AN ANALYSIS OF LONG-RANGE CORRELATION AND HEAVY TAIL: *KSE – 100 INDEX CLOSING BASED ON NEWS SENTIMENTS AS CASE STUDY*

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Abstract:

KSE-100 index (1^{st} -12^{th}) cycles are stationary behavior. Heavy tail analysis behavior is examined. Long-range correlation persistency is calculated in the perspective of heavy tail analysis. Each value of KSE-100 index data is strongly correlated to previous data. The differencing parameter of all KSE-100 index cycles have ranging from 0< d < 0.5 in both self-affine (d_A) and self-similar (d_S) fractal dimension. Heavy tail parameter (α) asymptotically adhere to the Pareto law that indicate the dynamics is periodic and regular. Heavy tail parameter (α) and differencing parameter ($d = H$-0.5) is developed from the Hurst Exponent 0.5 < H < 1(persistent). The self-similar long-range correlation strength is ($1 < \beta_S < 3$) and self-affine long-range correlation strength is ($-1 < \beta_A < 1$). KSE-100 index cycles are strongly long-range correlated besides cycles 9^{th}. The Phillips-Perron (PP) unit root tests is applied in KSE-100 index cycles which are shown, every cycle has stationary nature. This study confirms that the six months break up shown that KSE-100 index market was persistent in evaluate years. The economy is steadily progress in the direction of established state of the structure of market. The concept of efficiency would accordingly integrate time varying, evolutionary and behavioral aspect of the development of market.

Keywords: Long-range correlation, Heavy Tail Analysis, Hurst Exponent (H), Persistent, KSE-100 index cycles.

1. **Introduction**

The stock market acts as a bridge and helps individuals and institutions to add to the country's wealth by contributing to the country's second market. Stock market forecasting is an important part of determining the future value of a company's stock or other financial instrument used in financial trading. The profitability of a successful future stock price may generate significant returns. The stock market is not a savings market. Research to predict stock recovery has a major impact at this time.
Pakistan is divided as a developing market. Pakistan has three stock exchanges where the presence of the KSE is the largest liquid in terms of market capitalization and trading volume. KSE received the award for best performance in global stock market growth in 2002 during

Business Week. Similarly, all other market investment conclusions are postponed for certain important economic reasons or technical indicators.

The first case of COVID-19 in Pakistan was reported on 26 February 2020. Its impact led to a decrease of about 62% of the KSE-100 index, the lowest to 27,200 on March 25, 2020, from a high point of 43,218 points January 13, 2020. Despite the catastrophic fall of 2005 and 2008, the market remained calm and stable, and no investors have been accused of market fraud and unfair trade [1]. The Karachi Stock Exchange reached a milestone when the KSE-100 Index surpassed the psychological level of 15,000 in the first quarter and reached a peak of 15,737.32 on 20 April 2008. In addition, a 7.4% increase in 2008 has made it perform well among the major emerging markets [2, 3].

People need good marketers to have an idea about market trend [3, 5, 6]. Therefore, stock price forecasts and market trends are becoming increasingly important among the people. The stock market is often an idle, indirect, active, and volatile market [4, 5, 7]. Predicting stock returns has become very important this season for the researcher and attempts to build a linear relationship between the variables of macroeconomic inputs and stock returns [8].

2. Materials and Methodology

This study examines and analyzes heavy tail parameters and longitudinal relationships (persistence). In this regard, the KSE-100 index data from 2015 to 2020 [cycles (1st-12th)] are the basics under which transactions are converted into cycles and each cycle has a period of six months. Data is collected at www.investing.com. The study has three categories. The first section contains the behavior of heavy tail, the second section includes, long-distance correlations, and the final section shows Phillips' individual test parameters for the parameter of tail and the strength of long-range of KSE-100 index cycles.

2.1. Self-Affine and Self-Similar Fractal Dimension (F):

The fractal dimension (F) feature is affected, two elementary types are visible. One is self-Affine and the other is self-Similar. The same shows the first thing the duplicate copies are calculated to calculate the fractal size (F) when using just a box counting or Hausdorff - Besicovich dimension. Fractal magnitude (F) can be express by defining the ratio between object log size changes and log scale scale changes ($F_s = \frac{\ln R}{\ln S}$). Although all affine replicas are used. Reduced width analysis is calculated using the Hurst effect by measuring the scale $\frac{R}{S} \propto \tau^{H}$ when R defines the width, S indicates the normal deviation. Part of the measurement is coefficient τ, while H is the element of Hurst. Hurst opponent values range from 0 to 1. The data of time series are the same (persistent) when the approaches of Hurst exponent (H) is 1. Although when the value of Hurst exponent (H) approaches to zero it indicates that it is rare (anti-persistent) time series data [9, 10]. If value of H is equal to 0.5, describe that the time series given data covers the Brownian process. Hurst exponent (H) values have ranging from 0 and 0.5, indicating persistence (random movement process). When the Hurst H element with a diameter between 0.5 and 1 indicates persistence. Persistence in having a good relationship. The behavior of anti-persistent data is related to negative. The corresponding $0 < H < 1$

parameter of the coupling processes is also called as the Hurst (or roughness) exponent. The Hurst exponent (H) is calculated to estimate the long-term dependence of the stochastic process. The study found that the relationship between long-term law brings a series of ideas newly.

The Self-affine nature and the nature of self-Similar are subsequent change. Fractal dimension (F) and Hurst exponent (H) are related as F + H = 2.

Heavy tail and long distance connection parameters depend on two different parameters (d). The complexity of the KSE-100 index using the same fractal magnitude and Self-affine fractal dimension as well as comparing both strategies and predicting long-term memory persistence of data is discussed in the outcome and discussion section.

2.2. The Parameter of Heavy Tail along with The Dependency of Long-Range (*LRD*)

The analysis of the parameter of heavy tail is based on the parameter of self-similarity *H* (Hurst exponent). If the persists data, the parameter of the heavy tail α is ranging from 0 to 2. In addition, the dependence parameter of long-range dependence *d* is important for the range 0 - $1-\frac{1}{\alpha}$. This condition is appropriate if $H < 1$. For the finite variance case $H = d + \frac{1}{2}$, whereas for infinite variance case $H = d + \frac{1}{\alpha}$. The long-range dependence parameter, the following formula is defined by [11].

$$H = \frac{(3-\alpha)}{2} \quad (1)$$

However, the width of the parameter of heavy tail (α) be contingent on the different parameter (*d*). If $d > 0$, then the parameter of the heavy tail (α) will be greater than 1. In this case, in any noise the parameter of the heavy tail α range from 0 to 2 [12]. The second condition, if d < ½, then represents the expansion of the power series across the KSE-100 index cycles. Although $\alpha < 2$, then the tail is equal in contrast to the law of Pareto [13]. The KSE-100 index cycle consists of index activity divided into increments.

Throughout the KSE-100 index cycle α has range from 1 to 2. This study develops the parameter of heavy tail (α) calculation using the parameter of Hurst exponent in both method Self-similar (H_S) methods combined with the Hausdorff - Besicovich method (Box Technique Calculation) and the self-affine (H_A) method obtained by analysis of rescaled range. d_S and d_A distinguish as the parameter of differencing self-similarity and self-affinity respectively. α_S is described heavy tail parameter of self-similar, whereas α_A is calculated as the parameter of self-affine heavy tail.

Long range dependency (LRD), also known as long range. Scope is the event that leads to the analysis of time series data. In stationarity *LRD* is the procedure of self-similar with stationary asymptotically intensification, in a measurement of time series, the parameter of Hurst exponent *H* is a long- range dependence (the process of self-similar context). The self-similar process with the Hurst exponent index increases $H > 0.5$. This increase (continuous transformations of act) is stationary *LRD* sequence. The result of short range sequence shows the Brownian motion (*H* equals 0.5). Similarly, *LRD* provide the action of same type. The self-similar procedure with *H* = 0.5, is the most frequently a Brownian motion of partial fractional.

2.2.1 The Analysis of Long Range Correlation

The time series in Financial Science always immerses itself in the long-range persistent of self-affine. The spectrum density power (S), Frequency expressed via *f*, *S (f)* ~ *f* - *α*, be contingent on the strength and persistence of *α* constant. For the long-term model, the long-affine correlation effect of persistence (α) the feasible evaluation extent of approximation. The heavy tail parameter shows the time series data is magnified on one side representing the data arising from the long range correlation amongst them. A heavy tail indicates a probability which have very large numbers. The representations of heavy tail have a different feces than a small random one. The specific distribution of the heavy tail is a subclass of the laws of power, which indicates that the power function of the Probability distribution. Here, two kind of correlation are measured. Firstly, short-range correlation (persistence) [14, 15] and secondly, the long-range correlation (persistence) [16, 17]. Short-range correlation is achieved by decreasing the automatic coupling function. It is tied to the exponential exposure of the large lags graph. In a time-series (functional noise or 1/*f* noise), a long-range correlation (persistence) which shows the current value is associated with all past values. The long- range correlation (persistence) is characterized via the unmistakable and straightforward Power Law behavior is decreased. Data values persistent as a function of the temporal (or lags) between them. If there is a long-range correlation strength, higher data values are associated with each other with longer delays in the time series [16, 17]. The variability in accumulated spatial and temporal variables can be attributed to long-range persistence [17].

The long-range persistence method shows a scaling of Power-Law of the autocorrelation function

$$[C\,(\rho) = \frac{1}{\sigma_x^2(N-\gamma)}\sum_{k=1}^{N}(x_k - \bar{x})(x_{k+\rho} - \bar{x})] \quad (2)$$

Such that

$$|C(\rho)| \sim \rho^{-(1-\gamma)}\ , \qquad \rho \to \infty \qquad , -1 < \beta < 1 \quad (3)$$

Large time lags is represents as δ. Where γ is called the long-range persistency strength. Where $\bar{x}$ is shown the sample mean, σ_x^2 called the sample variance, the number of values in the time series is represent as by N . For process contemplated in this study, as the lags ρ, increase, ρ = 1, 2, 3, .., *N*-1. Whereas, the autocorrelation function $C(\rho)$ decline and the correlation between $x_{k+\delta}$ and $x_k$diminutions. The $C(\rho)$ positive value represent that persistence and negative values indicate that the anti-persistence. Whereas, $C(\rho)$ =0 expresses that no correlation. If β = 0 shows that there long-range persistence is no among the values. $\beta > 0$ indicates long-range persistency whereas, $\beta < 0$ suggests long-range anti-persistency. The strength of long-range persistency is estimated by self- similar and self- affine Hurst exponents. The Hurst exponents are computed by the techniques of self-similar (H_S) and self-affine (H_A). The Hurst exponents of self-affine H_A is correlate to the long-range correlation γ strength by the relation

$$\beta_A = 2H_A - 1 \qquad -1 < \beta_A < 1 \qquad (4)$$

[18].

The Hurst exponents of self-similar H_S are linked with the long-range correlation γ strength by the resulting formula

$$\beta_S = 2H_S + 1 \qquad 1 < \beta_S < 3 \qquad (5)$$

[19, 20]. If $\beta_S = 2$ shows that long-range persistence is not exists between the values. If $\beta_S > 2$ long-range persistent and $\beta_S < 2$ is anti-persistent of long-range.

2.3 Phillips-Perron (*PP*) Unit Root Test

Phillips and Perron (1988) developed a comprehensive theory of unit root non-stationarity. The test is similar to the *ADF* test. Phillips-Perron (*PP*) unit root testing differs from ADF testing especially in the way they respond to serial correlation and heteroskedasticity in error. The *ADF* test uses parametric autoregression to quantify ARMA (*p*, *q*) of errors in test retrieval, whereas *PP* testing removes any serial correlation in test testing. The results of the *PP* test are similar to the ADF test. The model is defined as,

DF: a_t ~ iid (Sequences are statistically independent and distributed equally random random meanings and variations)

PP: at ~ associated serial

Test equation (PP): $\Delta X_t = \vartheta_0 + \aleph X_{t-1} + \beta_t$

Additionally, a correction factor to the DF test statistic. (ADF is to add lagged ΔX_t to 'whiten' the serially correlated residuals). The hypothesis to be tested: H_0: $\aleph = 0$ and H_1: $\aleph < 0$

The PP tests for any serial correlation and heteroskedasticity in which the errors a_t of the test regression by directly modifying the test statistics $t_{\aleph=0}$ and $n\hat{\aleph}$. These modified statistics, signified τ_t and $\tau_\aleph$, are given by

$$\tau_t = \sqrt{\frac{\hat{\sigma}^2}{\hat{\omega}^2}}\, t_{\hat{\aleph}} - \frac{1}{2}\left(\frac{\hat{\omega}^2 - \hat{\sigma}^2}{\hat{\omega}^2}\right)\left(\frac{n(s.e.(\hat{\sigma}))}{\hat{\sigma}^2}\right)$$

$$\tau_\aleph = n\hat{\aleph} - \frac{1}{2}\frac{n^2\left(s.e.(\hat{\aleph})\right)}{\hat{\sigma}^2}\left(\hat{\omega}^2 - \hat{\sigma}^2\right)$$

The terms $\hat{\sigma}^2$ and $\hat{\omega}$ are consistent estimates of the variance parameters.

$$\sigma^2 = \lim_{n\to\infty} n^{-1}\sum_{t=1}^{n} E(a_t^2), \quad \omega^2 = \lim_{n\to\infty}\sum_{t=1}^{n} E\left(\frac{1}{n}\sum_{t=1}^{n} a_t^2\right)$$

Underneath, the null hypothesis that $\aleph = 0$, the PP τ_t and $\tau_\aleph$ statistics have the equivalent asymptotic distributions as the ADF t-statistic and normalized bias statistics. One benefit of the

PP tests across the ADF tests is that the PP tests are robust to general forms of heteroskedasticity in the error term a_t. Additional advantage is that the user does not have to specify a lag length for the test regression.

2. Results and Discussions

The heavy tail analysis (self-affine and self- similar) of parameters α_S and α_A parameters can only be used for fixed time series data. KES -100 index cycles (1st to 12th) from 1.1.2015 to 31.12.2020 were tested. Long-range dependence parameters d_S and d_A are calculated at baseline. The parameter of heavy tail (α) is obtained with the assistance of a different parameter (d).

Cycles	Duration	F_S	H_S	$0 < d_S < 1/2$	$1 < \alpha_S < 2$	F_A	H_A	$0 < d_A < 1/2$	$1 < \alpha_A < 2$
1	1.7.2020–31.12.2020	1.105	0.895	0.395	1.210	1.319	0.681	0.181	1.638
2	1.1.2020 – 30.6.2020	1.400	0.600	0.100	1.800	1.295	0.705	0.205	1.59
3	1.7.2019– 31.12.2019	1.335	0.665	0.165	1.670	1.375	0.625	0.125	1.75
4	1.1.2019 – 28.7.2019	1.303	0.697	0.197	1.606	1.286	0.714	0.214	1.752
5	2.7.2018– 31.12.2018	1.480	0.520	0.020	1.960	1.315	0.685	0.185	1.63
6	1.1.2018 – 29.6.2018	1.424	0.576	0.076	1.848	1.292	0.708	0.208	1.584
7	3.7.2017– 29.12.2017	1.313	0.687	0.187	1.606	1.318	0.682	0.182	1.636
8	1.1.2017 – 30.6.2017	1.685	0.315	-0.185	2.370	1.500	0.500	0	2
9	4.7.2016– 30.12.2016	1.631	0.369	-0.131	2.260	1.546	0.454	-0.046	2.092
10	1.1.2016 – 30.6.2016	1.261	0.739	0.239	1.522	1.394	0.606	0.106	1.788
11	1.7.2015 – 30.6.2015	1.497	0.503	0.003	1.994	1.385	0.615	0.115	1.77
12	1.1.2015 – 30.6.2015	1.479	0.521	0.021	1.958	1.342	0.658	0.158	1.684

Table 1: The fractional differencing parameter and heavy tails parameter of KSE-100 Index (1^{st} -12^{th}) cycles

Table 1 defines the parameter of fractional differencing and the heavy tail parameters of the KES -100 (1st -12th) index cycles in terms of the Hurst exponent (H). Table 1 shows the parameter values of the heavy tail within the range $0 < H < 1$ indicating that the KES -100 index cycles are dynamic is regular. Less than 2 parameters of the heavy tail (α) indicate that the probability is equal to the distribution of the law of Pareto (heavy tail on either side). The parameter of heavy tail (α) indicates that the dynamics force is consistent and periodic in all KSE-100 index cycles (1st-12th) except for the 9th cycle. The length of the 9 cycles is from 4.7.2016 to 30.12.2016. Other important events occurred at that time as a result of which the behavior of the 9th cycle was unusual and inconsistent. Significantly, on 13 November 2016, CPEC began operating in part as Chinese goods were transported from Gwadar Port to continue shipping to Africa and West Asia. Investments in Pakistan stock exchange and shanghai stock exchange have been influenced by the announcement of 54 billion USD by the Chinese president for the implementation of CPEC (Wolf, 2016). The divestment brings good relations for the development of the financial market in Pakistan. The arrival of a Chinese investor will be another step towards promoting economic development in the region. Most buyers thought that the sale of controlling stock was pricey. A market expert said the decline would increase value and aid in index trading, new product, and listing of parameters. The 9th Cycle has self-similar heavy tail parameter (α_S) value of 2,260. while the self-affinity heavy tail (α_A)

parameter of the 9th cycle is 2.092. Table 1 shows the parameter of fractional differencing and the heavy tail parameters of the KSE-100 Index cycles (1st -12th). In each KES-100 (1st -12th) cycle there are profound heavy tails. The parameter of heavy tail (α) and the different parameter ($d = H$-0.5) are found in the Hurst parameter. The parameter of heavy tail (α) value close to 2 represented the heavy tail strength. This study novelty concludes that the corresponding the parameter of heavy tail (α_S) has a lengthier persistent and correlated relative to the heavy tail parameter (α_A) of self-affine.

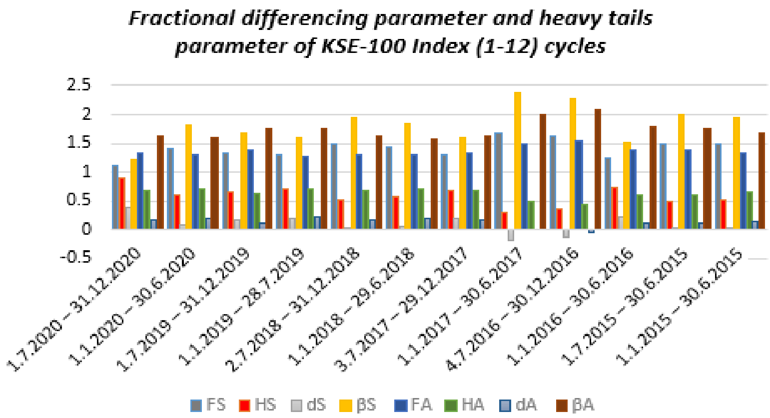

Figure 1: The fractional differencing parameter and heavy tails parameter of KSE-100 Index (1st-12th) cycles

Figure 1 shows the parameter of fractional differencing and the heavy tail parameters of the KSE-100 index cycles (1st -12th).

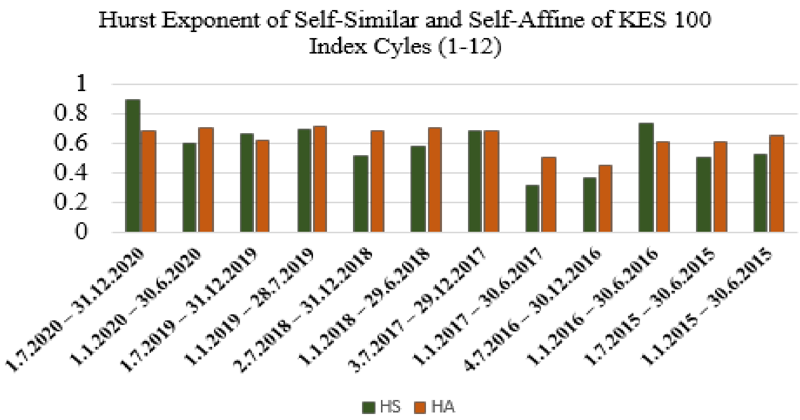

Figure 2: The self-similar and self-affine Hurst Exponent of KSE-100 Index (1st-12th) cycles

Figure 2 shows a similar Hurst Exponent and self-affine KSE-100 Index (1st-12th) cycles.

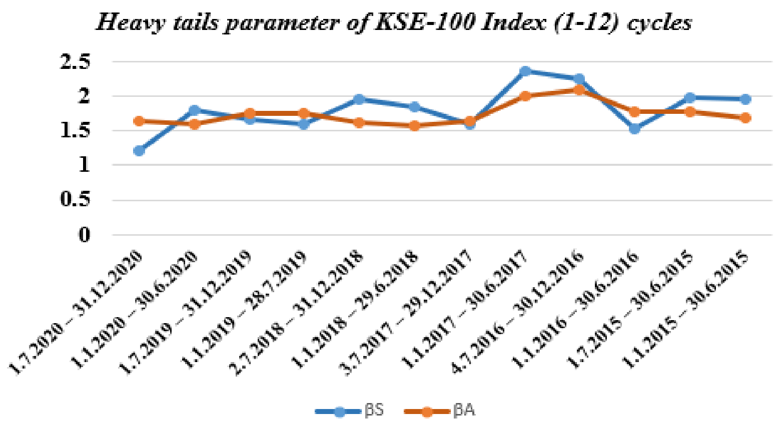

Figure 3: The self-similar and self-affine Heavy tails parameter of KSE-100 Index (1st-12th) cycles

Figure 3 shows the corresponding parameter and self-affine Heavy tails of the KSE-100 Index cycles (1st -12th).

The second phase involves the analysis of KSE-100 indicator cycles (1st -12th) in long-range correlation. The study to analyze the long- range correlation of the KSE-100 index (1st -12th) in the term of self-affine and self- similar Hurst's exponent and to compare both.

Cycles	Duration	H_S	$1 < \beta_S < 3$	H_A	$-1 < \beta_A < 1$
1	1.7.2020 – 31.12.2020	0.895	2.790	0.681	0.3620
2	1.1.2020 – 30.6.2020	0.600	2.200	0.705	0.410
3	1.7.2019 – 31.12.2019	0.665	2.330	0.625	0.250
4	1.1.2019 – 28.7.2019	0.697	2.394	0.714	0.428
5	2.7.2018 – 31.12.2018	0.520	2.040	0.685	0.370
6	1.1.2018 – 29.6.2018	0.576	2.152	0.708	0.416
7	3.7.2017 – 29.12.2017	0.687	2.374	0.682	0.364
8	1.1.2017 – 30.6.2017	0.315	1.630	0.500	0
9	4.7.2016 – 30.12.2016	0.369	1.738	0.454	-0.092
10	1.1.2016 – 30.6.2016	0.739	2.478	0.606	0.212
11	1.7.2015 – 30.6.2015	0.503	2.006	0.615	0.230
12	1.1.2015 – 30.6.2015	0.521	2.024	0.658	0.316

Table 2: The strength of long range-correlation of KSE-100 Index (1st -12th) cycles

Table 2 shows the persistence of long-term for each KSE-100 (1st -12th) cycle indicator. The long-range correlation (β_S) strength of self-similar ranges from 1 to 3 and the self-affine long-range correlation (β_A) strength is ranges from -1 to 1. The value of $\beta_S > 2$ indicates long-range persistence and β_S<2 shows the anti-persistency of long-range. The value β_A> 0 indicates the persistent of long range and β_A<0 indicates long-range anti-persistency. The KSE-100 8th and 9th index cycles with the same dynamics of the long-range correlation (β_S) strength self-similar shows that anti-persistent apart from this all cycles are persistent and strongly correlated. Similarly, each KSE-100 index cycle (1st -12th) has β_A> 0 which specifies that the entire KSE-100 index cycle is highly correlated with the previous one, whereas the 9th cycle also shows anti-persistent. Cycle 8th shows $\beta_A = 0$ which means that long-range is anti-persistence between values between numbers. The self-similar (β_S) has strong long-range correlation strength as compared to self-affine (β_A) [21].

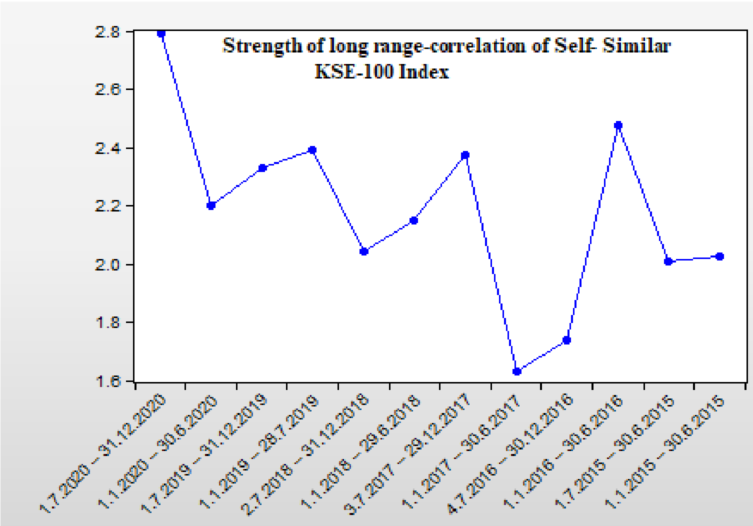

Figure 4: The strength of long range-correlation of Self- Similar KSE-100 Index (1^{st}-12^{th}) cycles

Figure 4 shows that the long range-correlation strength of self- similar KSE-100 Index (1^{st}-12^{th}) cycles.

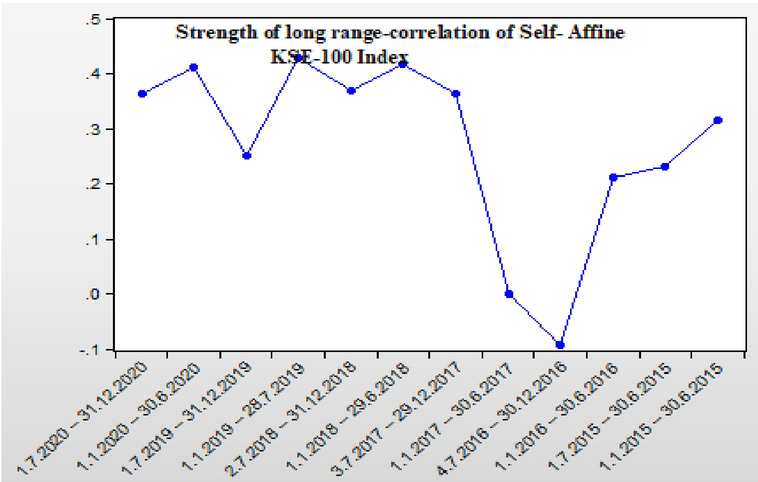

Figure 5: The strength of long range-correlation of Self- Affine KSE-100 Index (1^{st}-12^{th}) cycles

Figure 5 explain the long range-correlation strength of self- affine KSE-100 Index (1^{st}-12^{th}) cycles.

Phillips-Perron (*PP*) Unit Root Test of the KSE-100 index (1^{st}-12^{th}) cycles for stationarity explored that each cycle has stationary behavior.

Null Hypothesis H_0: KSE-100 index cycle 1 has a unit root		
	Adj.t-statistics	prob*
Phillips-Perron test Statistics	-10.23678	0.0000

Test Critical vales	1% level 5% level 10% level	-3.482879 -2.884470 -2.579080	

Null Hypothesis H_0: KSE-100 index cycle 2 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-9.868545	0.0000
Test Critical vales	1% level 5% level 10% level	-3.485115 -2.885450 -2.579598	

Null Hypothesis H_0: KSE-100 index cycle 3 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-9.774250	0.0000
Test Critical vales	1% level 5% level 10% level	-3.482879 -2.884477 -2.579080	

Null Hypothesis H_0: KSE-100 index cycle 4 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-8.864206	0.0000
Test Critical vales	1% level 5% level 10% level	-3.485586 -2.885654 -2.579708	

Null Hypothesis H_0: KSE-100 index cycle 5 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-10.10367	0.0000
Test Critical vales	1% level 5% level 10% level	-3.484198 -2.885051 -2.579386	

Null Hypothesis H_0: KSE-100 index cycle 6 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-8.751516	0.0000
Test Critical vales	1% level 5% level 10% level	-3.484653 -2.885249 -2.579491	

Null Hypothesis H_0: KSE-100 index cycle 7 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-11.25826	0.0000
Test Critical vales	1% level 5% level 10% level	-3.484198 -2.885051 -2.579386	

Null Hypothesis H_0: KSE-100 index cycle 8 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-7.759795	0.0000
Test Critical vales	1% level 5% level 10% level	-3.484653 -2.885249 -2.579491	

Null Hypothesis H_0: KSE-100 index cycle 9 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-10.77861	0.0000
Test Critical vales	1% level 5% level 10% level	-3.484198 -2.885051 -2.579386	

Null Hypothesis H_0: KSE-100 index cycle 10 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-7.975370	0.0000
Test Critical vales	1% level 5% level 10% level	-3.482879 -2.884477 -2.579080	

Null Hypothesis H_0: KSE-100 index cycle 11 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-9.655357	0.0000
Test Critical vales	1% level 5% level 10% level	-3.484115 -2.885450 -2.579598	

Null Hypothesis H_0: KSE-100 index cycle 1 has a unit root			
		Adj.t-statistics	prob*
Phillips-Perron test Statistics		-14.10753	0.0000
Test Critical vales	1% level 5% level 10% level	-3.483751 -2.884856 -2.579282	

Table 3: Phillips-Perron (PP) Unit Root Test (stationary) for KSE-100 index (1st-12th) cycles.

Table 3 show that each KSE-100 index cycles has stationary behavior and reject the unit root test. The data behavior is not stationary which is shows like a unit root. The rejection of H_0 is based on the *p*-value is less than 5% or the critical value of the absolute value of Phillips-Perron (*PP*) test is greater than at significance level 1% and 5%.

3. Conclusion

Stock markets is one of the foremost elements of financial system of the capitalistic world. They provide spot for the exchange of financial resources such as stocks and bonds of joint stock companies, unit trusts, guilt age securities and other financial products effectively, analytically, and by keeping the interest of investors. The heavy tail parameter is analyzed for KSE-100 index (1^{st}-12^{th}) cycles. All KSE-100 index cycles (1^{st}-12^{th}) have nature stationary as the parameter of differencing ($0 < d < 0.5$) in both perspectives self-affine (d_A) and self-similar (d_S) which characterize that the dynamic is regular more besides cycle 9^{th} of KSE-100 stock index. The parameter of heavy tail α_S besides α_A discovering that asymptotically equal to the Pareto law of probability which is screening that the dynamics strength is regular and periodic for all the KSE-100 index (1^{st}-12^{th}) cycles besides 9^{th} cycle and heavy tails are profound. Some important events happen in 9^{th} cycles due to this the behavior is unusual. Alike, collaboration of Pakistan stock exchange and shanghai stock exchange via investment of 54 billion USD and most brokers and market participants thought that the sale of controlling stock was priced. The parameter of heavy tail (α) and the parameter of differencing ($d = H$-0.5) is persistent if the parameter of Hurst exponent ($0.5 < H < 1$). The heavy tail parameter (α) value greater than 2 described that the heavy tail strength reductions and anti-persistent. The data which is Persistent having the heavy tail since for $d > 0$ the heavy tail parameter $\alpha > 1$. The tail parameters in time series data behavior show to the long-term dependency and persistency analysis. In statistics modeling, correlation is consisting of two types first one is short range correlation and second one is long range correlation. All KSE-100 index cycles described the long-range correlation strength (β). The self-similar long-range correlation strength ($1 < \beta_S < 3$) and the self-affine long-range correlation strength ($-1 < \beta_A < 1$) is persistent in the view of $0.5 < H_S < 1$ and $0.5 < H_A < 1$. The study accomplishes that each value of KSE-100 index cycles is correlated strongly to preceding in both methods self-affine as well as self-similar. The techniques of self-similar are more appropriate as compared to self-affine. The Phillips-Perron (PP) unit root tests is calculated for non-stationarity data. The value of H_0 is rejected when the p-value is less than 5% or the critical value of the absolute value is greater than at the significance level 1% and 5%. Conclusion shows that the KES -100 index cycles have stationary in nature because of this Unit root test is applied to confirm the linearity of the long-range correlation and heavy tail. The six months break up express that market was persistent in evaluate years which are shown that economy is steadily progress in the direction of established state of the structure of market. The concept of efficiency would accordingly integrate time varying, evolutionary and behavioral aspect of the development of market.

Abbreviations

F: Fractal Dimension; d: Differencing Parameter; H: Hurst Exponent; α : heavy tail parameter; β : long-range correlation; PP: Phillips-Perron.

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