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DOES THE 'GOOD' PERFORMANCE MEASURES SHOW CONSISTENCY ACROSS TIME HORIZONS? APPLICATION OF OLS AND FISHER-Z TRANSFORMATION METHOD ON MUTUAL FUNDS CATEGORIES OF PAKISTAN

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ABSTRACT

The first objective of our paper is to identify if the skewness and kurtosis having an impact on the end result in relation to the distribution return pattern of returns in mutual fund industry of Pakistan. The second objective evaluates the persistency in the performance of chosen performance measures against Sharpe measure. In this regard, ordinary least square (OLS) method approach has been applied first and secondly, the fisher z-transformation approach has been used to evaluate the degree of concordance among the alternative performance measures and the Sharpe ratio. The results from (OLS) method verified that the skewness and kurtosis had no impact on the relationship between the alternative measures and Sharpe ratio in evaluation of mutual funds classes. Whereas, from degree of concordance analysis the alternative measures against the non-normal distribution seem more logical choice simply because the deviation is far lower than ones based upon assumption of normal distribution.

1. INTRODUCTION

The past literature has implicitly endorsed the fact that the fund's returns have the tendency of deviating from the normality and thus, significant results. Since the Sharpe ratio is based on the theory of mean-variance because it can be applicable to produced results when the returns of the funds are normally distributed, see, e.g., (Tobin, 1969). The study on the open-end mutual funds has shown results with the evidence of the persistency of the Sharpe ratio (Sharpe, 1966). Later on, this measure was criticized on providing misleading information about the persistency of the results generated by the funds mainly because the returns have the greater tendency of deviating for being normally distributed specifically in case of hedged funds, see, e.g., (Kat and Lu (2002) and Malkiel and Saha (2005)). This leads to the fact that when the distributed returns are abnormal then the Sharpe

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measure generated the unsatisfactory paradoxes i.e. the standard deviation couldn't able to measure the risk and seems to be dubious. Thus, the care has been taken in the past while analyzing the magnitude of the risk impounded in funds investment and how should the investors measure the level of the risks when encountered with different risk classes of funds (see e.g., Agarwal and Naik (2004); Jarrow and Zhao (2006); Rachev et al. (2007) and Farinelli et al. (2008)).

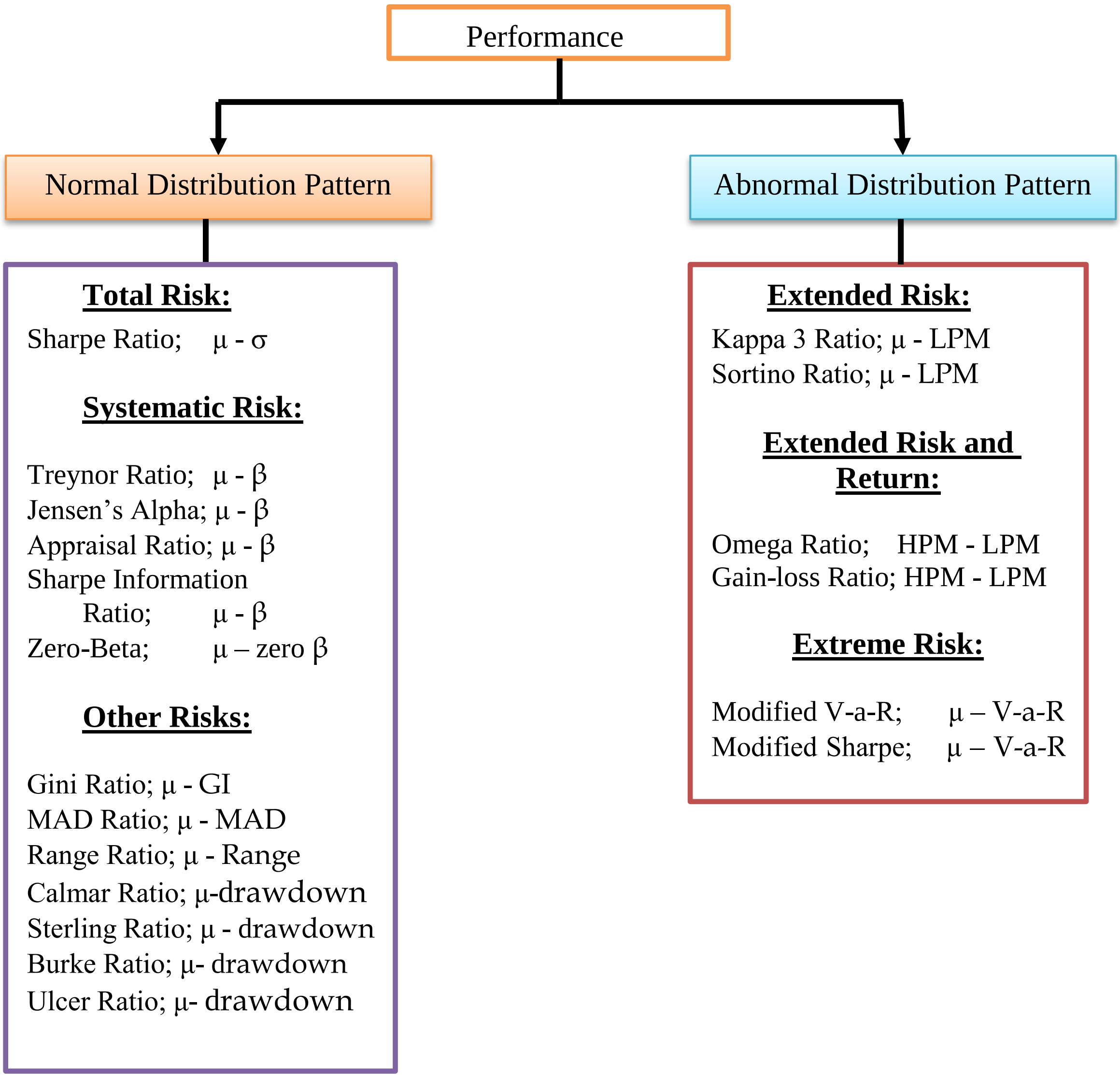

Figure 1: Choosing correct performance measures with respective risk classes

In the recent past, various methodologies have been proposed in order to suggest certain standards for performance measures after combining conventional and non-conventional performance measures (e.g., see, Eling (2008); Schuhmacher and Eling (2011) and Caporin (2011). The main issue drawn out of the recent study by Caporin (2011), is that, for a 'good' performance measure, it must have the capability to have significantly indifferent results during a considerable time period. Moreover, this study proposes mutual fund categories of assets belong to diversified risk classes instead of equity asset class Caporin (2011). The selection of performance measures must be carefully inspected under different asset managed frameworks i.e. asset classes, market conditions, investment policy style, investor risk preferences at different levels, etc. Secondly, in the study the distribution patterns of the returns of different categories of mutual fund has been identified after applying statistical values of skewness and kurtosis and then try to match up the appropriate performance measures at distinct risk levels. For instance, the normal distribution of return of funds can only be matched with those performance measures which has the creditability of doing so, and thus without violating the fundamental rule of measurement. So in this study the performance measures selecting have been distributed at different risk levels on the basis of normal and abnormal return distribution pattern, which has not been applied before. The skewness and kurtosis values, based on the distribution of returns, have been closely monitored from the sample of 213 mutual funds sample and then apply the rank test.

In the past, many studies have been done to propose the framework on the investment style of the funds under observation i.e. hedge funds based on the Sharpe type factor model e.g., see, (Fung and Hsieh (1997)). The study has concentrated on the second main area of proposing a framework for the practitioners comprises of risk-adjusted performance measures with respective risk classes of mutual funds categories. Similar works Eling and Schuhmacher (2006a) and Eling and Schuhmacher (2007); Eling (2008) and (Schuhmacher and Eling (2012)) have proposed that mainly all the chosen performance measures has shown a similar rank-order correlation of respective classes of hedge funds with respect of 'universal' ratio Sharpe ratio. But the results of Eling and Schumacher, (2007) generated out of the investment schemes of funds represents the normal distribution pattern, which makes the end results bias Zakamouline (2010).

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This further asks for yet another investigation that when the return distributions are non-normal, does the choice of appropriate performance measures going to influence the end results of mutual funds? Figure 1 represents the choice of appropriate performance measures, selected for this study, at various risk levels based on the return distribution of investment schemes.

2. LITERATURE REVIEW

Performance measures (PMs) have an integral part in the field of international corporate finance. It enhances the valuable work of not only private investors but also portfolio managers that allows them to compare their respective past performances with the current ones. It helps them to extract the real skill work from the luck by evaluating the real added value of fund managers. These performances have a real contribution towards the flow streams of funds too, which in way help to identify the asset allocation problems more generally in managed portfolios (e.g., see, (Hendricks et al. (1993)); (Grinold and Kahn (1995)); (Grinold and Kahn (2000)); Farinelli and Tibiletti (2008)and

Farinelli et al. (2008).

Since the early 70’s there has an evidence of new measures emerged in the literature with their empirical evidence, for example- the most comprehensive study carried in this perspective was done by (Aftalion and Danaila, 2003, Aftalion et al. (2003)), (Le Sourd (2007)), (Bacon (2008)) and (Cogneau and Hübner, 2009a, Cogneau and Hübner (2009b)), which carried a substantial weightage to the actual body of performance measures. Due to the new emerging demands from the investors have continuously imposed new challenges to fund managers, it has drawn intention to develop a mechanism for the fund managers which can facilitate their professional work relative to add a contribution to value of the managed funds.

Despite the fact that a lot of efforts have been made in the past to tie up different combination of performance measures i.e. traditional and alternative, they are unable to conclude which is best to correctly measure the performance in literature (e.g., see, (Lehmann and Modest (1987)); Eling and Schuhmacher (2006b). Sharpe ratio gave the best measure of the degree to which excess returns generated by the fund portfolio in excess of risk-free return to safe assets, with respect to the degree of per unit of risk. The term volatility has been used as a regression co-efficient of fund portfolio on the market index, whereas the term variability is the standard deviation of that return (Sharpe, 1994). However, modern use of term “volatility” refers to the standard deviation of the returns and the “beta” of the fund refers to the regression coefficient.

Although this measure evaluates the earning compensations of the fund manager, with respect to per unit of partially systematic and partially idiosyncratic risks, however, it has some limitations too. It is unable to transform the excess negative or positive returns, through the measure of standard deviation, on the unequal terms that led to miss interpretation (Goetzmann et al. (2007)). Sharpe ratio assumed the constant risk-free rate for both the lenders and borrowers which implied that it couldn’t absorb all the risk tolerance behavior of the related investor’s classes in general terms. In order to estimate the measure of volatility of estimated Sharpe ratios the bootstrapping methodology has been used for the observed excess returns (Memmel, 2003a, Memmel (2003b)) and (Ledoit and Wolf (2008)).

Recently many performance measures have been offered to practitioners to do an effective evaluation of funds under observation. For instance, Treynor (1965); (Treynor and Mazuy (1966)) and Jensen (1968) in later 60’s come up with ratios that seemed to be addressing the issues relating to the best allocation of assets in a portfolio and manager’s ability/skill to outperform the market forces. There existed few critics of this measure i.e. (Roll (1978)) indicated the problem that the final ranking of the portfolio changes due to the misspecification, which leads to the error. Also, the measure has been a victim of single risk factor model, which totally denied the fact that in case of any variations in the market happened that made the managers changed their respective portfolio beta (e.g., see, (Fama (1972), Fama and Miller, 1972); Treynor and Mazuy (1966)).

Later on the Black (1992) and (Treynor and Black (1973)) proposed measures that were related to the market benchmark portfolios and fund manager’s own portfolios. They held the point that it would help to evaluate the fund manager’s skill with respective deviations from their own portfolios to benchmark portfolios. In the 80’s, Yitzhaki (1982) and Connor and Korajczyk (1986) proposed the

Gini ratio index and generalized version of the CAPM model. The main highlighted feature of this generalized version of CAPM is that it facilitates the practitioners through observing the skewness parameters which relates to the distributed pattern of returns of funds Hwang and Satchell (1998).

During the era of 90's and 20's many performance measures have been introduced in order to capture the results of the funds at specific risk levels. For instance, few of the performance measures have been chosen in this study are MAD ratio by Konno and Yamazaki (1991); Sharpe information ratio by Sharpe (1994); Dowd (2000); Keating and Shadwick (2002), etc. Then these alternative performance measures have been categorized into three separate types on the basis of their risk assessment characteristics i.e. relative, absolute and density-based. Then they have been further arranged with relevant distribution patterns of funds with respective proposed risk levels as given in Figure 1.

The value at risk has been widely used in the field of international finance; banking and insurance related to risk management and for capital (Caporin et al., 2014). The recent studies did emphasize on the improvement in performance measures while evaluating the assets classes such as Farinelli et al. (2008), Zakamouline and Koekebakker (2009), Pekár and Brabec (2016), etc. The main focus is to take into account the mutual fund classes in such a way that their respective classes should be given separate treatments that possessed distinct risk features e.g., equity, income, pension, Sharia categories, etc.

3. RESEARCH METHOD

This section discusses the dataset which is based on the monthly returns of all the mutual funds' categories of Pakistan mutual funds i.e. open-ended, close-ended, pension and Sharia-compliant funds. The data comprises of sample period from 2004 to 2014 of overall composites of different asset classes of 213 mutual funds schemes. In this study, the distribution pattern of the returns of different categories of mutual funds has been identified after getting statistical values from skewness and kurtosis and then try to match up the appropriate performance measures at distinct risk levels. For instance, the normal distribution of return of funds can only be matched with those performance measures which has the creditability of doing so, and thus without violating the fundamental rule of measurement. So in this study the performance measures selecting have been distributed at different risk levels on the basis of normal and abnormal return distribution pattern, which has not been applied before. Moreover, the skewness and kurtosis values, based on the distribution of returns, have been closely monitored from the sample of 213 mutual funds sample and then apply the rank test.

3.1 ORDINARY LEAST SQUARE (OLS)

The performance measures have been analyzed after applying the regression on both the normal and abnormal return distribution patterns of the mutual funds' empirical sample. The purpose of doing this analysis is two-fold. Firstly, the regression is going to compute the impact of the variability of alternative performance measures with respect to Sharpe ratio which will be linked with the larger deviation of return distribution from the standard mean. Secondly, this will further enlighten the varied issue of invariability among alternative performance measures when there is an existence of higher moments of distribution and the role they play in the final evaluation for the practitioners.

The sample of return distributions of all the categories of mutual funds possess the different values of Sharpe ratio with respective skewness and kurtosis which is known as the dimensional grid (SR, Sx, Kx). These values vary among the two different streams of distribution pattern along with the computation of alternative performance measures against Sharpe ratios, ranking order on the basis of correlation coefficient values as reported earlier. Now, to evaluate the alternative performance measures variability against Sharpe, the parameters' values will be estimated of the dimensional grid (SR, Sx, Kx), which can be obtained from the given model:

$$\check{A}(x) = \alpha SR\beta\ (x)e\beta sSx+\beta KEKx+\ \mu \quad (1),$$

$$\check{A}(x) = \alpha SR\beta\ (x) \quad (2).$$

And, after taking the logarithm it will become as

$$Log[\check{A}(x)] = \log(\alpha) + \beta\log[SR(x)] + \beta sSx + \beta KEKx + \mu \quad (3),$$

$$Log[\check{A}(x)] = \log(\alpha) + \beta\log[SR(x)] \quad (4),$$

Where, Ă(x) represents the alternative performance measures under observations, μ represents the error term, EKx and Sx represents the excess kurtosis and skewness respectively. Also, from the equations (3) and (4) the parameters of Equation (1) and (2) can be estimated using the ordinary linear regression method.

The equation models (1) and (2) can be compared for the purpose of confirming the variability element between the alternative and Sharpe ratio. For instance, when the goodness of fit criteria is being met from the value of the R-square statistic from the model, it will determine that the alternative performance measure rankings and the ranking produces by the Sharpe ratio are identical. The model equation (1) is demonstrating an adjustment for skewness of the returns distributions with respective density of kurtosis i.e. $e^{\beta sSx+\beta_K EKx}$. The values of these factors will determine either the distribution pattern of returns based on skewness and kurtosis will bring variability in the performance measures evaluation. For instance, if the estimated values of these respective factors somehow become statistically significant than one can conclude that these factors have an influence over the performance measures evaluated values. So the bottom line is that when the goodness of fit statistics i.e. (R^2) of both the equations of model is insignificantly different then there will be no difference of ranking order among the alternative ratios and the Sharpe ratio.

3.2 FISHER-Z TRANSFORMATION

One of the models has been proposed by the study i.e. (Fisher (1915a), Fisher, 1915b), in which the resulted values of correlation commensurate with the normal distribution values, known as 'z-distribution'. This study section has undertaken the approach proposed by Caporin (2011), Caporin and Lisi (2011), where the authors have shown the technique of defining the decision rule of identifying the 'low' rank correlation instead of high ranked in the previous studies. In this study the choice of low-rank correlation has been selected as low as -0.9 for two reasons. Firstly the sample data set is based on all the main categories of mutual funds, compared to what studied previously by Eling and Schuhmacher (2007) and Caporin and Lisi (2011) where the authors fixed the value as low as 0.8, as an arbitrary value. Secondly, the resulted precise threshold would validate the results based on the degree of concordance among these measures with distinct risk assessment features in the context of Pakistan mutual fund industry. The precise threshold can be defined considering the asymptotic distribution of R_S, with the critical value of α at 1% level of significance. If is z the fisher transformation then we have:

$$z = 0.5 \ln\left(\frac{1+\hat{R}_S}{1-R_S}\right) \quad (5),$$

whereas $\hat{R}_S$ = sample correlation, R_S = population correlation.

The objective is to address the degree of high concordance in relation to higher correlated ranking order among the alternative performance measures from the given data set of N mutual funds schemes. For that the required threshold for R_S would be obtained from

$$R_S(\alpha) = \frac{\left(exp\left(\ln\left(\frac{1+R_S}{1-R_S}\right)+2Z_1-\alpha\sqrt{\frac{1}{N-2}}\right)\right)-1}{\left(exp\left(\ln\left(\frac{1+R_S}{1-R_S}\right)+2Z_1-\alpha\sqrt{\frac{1}{N-2}}\right)\right)+1} \quad (6),$$

whereas Z_1-α is $(1-\alpha)$ quartile of the standard normal distribution at the confidence interval value α.

The threshold value on the basis of our data sample set based on monthly returns of mutual funds with a number of values of N = 213 and α = 1%, defined the low value of correlation equal to -0.17 or -0.2 after rounding. Moreover, the possible null hypothesis drawn to test the results would be H_0: $R_S \le -0.2$ against the alternative H_1: $R_S > -0.2$. The important thing to understand is that the decision rule also influenced by the data sample set and thus can produce different values across the investigation of the assets based on differential of numbers among asset classes (Caporin and Lisi, 2011).

4. ANALYSIS

4.1 SKEWNESS AND KURTOSIS ANALYSIS

We need to get the statistic results from the values of skewness and kurtosis. On the general understanding, there is a fallacy in implementing the universal performance measure i.e. Sharpe ratio, from the for assessing the investment funds where there is an existence of abnormal behavior in returns distribution, like in case of Pakistan mutual fund industry. The practitioners definitely likely to use those risk-adjusted performance measures which can bear the abnormal pattern of returns distribution and thus helps them to analyse these resulted in probability-based losses and thus propose appropriate strategies as well. In the reflection of these findings it is an utmost need to allocate performance measures according to the respective returns distribution of mutual funds categories under study. However, we understand the risk attitude of investors towards different investment policies also relevant issue and due to this we take into account the responses of chosen performance measures at a certain level of risk. This will further boost up the final conclusion and discussion in proposing the policies for the practitioners to get guidance and assess the end performances accordingly.

The choice of performance measure relates to the decisions of investments that the investor takes depends upon the distribution pattern of returns. This deviation from the mean can be assessed from the skewness values and thus it plays an important part in financial decision making. The results from mean-variance i.e. normal distribution pattern and mean-semi variance i.e. abnormal distribution pattern cannot be identical and thus it will have an impact on the decision made by the investors at investment policy level (e.g, see, Marmer and Ng (1993); Agarwal and Naik (2004); Jarrow and Zhao (2006); Farinelli et al. (2008), etc).

Table 1: Distribution pattern of Mutual funds monthly returns based on the values of skewness and kurtosis from 2004-2014.

	Open-Ended Funds					
Kurtosis	Skewness					Sum
	< -1.5	€(-1.5, -0.5)	€(-0.5, 0.5)	€(0.5, 1.5)	> 1.5	
< 5	12	40	14	2	1	69
€(5, 10)	19	2	0	2	0	23
> 10	20	0	0	0	0	20
Sum	51	42	14	4	1	112
	Close Ended Funds					
Kurtosis	Skewness					Sum
	< -1.5	€(-1.5, -0.5)	€(-0.5, 0.5)	€(0.5, 1.5)	> 1.5	
< 5	1	0	0	0	0	1
€(5, 10)	1	1	0	0	0	2
> 10	0	0	0	0	0	0
Sum	2	1	0	0	0	3
	Sharia Funds					
Kurtosis	Skewness					Sum
	< -1.5	€(-1.5, -0.5)	€(-0.5, 0.5)	€(0.5, 1.5)	> 1.5	
< 5	3	15	6	1	0	25
€(5, 10)	12	2	0	0	0	14
> 10	10	1	0	0	0	11
Sum	25	18	6	1	0	50
	Pension Funds					
Kurtosis	Skewness					Sum
	< -1.5	€(-1.5, -0.5)	€(-0.5, 0.5)	€(0.5, 1.5)	> 1.5	
< 5	0	11	9	6	0	26
€(5, 10)	1	4	2	0	3	10
> 10	3	0	0	0	1	4
Sum	4	15	11	6	4	40

Table 1 represents the cross-sectional distribution of the returns of 205 mutual funds schemes comprises of categories over the sample period 2004 till 2014. The main categories are open-ended, close-ended, Sharia-compliant and pension funds. The statistics values base on the skewness and kurtosis values and show the respective degree of normality across the mutual funds returns. The respective column of all tables have various combination based on specific bandwidth of skewness and kurtosis values i.e. the first cell of the row and column has the bandwidth of <-1.5 and <5 of skewness and kurtosis values respectively. Each scheme of a mutual fund with their respective categories has been summarized with the total number of funds in the last column.

The distribution pattern of mutual fund categories' returns based on the skewness and kurtosis values. We know that the return distribution to be normally needed to have '0' and '3' values of skewness and kurtosis. For instance, the return distribution of open-ended mutual funds schemes show statistically abnormal trend on the basis of skewness and kurtosis values, and the deviations of only a few of open-ended fund schemes from the normality are moderate i.e. approximately 13% are closest to normality on the basis of skewness and kurtosis. Similar is the case with the other categories of the mutual funds under observation like in case of pension and Sharia-compliant mutual funds that only few fund schemes have shown the low negatively skewed with moderate kurtosis values i.e. 23% and 12% from overall schemes of investments.

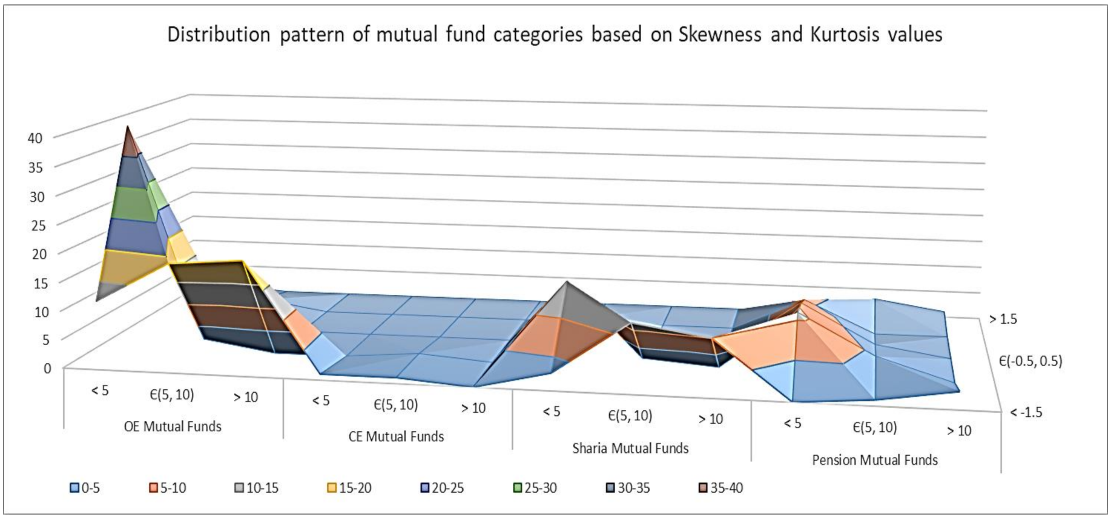

Figure 2: Surface area covered by mutual fund categories based on skewness and kurtosis values (2004 - 2014)

Description: Figure 2 represents the surface area of the distribution pattern of mutual funds categories based on the skewness and kurtosis values. The bandwidth skewness ranging from < -1.5, (-0.5, 0.5) and > 1.5, and for kurtosis the bandwidth ranging from <5, (5, 10) and > 10 respectively. On the left side of y-axis, the bandwidth range for skewness is given and on right side the number of classes from mutual fund categories is placed. The x-axis contains the bandwidth range for kurtosis with each of mutual fund categories.

Table 2: OLS Regression Models Comparison among the Performance measures based on Normal Distribution of Returns.

PM	SR(interval)	β_s	β_k	Kendall's (ɤ)	$R^{2\ Model\ 1}$	$R^{2\ Model\ 2}$
Systematic risk						
Alpha	-0.45 - 0.44	-0.23	0.04	0.7	0.7	0.6
Appraisal	-0.45 - 0.44	-0.85	0.09	0.7	0.8	0.6
Treynor	-0.45 - 0.44	-0.57	-0.01	-0.6	0.5	0.01
Zero Beta	-0.45 - 0.44	1.19	-0.32	-0.07	0.5	0.2
IR	-0.45 - 0.44	-1.27	0.19	0.2	0.9	0.7
Other risks						
Calmar	-0.45 - 0.44	-0.43	0.07	0.9	0.9	0.9
Range	-0.45 - 0.44	-0.23	0.06	0.3	0.6	0.3
MAD	-0.45 - 0.44	-0.07	-0.07	0.8	0.6	0.2
UR	-0.45 - 0.44	-0.48	0.05	0.7	1	1
BR	-0.45 - 0.44	-1.59**	0.19***	0.7	1	1
Sterling	-0.45 - 0.44	-114**	19.97**	-0.4	0.6	0.2
Gini	-0.45 - 0.44	-0.23	0.04	0.8	1	1

* *p*-value 1% is a level of significance; ** *p*-value 5% is a level of significance; ****p*-value 10% is a level of significance.

Description: Table 2 represents the regression and Kendall's rank-order correlation using a sample of normally distributed returns. The R2 values represent the goodness of fit statistical values of both models. The values of respective parameters β_s and β_k are statistically significant at 1%, 5%, and 10% level.

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Table 3: OLS Regression Models Comparison among the Performance measures based on Abnormal Distribution of Returns.

PM	SR(interval)	β_s	β_k	Kendall's (ɤ)	$R^{2\ Model\ 1}$	$R^{2\ Model\ 2}$
Extended risk						
Kappa3	-2.77 - 0.47	-0.83	0.24	0.4	1	1
Sortino	-2.77 - 0.47	0.08	-0.01	0.6	0.9	0.9
Extended risk-return						
Gain-Loss	-2.77 - 0.47	0.13	-0.04***	0.6	0.6	0.5
Omega	-2.77 - 0.47	-0.08	-0.05	0.6	0.3	0.2
Extreme risk						
Mod. Var	-2.77 - 0.47	-0.27	-0.06	0.4	0.13	0.03
Mod. Sharpe	-2.77 - 0.47	0.26***	-0.001	0.5	0.8	0.8

Description: Table 3 represents the regression and Kendall's rank-order correlation using a sample of non-normally distributed returns. The R^2 values represent the goodness of fit statistical values of both models. The values of respective parameters β_s and β_k are statistically significant at 1%, 5%, and 10% level.

In the nutshell, these findings confirm by the overall statistical results generated from the skewness and kurtosis criteria that are further going to affect the application of alternative measures under study since the normality condition is not being met in case of overall mutual fund industry of Pakistan.

4.1 ORDINARY LEAST SQUARE (OLS) ANALYSIS

The respective values from the tables demonstrate the magnitude of influence due to the Sharpe ratio interval after analysing the models 1 and 2. In all of the cases of the normally distributed returns of the mutual fund categories and sub-categories, the values of the respective parameters of constant α and Sharpe ratio β are statistically significant with model 2 after excluding the other two parameters i.e. skewness βs and kurtosis βK. This shows that the standard Sharpe ratio value plays a significant role in influencing alternative performance measures values. However, in model 1 with the inclusion of parameters of skewness and kurtosis βs, and βK respectively the results are mixed with respective Sharpe ratio interval value.

Since the majority of the normally distributed returns are negatively skewed it is depicted from the coefficient values of skewness, βs. It means that the alternative performance measures penalize the negative value of skewness with respective Sharpe ratio value of interval. However the kurtosis coefficient βK is positive with few exceptions, which means that the excess kurtosis appreciates by the alternative performance measures. Out of all half of the alternative performance measures rankings are closest to the Sharpe ratio with the given Sharpe ratio interval value i.e. SR ϵ [-0.45, 0.44] under the normal distribution pattern of returns among the mutual funds in Table 1. Under the 'other risk' level the Calmar, Ulcer index performance, Burke and Gini ratio performance measures the Sharpe ratio explains 100% variation in these three alternative performance measures even after the adjustment of skewness and kurtosis of return distribution. Also, when comparing the R-square values of model 1 and model 2 are same i.e. 0.9, 1, 1 and 1 respectively (see Table 2).

Table 4: Fisher Z-transformation rank order correlation on normally distributed returns.

PM	Systematic risk		
	Period 2	Period 3	Period 4
Window length	24	60	96
Alpha	0.91125	0.729939	0.646486
Appraisal	*-0.946*	*-0.2393*	0.222441
Treynor	*-0.66926*	*-0.46952*	-0.19632
Zero Beta	*-0.97488*	0.190498	0.099924
IR	*-0.96668*	*-0.46179*	0.150921
PM	Other risks		
	Period 2	Period 3	Period 4
Window length	24	60	96
Calmar	0.979801	0.801472	0.66773
Range	0.767568	0.510771	0.437641
MAD	0.953362	0.310198	0.063191
UR	*-0.94803*	*-0.45742*	0.424157
BR	*-0.97293*	*-0.63002*	0.243319
Sterling	0.960472	0.470571	*-0.3793*
Gini	*-0.87919*	*-0.44571*	0.529215

Description: Table 4 represents the rank order correlation using a sample of normally distributed returns among the performance measures at the systematic and other levels of risk. The column 2nd through 4th displays the rank order correlations values across the window length against the Sharpe ratio over three sample dimensions (24, 60 and 96 months). The correlation values in Italic represent the values below the required threshold value of -0.2.

This value shows the goodness of fit criteria of two models i.e. model 1st, inclusive of skewness and kurtosis, and model 2, exclusion of these two parameters. Also, under the 'systematic risk' level Alpha and Appraisal performance measures have shown similar results. On the contrary note, other alternative performance measures have a greater sensitivity to the higher moments of distribution with the respective Sharpe ratio interval. For instance, the Zero-beta having the positive value of the coefficient of skewness i.e. $\beta s = 1.19$ shows that this ratio jumps up to 1.19 times due to the inclusion of skewness and eventually changes the ranking order correlated value with respect to the Sharpe ratio.

In Table 3 the alternative performance measures sensitivity to skewness and kurtosis of abnormal distributed returns are given at the different risk levels. Under the 'extended risk' level all the selective performance measures prove to negate the effect of kurtosis and skewness on the end results of mutual funds performances. For instance, the Kappa3 positive beta coefficient value shows the Kappa3 ratio sensitivity towards the higher moment distribution of returns of mutual fund categories under the study with respective Sharpe ratio interval of SR ϵ [-0.45, 0.44]. Also under the 'extended risk-return' and 'extreme risk' levels we have one each alternative performance measures i.e. Omega and Modified Sharpe ratio, that have a similar understanding in terms of addressing the issue of skewness and kurtosis against Sharpe ratio.

4.2 FISHER-Z TRANSFORMATION ANALYSIS

The analysis has been drawn after considering the ratios under a set of samples following the rolling window approach proposed by the Caporin and Lisi (2011). The results have been given in

Table 4 of the ratios for the purpose of validating the persistency of alternative performance measures against the standard ratio i.e. Sharpe on the basis of selective sample sets comprises of 24, 60 and 96 months of window length. The correlation results have shown that at the ‘systematic level’ of risk the only ratio that possesses similar information with respect to Sharpe across all the periods is Alpha measure. Also, the results have not changed in relation to the number of returns used for the assessment of Alpha measure. This further confirms the fact that this result has rejected the null hypothesis of being independently seen for evaluation of access returns and thus can be ignored.

Apart from that, the results of the remaining ratios have accepted the null hypothesis of being independently considered for the evaluation of mutual funds at different quartiles rather at 1%. The negative signs, however, suggest there is no degree of concordance among the measures and thus must be used with their respective risk assessment credibility. The findings produced by the systematic risk evaluator measures, except that of Alpha measure, contradict the past findings (Caporin and Lisi, 2011, Eling, 2008, Eling and Schuhmacher, 2007, Caporin, 2011). At the ‘other risk’ level and it is evident that the Calmar, Range, and MAD measure showed an equivalent of results compared to Burke and Sterling ratios which have accepted the null hypothesis of being independent compared to rest in the group. These findings contradict the findings of Eling and Schuhmacher (2007) that found the evidence otherwise when the analysis has been drawn from the sample set showing the normally distributed pattern.

Table 5: Fisher Z-transformation rank order correlation on non-normal distributed returns.

PM	Extended risk			
	Period 1	Period 2	Period 3	Period 4
Window length	36	60	96	132
Kappa 3	0.286576	0.246471	0.248989	0.264168
Sortino	0.988668	0.933417	0.707626	0.617831
PM	Extended risk and returns			
	Period 1	Period 2	Period 3	Period 4
Window length	36	60	96	132
Omega	0.393555	*-0.2043*	*-0.35228*	*-0.31971*
Gain Loss	0.760984	0.627375	0.647318	0.623875
PM	Extreme risk			
	Period 1	Period 2	Period 3	Period 4
Window length	36	60	96	132
Mod. Var	*-0.500733*	*-0.47528*	*-0.48582*	*-0.44561*
Mod. SR	0.935325	-0.0364	-0.05126	0.033374

Description: Table 5 represents the rank order correlation using a sample of abnormally distributed returns among the performance measures at the extended risk, extended risk and returns and extreme level of risk. The column 2nd through 5th displays the rank order correlations values across the window length against the Sharpe ratio over four sample dimensions (36, 60, 96 and 132 months). The correlation values in Italic represent the values below the required threshold value of -0.2.

Apart from that, the results of the remaining ratios have accepted the null hypothesis of being independently considered for the evaluation of mutual funds at different quartiles rather at 1%. The negative signs, however, suggest there is no degree of concordance among the measures and thus must be used with their respective risk assessment credibility. The findings produced by the systematic risk evaluator measures, except that of Alpha measure, contradict the past findings (Caporin and Lisi, 2011, Eling, 2008, Eling and Schuhmacher, 2007). At the 'other risk' level and it is evident that the Calmar, Range, and MAD measure showed an equivalent of results compared to Burke and Sterling ratios which have accepted the null hypothesis of being independent compared to rest in the group. These findings contradict the findings of Eling and Schuhmacher (2007) that found the evidence otherwise when the analysis has been drawn from the sample set showing the normally distributed pattern.

Table 5 has reported the results based on the abnormal distribution pattern of returns of mutual fund schemes under observation. There is an evident from the Spearman rank correlation approach, at the extended risk level, that the Kappa3 and Sortino ratio has produced the equivalent results and thus cannot be considered when computing for the lower partial moment order of returns. There found a consistent higher element of concordance across the various time windows based on the fact that this ratio has rejected the null hypothesis threshold value of -0.2. This result further suggests that the Kappa3 measure couldn't be considered separately for the evaluation of the lower partial moment of the returns which is aligned with the past findings (Caporin and Lisi, 2011, Eling, 2008, Eling and Schuhmacher, 2007).

The next section represents the analysis based on the correlation ranking produced by the alternative performance measures at extended risk and return level. The Gain loss ratio found to produce similar results and thus need not seem independent. The resulted correlation has shown the value that is above the thresholds of -0.2. However, the Omega measure has shown that negative correlated values which totally reject the equivalent element and thus needed to be seen independently for evaluating the returns on the lower thresholds values instead of risk-free in the Gain-loss ratio. The last section of the table has shown the results based on the correlation ranking order of Spearman at the extreme level and it found that the Modified Sharpe measures have rejected the null hypothesis compared to the modified V-a-R measure. The Modified V-a-R ratio has been seen at the 1% quantile level and thus it has accepted the null hypothesis. The findings further confirmed the past findings of Caporin and Lisi (2011) that the Modified V-a-R should be considered independently not at the 1% quantile level rather at 5% and 10%.

5. DISCUSSION

Since the decision based on the mean-variance analysis could be misleading as the kurtosis and the skewness of the returns distribution played a vital role in this respect. There is a problem with implementing the Sharpe ratio as universal standard measure for assessing the investment funds as majority of the mutual funds showed abnormal distribution patterns as far as Pakistani mutual fund industry is concerned. This leads to conclude that practitioners are better off using risk-adjusted performance measures which are based upon abnormal distribution patterns as their results are more likely to reflect the actual performance of the mutual funds.

In order to further validate these results we also performed OLS regression on the alternative performance measures in order to verify their time invariability claims against Sharpe. The two models were formulated in order to justify the point raised earlier; in first model skewness and kurtosis were taken into consideration, while the second one was based on assumption that the skewness and kurtosis had no impact on the end results. The results from both models verified the latter assumption that the skewness and kurtosis had no impact on the relationship between the alternative measures and Sharpe ratio. In the last part, the fisher z-transformation model approach has been followed and evaluates the persistency among the alternative performance measures and the Sharpe ratio across the time length windows. The results seemed not much to deviate from the previous results of the study. There found to be a consistency of results among the performance measures under the normal distributed return patterns of mutual funds in Pakistan context.

Moreover, the results are encouraging and found to be greater persistency among the performance measures against Sharpe when considered under the abnormal returns pattern of mutual funds under observation. The study aligns with the past methodology proposed by Caporin and Lisi (2011) in order to investigate the performance persistency of selective performance measures with respect to the Sharpe ratio. The descriptive statistical values of skewness and kurtosis have been derived from the specific bandwidth tabulation values comprise of the selective sample of mutual fund industry in Pakistan. The results of overall mutual funds categories in Pakistan display an abnormal distribution return pattern and thus the validity of many commonly used performance measures becomes questionable at best.

6. CONCLUSION

In a nutshell, these analysis setups a basic framework for practitioners by suggesting and proving that the abnormal distribution-based measures are much better indicators of the mutual fund performances when it comes to Pakistan since the abnormal distribution of returns prevails in the market. The non-conventional measures (non-normal distribution based) seem more logical choice simply because their deviation is far lower than ones based upon the assumption of normal distribution. The study is limited to the mutual funds' industry of Pakistan where the chosen measures have been evaluated among the standard Sharpe ratio. We suggest that in the future time other performance measures from the utility-based family must be included to support the research findings. Moreover, instead of mutual funds other venues such as the capital market, derivative markets, etc can be taken into consideration to further check the credibility of performance measures under different anomalies too.

7. AVAILABILITY OF DATA AND MATERIAL

Data can be made available by contacting the corresponding authors

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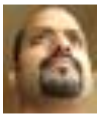

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