagged multi-index model)												
1	2	3	4	5	6	7	8	9	10	11	12	13
0.438	0.426	0.412	0.422	0.416	0.538	0.518	0.552	0.431	0.499	0.674	0.498	0.571
14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	23	24	25	26
0.534	0.550	0.501	0.495	0.418	0.540	0.522	0.555	0.435	0.502	0.678	0.500	0.573
27	**28**	**29**	30									
0.538	0.495	0.420	0.448									

Table 6: (Continue)

Model 3 (Lags 1 Month, 2 Month, Quarterly)									
α	$\beta_{t, BSE}$	$\beta_{t, NSE}$	$\beta_{t-1, BSE}$	$\beta_{t-1, NSE}$	$\beta_{t-2, BSE}$	$\beta_{t-2, NSE}$	$\beta_{t-3, BSE}$	$\beta_{t-3, NSE}$	R^2
0.376	-0.139	0.683*	0.199	-0.048	-0.134	0.320	-0.223	0.274	0.441
0.901*	-0.451	1.082	0.006	-0.011	-0.071	0.258	-0.656	0.551	0.428
0.414	0.061	0.159	-0.450	0.481	-0.319	0.344	-0.184	0.255	0.420
0.660*	0.188	-0.108	0.070	-0.021	0.226	-0.170	-0.334	0.299	0.425
1.005*	0.198	-0.139	0.247	-0.214	0.304	-0.300	-0.198	0.175	0.416
0.871*	0.121	-0.135	0.185	-0.158	0.159	-0.164	-0.096	0.125	0.539
0.944*	0.297	-0.241	-0.107	0.089	0.290	-0.264	-0.160	0.130	0.521
0.915	0.209	-0.063	-0.491	0.582	-0.448	0.402	-0.450	0.433	0.554
0.862*	0.126	-0.059	0.041	-0.025	0.085	-0.077	-0.131	0.164	0.435
0.938*	0.183	-0.123	-0.213	0.238	0.009	0.038	-0.142	0.151	0.501
1.303*	0.317	-0.327	0.145	-0.163	0.062	-0.062	-0.081	0.038	0.678
0.916*	0.340	-0.322	0.214	-0.199	0.005	0.019	-0.268	0.270	0.501
0.955*	0.361	-0.300	-0.133	0.127	-0.084	0.125	-0.343	0.323	0.573
0.807*	0.979*	-0.874*	0.465	-0.410	0.296	-0.224	-0.150	0.140	0.535
0.820*	0.629*	-0.558*	0.157	-0.148	-0.281	0.334	-0.408	0.397	0.552
0.329	-0.036	0.064	0.292	-0.256	0.068	0.016	-0.055	0.139	0.502
0.996*	0.011	-0.027	0.221	-0.232	-0.372	0.394	-0.093	0.094	0.499
0.022	-0.006	0.017	0.185	-0.212	-0.476	0.550	-0.230	0.276	0.419
0.930*	0.034	-0.044	-0.038	0.041	-0.163	0.169	-0.114	0.108	0.542
1.169*	-0.038	-0.274	0.286	-0.029	0.022	0.002	-0.004	0.005	0.525
0.701*	-0.012	-0.498	0.469	-0.360	0.353	-0.130	0.155	-0.005	0.559
0.938*	0.015	-0.121	0.131	0.026	-0.047	0.046	-0.013	0.003	0.438
0.061	-0.069	0.014	0.084	0.029	0.074	0.073	0.126	0.026	0.506
1.437*	0.601	-0.577	1.309*	-1.250*	1.990*	-1.885*	1.012	-1.120*	0.681
0.791*	0.177	-0.142	0.542	-0.463	-0.195	0.315	0.336	-0.375	0.502
0.687*	0.079	-0.062	-0.288	0.296	-0.347	0.351	0.441	-0.474	0.576
0.645	0.201	-0.212	1.103	-1.027	0.847	-0.718	0.351	-0.335	0.539
0.425	0.679*	-0.610*	0.288	-0.259	-0.309	0.428	-0.988*	0.985*	0.496
0.549*	0.180	-0.137	0.037	-0.016	-0.098	0.101	-0.113	0.092	0.423
1.235*	0.002	-0.020	-0.007	0.020	-0.037	0.010	0.020	-0.029	0.449

Table 6: (Continue)

Model 3 (Lags 1 Month, 2 Month, Quarterly & Yearly)											
α	$\beta_{t, BSE}$	$\beta_{t, NSE}$	$\beta_{t-1, BSE}$	$\beta_{t-1, NSE}$	$\beta_{t-2, BSE}$	$\beta_{t-2, NSE}$	$\beta_{t-3, BSE}$	$\beta_{t-3, NSE}$	$\beta_{t-11, BSE}$	$\beta_{t-11, NSE}$	R^2
0.345	-0.165	0.697*	0.211	-0.062	-0.132	0.324	-0.195	0.242	-0.276	0.251	0.445
0.731*	-0.542	1.148	-0.059	0.021	-0.068	0.286	-0.532	0.463	-0.446	0.557	0.430
0.365	0.466	-0.192	-0.138	0.178	-0.195	0.245	-0.356	0.419	0.275	-0.213	0.421
0.942*	0.327	-0.225	0.315	-0.236	0.442	-0.374	-0.142	0.095	-0.018	-0.067	0.425
1.138*	0.372	-0.291	0.478	-0.418	0.438	-0.429	-0.135	0.108	0.006	-0.035	0.418
0.945*	0.263	-0.272	0.271	-0.215	0.208	-0.225	-0.002	0.043	0.377	-0.391	0.545
1.122*	0.469	-0.393	0.042	-0.037	0.404	-0.377	-0.060	0.036	0.212	-0.255	0.530
1.167*	0.526	-0.344	-0.337	0.472	-0.328	0.266	-0.341	0.337	0.619	-0.661	0.554
0.942*	0.402	-0.311	0.349	-0.098	0.241	-0.212	-0.079	0.107	0.319	-0.315	0.440
1.038*	0.340	-0.268	-0.022	0.069	0.134	-0.073	-0.038	0.045	0.269	-0.291	0.512
1.217*	0.318	-0.322	0.099	-0.112	0.019	-0.022	-0.096	0.058	0.087	-0.085	0.679
0.850*	0.355	-0.337	0.260	-0.249	0.018	0.013	-0.326	0.320	-0.118	0.132	0.501
0.918*	0.348	-0.288	-0.140	0.136	-0.100	0.139	-0.333	0.311	-0.024	0.018	0.575
0.788*	0.986*	-0.880*	0.463	-0.416	0.329	-0.249	-0.154	0.139	0.018	-0.033	0.539
0.748*	0.637*	-0.561*	0.153	-0.147	-0.287	0.350	-0.478	0.455	-0.156	0.155	0.554
0.484	-0.101	0.131	0.284	-0.248	0.091	-0.007	-0.030	0.106	-0.279	0.222	0.505
0.997*	-0.009	-0.005	0.284	-0.260	-0.360	0.384	-0.135	0.130	-0.207	0.209	0.501
0.081	0.001	0.015	0.248	-0.281	-0.469	0.556	-0.368	0.403	-0.284	0.319	0.421
0.918*	0.039	-0.050	-0.048	0.048	-0.144	0.146	-0.092	0.088	0.043	-0.046	0.546
1.166*	-0.041	-0.301	0.308	-0.056	0.050	0.003	-0.008	0.007	0.012	-0.011	0.528
0.585	-0.008	-0.524	0.493	-0.393	0.383	-0.129	0.156	-0.006	0.010	0.016	0.561
0.952*	0.015	-0.123	0.131	0.031	-0.052	0.058	-0.024	0.003	0.008	-0.007	0.440
0.079	-0.081	0.022	0.088	0.030	0.083	0.079	0.118*	0.221	-0.201	-0.054	0.508
1.561*	0.668	-0.656	1.218	-1.153	1.965*	-1.874*	1.228	-1.307*	0.883	-0.890	0.683
0.865*	0.090	-0.057	0.522	-0.441	-0.158	0.271	0.212	-0.260	-0.224	0.127	0.505
0.646*	0.061	-0.044	-0.331	0.342	-0.335	0.330	0.373	-0.402	0.044	-0.066	0.581
0.808*	0.021	-0.034	1.044	-0.968	0.941	-0.829	0.552	-0.554	-0.577	0.400	0.541
0.401	0.714*	-0.640*	0.226	-0.201	-0.322	0.444	-0.973*	0.976*	0.306	-0.306	0.499
0.525*	0.179	-0.136	0.041	-0.021	-0.086	0.089	-0.111	0.088	-0.041	0.037	0.428
1.269*	0.000	-0.019	-0.010	0.028	-0.039	0.015	0.019	-0.022	0.004	-0.002	0.451

Table 7 shows the estimated coefficients based on conditional single index measure. It is observed from the table that the estimated alpha values of 23 schemes are statistically significant that means that the managers are efficient to select under priced stocks in the BSE market after inclusion of lagged public information variables in the conditional measure. If we observe the R^2 values we find that the values have improved as compared to the previous model which is a good indication of managers' performance related to style analysis. Hence, it may be said that conditional model is more representative as compared to the traditional single index measures. In this measure we have also shown the beta exposures of conditional public information variables.

Table 7: Estimated Coefficients Based on Conditional Single Index Model

Model 16 (BSE Sensex)								
Sl. No	α_c	β_{0c}	β_{1c}	β_{2c}	β_{3c}	β_{4c}	β_{5c}	R^2
1	1.256*	-0.399	-1.289	-0.150	-0.103	0.101	0.003	0.434
2	0.329	0.564	0.254	-0.285	0.063	-0.106	-0.004	0.416
3	1.008	0.121	0.419	-0.011	0.027	-0.015	0.005	0.480
4	0.968*	0.632*	0.888*	-0.055	-0.033	-0.075*	0.013*	0.398
5	1.224*	0.534*	0.934*	-0.073	-0.036	-0.083*	0.014*	0.412
6	1.517	0.421	0.796	-0.046	-0.112	-0.089	0.020*	0.533
7	0.999*	0.502*	0.846*	-0.087*	-0.016	-0.079*	0.012*	0.511
8	0.622*	0.129	0.767	-0.116	0.090	-0.057	0.003	0.540
9	1.124*	0.629*	0.669*	-0.044	-0.010	-0.058*	0.009*	0.419
10	1.157*	0.524*	0.741*	-0.052	-0.031	-0.069*	0.010	0.479
11	2.753*	0.017	-2.753	0.564*	0.108	-0.428	0.001	0.468
12	3.351*	0.063*	0.495	0.238	0.042	0.125	0.002	0.490
13	0.571*	0.037	1.758	0.061	-0.083	0.099	0.003*	0.564
14	0.662*	0.036	0.341*	-0.286	-0.024	-0.424*	0.000	0.524
15	1.200	0.035	-0.052	-0.125	0.032	-0.218	0.005*	0.544
16	0.587*	0.005	1.711	-0.437*	-0.018	-0.172	0.002	0.598
17	2.297*	0.030	-0.564	0.120	0.064	0.149	0.001	0.492
18	0.366	0.051	0.912*	-0.465	-0.084	0.678*	0.003	0.478
19	1.963*	0.007	-0.094	0.194	0.039	0.001	0.000	0.401
20	3.010*	-0.003	-0.299	0.193	0.081	-0.120	0.001	0.349
21	1.366	0.022	-0.258	-0.052	0.006	-0.134	0.000	0.414
22	2.100*	0.029	-1.769	-0.133	0.138	0.029	0.001	0.528
23	0.106*	0.001	-0.041	-0.002	0.004	0.000	-0.005	0.602
24	0.985*	-0.150*	0.833*	-0.202	-0.656	-0.859	0.004	0.586
25	0.562	-0.045	0.588*	0.214	-0.215	-0.897*	0.004	0.548
26	0.582*	-0.007	-1.905	0.151	0.184*	-0.265	0.002	0.578
27	0.456*	-0.078	0.564*	0.295	-0.479*	-1.255*	0.002	0.525
28	0.742*	0.028	0.336	0.107	-0.183	-0.159	0.004	0.488
29	2.623*	0.017	-0.120	-0.084	0.080	0.138	0.001	0.414
30	1.407*	-0.003	-0.642	0.058	0.013	-0.104	0.002	0.439

Similarly, table 8 shows the estimated coefficient based on conditional measure in the NSE market. It is observed that the statistically significant alpha value (22) is lower than the BSE market. Though, the change is insignificant. But, it may be concluded from the analysis that BSE is more representative when compared with the NSE. The table also shows the beta exposures of conditional information variables. The R^2 values are more or less same as compared to the BSE Sensex. Here, the managers also apply almost the same style strategy like BSE.

Table 8: Estimated Coefficients based on Conditional Single Index Model

Model 16 (NSE Sensex)								
Sl.No	α_c	β_{0c}	β_{1c}	β_{2c}	β_{3c}	β_{4c}	β_{5c}	R^2
1	1.214	-1.764	-1.505*	-0.004	-0.006	0.275*	-0.001	0.433
2	0.071	0.716	0.420	-0.270	0.047	-0.056	-0.005	0.415
3	0.621	-0.299	0.374	0.015	0.033	-0.008	-0.001	0.482
4	0.828	0.585	0.501	-0.027	-0.010	-0.048	0.006	0.401
5	1.185*	0.835*	0.692*	-0.034	-0.027	-0.055*	0.009	0.412
6	1.033	0.379	0.613	-0.078	-0.006	-0.060	0.010	0.534
7	1.026*	0.569	0.374	-0.035	0.004	-0.033	0.004	0.514
8	0.704	-1.487	-0.328	-0.108	0.201*	0.049	-0.010	0.542
9	1.280*	0.295	0.389*	-0.016	-0.017	-0.033	0.007	0.420
10	1.248*	0.625*	0.376*	-0.036	-0.021	-0.041	0.006	0.481
11	1.406*	0.016	-0.032	-0.024	0.018	0.002	0.002	0.469
12	1.046*	0.044	-0.057	0.002	0.030	-0.001	-0.002	0.491
13	1.150*	-0.015	0.016	0.017	-0.004	-0.002	0.001	0.564
14	1.097*	-0.026	-0.030	-0.036	-0.018	0.008*	0.003	0.525
15	1.292*	-0.014	-0.015	-0.010	-0.019	0.001	0.004	0.545
16	0.673*	0.019	-0.003	-0.021	-0.005	0.004	0.004	0.599
17	1.127*	0.076	-0.045	-0.021	0.033	0.002	0.001	0.492
18	0.013	0.040	-0.017	0.014	0.019	-0.001	-0.003	0.477
19	0.995*	-0.005	0.013	0.014	-0.015	-0.001	0.001	0.405
20	1.361*	-0.018	-0.003	-0.014	0.019	0.001	0.001	0.351
21	0.719*	-0.007	0.008	0.010	-0.003	-0.001	0.001	0.416
22	1.186*	0.084	-0.057	-0.028	0.030	0.003	0.002	0.529
23	0.595	0.185	-0.092	-0.047	0.015	0.007	0.005	0.602
24	0.699*	-0.373*	0.180	0.075	-0.092	-0.008	0.002	0.586
25	1.323*	-0.317*	0.155*	0.101*	-0.123*	-0.008	0.003	0.551
26	0.825*	-0.094	0.060	0.015	-0.044	0.000	0.002	0.579
27	1.299*	-0.412*	0.195	0.106	-0.132	-0.009	0.005	0.528
28	0.870*	-0.123	0.066	0.054	-0.048	-0.005	0.002	0.490
29	0.669*	0.037	-0.023	-0.030*	0.037	0.003	0.001	0.416
30	1.262*	-0.015	-0.008	-0.005	0.010	0.002	0.001	0.441

Finally, table 9 provides the estimated coefficients based on multi-index conditional lagged measure. It is observed from the table that the conditional alpha values of all the schemes are statistically significant. The managers are more efficient when conditional multi-index model is applied for stock selection purposes. Due to superior stock selection activities the schemes' performances have improved and the managers have provided to the investors higher returns as compared to the previous models which are applied in this study. The beta exposures towards both the markets have been shown in the table. Here, the estimated coefficients are market adjusted as well as time adjusted. Some of the beta coefficients are statistically significant. Here, the managers can easily switch over their portfolio composition to low beta portfolio to high beta portfolio when the market is upward rising and high beta portfolio to low beta portfolio when the market is going down. The estimated R^2 values of the schemes are higher than the previous measures which indicate that the model 17 is more representative than model 1, model 2, model 3 and model 16. Here, the managers are efficient in stock selection, risk exposures and investment style activities. The monthly deviation of returns has occurred due to style itself or selection of securities from one asset class or more asset classes or rotation among asset classes or both.

Table 9: Estimated Coefficients based on Lagged Multi-Index Conditional Model

Model 17 (BSE Asset Class Exposures)							Model 17 (NSE Asset Class Exposures)					
α_c	β_{0c}	β_{1c}	β_{2c}	β_{3c}	β_{4c}	β_{5c}	λ_{0c}	λ_{1c}	λ_{2c}	λ_{3c}	λ_{4c}	λ_{5c}
0.805*	-0.211	-0.411	-0.180	-0.008	-0.214	-0.027	-2.297	-1.724	-0.388	-0.007	-0.013	-0.043
0.783*	-0.125	-0.079	0.499*	0.058	0.043	0.007	-0.571	0.232*	-0.723	0.027	-0.015	-0.009
0.830*	-1.232	-0.270	0.309*	-0.168	0.046	0.016	1.220*	0.624*	-0.318*	0.199	-0.010	-0.015
1.044*	0.277	0.238	-0.066	-0.013	0.037	0.042*	0.311*	0.704	0.012	-0.030	-0.075*	-0.026
1.465*	-1.894	0.374	0.375	-0.330	0.029	0.043	0.306	0.590	-0.448	0.284	-0.083*	-0.025
1.648*	-1.279	1.564	-0.269	0.374	0.049	0.042	0.493	-0.664	0.221	-0.506	-0.093	-0.017
0.964*	1.551	0.793	-0.534	0.390	-0.239	0.037	1.330	0.099	0.447	-0.414	-0.077*	-0.023
0.531*	0.444	0.193	-0.568	0.425	-0.142	0.021	-0.298	0.640	0.454	-0.345	-0.060	-0.016
1.186*	-0.544	0.671	-0.113	0.191	-0.389	0.009	0.607	0.025	0.069	-0.209	-0.059	0.001
1.082*	0.010	0.404	-0.519	0.375	-0.445	0.020	0.541	0.386	0.468	-0.414*	-0.071*	-0.008
1.371*	-0.443	-0.324	0.170	-0.184	0.011	0.007	0.162	0.186	-0.185	0.202	-0.078	-0.005
0.976*	-0.322	0.785	-0.215	0.294	0.004	-0.001	0.008	-0.786	0.236	-0.275	-0.233	-0.001
1.196*	1.387	0.876	-0.345	0.363*	-0.021	0.006	-0.654	-0.737	0.361	-0.387	-0.068	-0.002
0.929*	-0.398	-0.104	-0.032	0.237	0.007	-0.045	0.246	0.171	0.013	-0.250	-0.037	0.046
1.309*	-2.531	1.088	0.213	0.042	0.001	-0.005	0.431	-1.049	-0.210	-0.024	-0.017	0.010
0.696*	0.429	-0.017	-0.463	0.026	-0.006	0.049*	-2.902	0.049	0.433	-0.051	-0.027	-0.042
1.181*	0.996	-0.151	-0.106	-0.038	0.007	0.035	-1.026	-0.017	0.093	0.049	-0.049	-0.032
0.719*	1.436	-0.002	-0.263	0.110	0.008	0.031	-1.588	-0.186	0.277	-0.100	-0.048	-0.032
1.038*	0.015	0.142	-0.044	0.056	0.001	0.006	-0.048	-0.183	0.055	-0.069	-0.026	-0.005
1.378*	-2.061	0.349	0.199	-0.051	0.012	0.006	1.669	-0.455	-0.213	0.080	-0.046	-0.005
0.783*	-1.230	0.322	0.099	0.001	0.006	0.018	0.812	-0.251	-0.087	0.003	-0.036	-0.016
1.199*	0.766	0.290	-0.224	0.206	-0.002	0.013	-0.710	-0.218	0.215	-0.204	-0.033	-0.009
0.806*	-5.197	0.343	0.534	0.093	0.025	-0.025	0.016	-0.859	-0.556	-0.114	-0.053	0.029
1.339*	1.043	0.956	-0.524	0.652	-0.006	-0.078	-1.337	-0.759	0.559	-0.646	-0.029	0.073
1.304*	-2.839	0.566	0.411	-0.383	0.008	0.036	0.574	-0.714	-0.373	0.334	-0.044	-0.032
0.917*	-2.792	-0.066	0.547	-0.413	0.003	0.014	0.703	0.102	-0.552	0.392	-0.023	-0.010
1.276*	0.398	0.390	0.316	-0.773	-0.017	0.091	0.376	-0.379	-0.293	0.705	-0.027	-0.081
0.830*	1.472	0.242	-0.257	0.303	-0.016	-0.011	-0.831	-0.227	0.290	-0.339	-0.025	0.013
0.676*	-1.035	0.258	0.081	0.066	0.004	-0.019	1.006	-0.316	-0.100	-0.036	-0.034	0.018
1.255*	-1.755	-0.029	0.094	0.154	0.012	-0.006	1.344	-0.079	-0.102	-0.136	-0.012	0.006

Table 9: (Continue) Estimated R^2 Values

R^2												
1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*
0.448	0.432	0.422	0.426	0.420	0.549	0.533	0.559	0.444	0.516	0.681	0.502	0.578
14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
0.542	0.559	0.509	0.512	0.426	0.548	0.530	0.568	0.445	0.510	0.685	0.510	0.589
27	**28**	**29**	**30**									
0.544	0.501	0.430	0.456									

6. Conclusion and Recommendations

Single index measure cannot provide to the investors an opportunity to select securities among different asset classes therefore, the exposure of risk is confined into the market. Whereas the multi-index measure offers a variety of asset class exposures. Here, the managers as well as the investors can obtain the chance to select stocks from varieties of markets and they can get the benefit to switch over their portfolio beta composition from one market to another according to the market movement for obtaining abnormal returns with lower degree of tolerable risk. In spite of many benefits the multi-index measures have failed to capture the time-lagged adjusted market effects. On the other hand, time-lagged multi-index measure is able to capture the market adjusted as well as time-lagged adjusted market effects and hence the estimated coefficients are more reliable and representative when compared to the single index and multi-index (without lagged effect) measures. Moreover, when conditional multi-index measure is introduced then the estimated coefficients provide better forecast as compared to multi-index lagged measure. Hence, it may be concluded that conditional multi-index measure is more representative than the other previous measures. Finally, it may be recommended that further research is necessary in this regard. In addition to this, the use of multi-index lagged conditional sustainable investment performance measures are the natural extension of this paper.

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