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Test of Proportional Runs Volatility Model As a Measure of Risk in Kenyan Listed Stocks

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Abstract: **Proportional runs volatility model is an innovation from the requirements volatility model that is employed in the Computer Science discipline and has the potential of measuring historical stock return volatility. This research employed balanced panel data consisting of monthly closing stock price data for a sample of 21 stocks listed in the Nairobi Securities Exchange that were selected using purposive sampling method from a population of 56 stocks during years 2001 and 2010. Historical stock return volatility was then measured using the proportional run volatility and standard deviation metrics for comparison purpose. The results were presented graphically and using inferential statistics including: Pearson's correlation and t-test tabulations. The findings indicated that graphically there seems to be some similar behavior in the relationship between the curves of proportional runs and standard deviation models. As per the Pearson's correlation analysis, there appeared a moderately strong relationship. However as pet the one sample t-test analysis, there was a significant difference between the proportional run volatility and standard deviation metrics. The conclusion was therefore that there was mixed findings as to whether the proportional runs volatility metric has the potential of measuring historical stock return volatility in a manner similar to that of the standard deviation metric.**

Keywords: **Historical stock return volatility, proportional runs volatility model, standard deviation.**

1. INTRODUCTION

Developed stock markets are expected to provide high stock returns with lower volatility in the long run (Raju and Ghosh, 2004). Weak form stock market efficiency is associated with high stock return volatility however excess stock volatility does not support weak form efficiency and implies that stock prices do not fluctuate as a result of changes in economic fundamentals (Cuthbertson, 2002). Stock return volatility is associated with randomness in the occurrence of economic fundamentals underlying the stock price which is also expected to change randomly (Stefan, 2009). Serial correlation tests can also be employed to assess existence of weak form stock market efficiency and zero serial correlation is associated with stock market efficiency as it implies that there is no pattern in the occurrence of stock returns and hence randomness in the occurrence of stock returns (Pearce, 1987).

A run of stock returns refers to an uninterrupted sequence of either positive or negative or zero stock returns (Gujarati and Porter, 2010). When there are two or more consecutive positive or negative or zero stock returns, a run is said to occur. When the consecutive occurrence of stock returns changes, the run is said to end and another one commences (Gujarati and Porter, 2010). The change in the consecutive occurrence of stock return runs represents inconsistency and hence stock return volatility can be seen to occur.

There is a relationship between serial correlation and runs of stock returns. Negative serial correlation is evidenced by numerous short runs and hence implying frequent change in the occurrence of runs which happens when the actual number of runs in a series of stock returns exceeds the expected number of runs. Positive serial correlation is evidenced by few long runs and is associated with infrequent change in stock return runs. This happens when the actual number of runs are less than the expected number of runs in a series. Zero serial correlation occurs when actual number of runs are equal to the expected number of runs in a series and is an indicator of randomness and weak form stock market efficiency (Adolph, 2007).

Research Objective:

The objective of this research is to test whether the proportional runs model can be employed successfully in the field of Finance to measure the historical stock return volatility in a manner similar to the conventional model of standard deviation.

2. RESEARCH METHODS

Population and Sample:

This research was carried out in the NSE during the years 2001 to 2010 when the bourse had 56 listed companies which form the research population. This research employed balanced panel data consisting of monthly closing stock price data for a sample of 21 companies that were selected using purposive sampling method from the population.

Data Analysis:

Arithmetic Stock Return:

The financial performance of an investment can be measured using simple arithmetic returns and are derived as the summation of periodic capital gains or losses and the periodic income from the investment (Copeland *et* al, 2005). The arithmetic stock return model is also referred to as holding period yield as follows (Cuthbertson, 2005):

Arithmetic stock return $(R_1) = (P_1 - P_0 + D_1) / P_0$ **(1)**

Where: R_1 = rate of return for current period

P_1 = price of current period

P_0 = price of previous period

D_1 = dividend income for current period

Proportionate Runs as a Measure of Volatility of Stock Returns:

The requirements volatility metric is imported from the Computer Science discipline for application in the test of volatility of requirements during software development and postulates an inverse relationship between requirements volatility and the cost and time schedule of software development projects. The requirements volatility model measures the proportionate changes of requirements during the software development cycle without focusing on deviations from an established mean value, and thus does not assume normality of distribution (Singh and Vyas 2012; Loconsole 2008):

$$\textbf{Requirements volatility} = \frac{\textbf{Number of changed words in a file}}{\textbf{Number of words per file}} \qquad \textbf{(2)}$$

The proportional runs volatility model is adopted in the current research from the requirements volatility model after developing it to become a non-parametric volatility metric. The numerator is the number of runs whether positive or negative or zero stock returns during a period while the denominator is the total number of stock return observations in the period (Author):

$$\textbf{Proportional Runs Volatility} = \frac{\textbf{Number of runs of stock returns in a period}}{\textbf{Total number of stock returns in the period}} \qquad \textbf{(3)}$$

The proportional runs volatility model as an application of the requirements volatility model, operates under similar principles by focusing on the proportionate number of runs in a series and does not assume that the series is normally distributed. Stock price change data usually is leptokurtic and positively skewed (Rachev *et al*, 2007).In this research, correlation analysis was employed to assess the level of the relationship between the 3 stock return volatility metrics (Blasco *et* al, 1999).

Standard Deviation Metric:

Standard deviation metric utilizes all the data under consideration and determines the dispersion from the mean. It is the most commonly employed volatility metric and it summarizes the probability of seeing extreme values. It is criticized for assuming that the distribution of stock returns is symmetrical or normal. It is modeled as follows (Sweeney, 2006):

$\sigma_p = \sqrt{} (R_t - \bar{R})^2 / n$ **(4)**

Where: σ_p = standard deviation of portfolio of stocks

R_t = return of stock t,

$\bar{R}$ = mean stock return, n = number of periods

3. RESULTS AND INTERPRETATION

Graphic Representation of Standard Deviation and Proportional Runs Volatility Metrics:

When stock return volatility based on standard deviation, range and proportional runs metrics were plotted after ranking of the volatilities in descending order, the results as per Figure 1 revealed diagrammatically that standard deviation, range and proportional runs indicated that the 2 metrics behaved in a somewhat comparable manner.

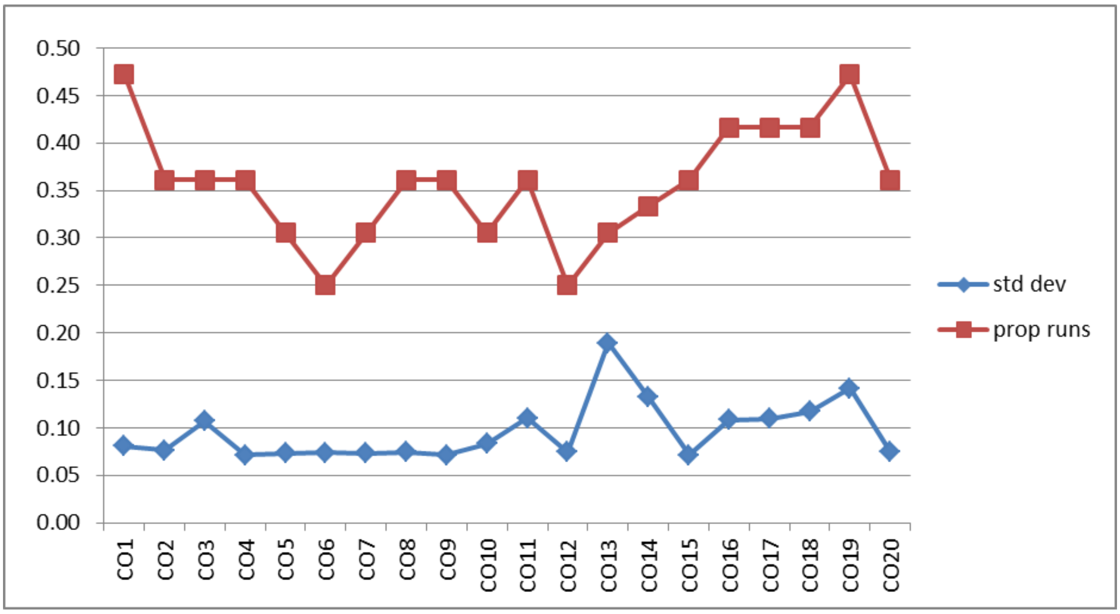

Figure 1: Graphic Representation of Standard Deviation and Proportional Runs Metrics

Pearson's Correlation Analysis of Standard Deviation and Proportional Runs Metrics:

The findings of Pearson's correlation analysis in Table 1revealed that the correlation between standard deviation and proportional runs model was 0.666 which implied moderately strong correlation between the two metrics (Rumsey, 2016). Hence the proportional runs model can be said to exhibit potential for measuring historical stock return volatility.

Table 1: Pearson Correlation Analysis of Stock Return Volatility Metrics

		Proportional runs
Standard deviation	Pearson Correlation	**.666****
	Sig. (2-tailed)	.001
	N	21

The findings of t-test in Table 2 revealed that the p-value was 0.000 which impliedthat there was a significant difference between standard deviation and proportional runs volatility metrics and hence the proportional runs model.

Table 2: One Sample T-Test of Standard Deviation and Proportional Runs Metrics

One-Sample Test						
	Test Value = 0					
	t	df	**Sig. (2-tailed)**	Mean Difference	95% Confidence Interval of the Difference Lower	Upper
Standard deviation – proportional runs	-18.862	19	**.000**	-.26200	-.2911	-.2329

4. CONCLUSION

According to the graphical, Pearson's correlation and one sample t-test display mixed results as to whether the proportional runs volatility model has the potential of measuring historical stock return volatility in a manner similar to the conventional historical stock return volatility model of standard deviation.

REFERENCES

[1] Adolph S. C (2007). Is a Basketball Free Throw Sequence Non-random? A Group Exercise for Undergraduate Statistics Students, *Journal of Statistics Education*, Vol.15, No.3

[2] Blasco N, Corredor P and Ferreruela S (1999). The Implications of Herding on Volatility: Case of the Spanish Stock Exchange, Working Paper, University of Navarra, Spain

[3] Cuthbertson K (2002). Quantitative Financial Economics, John Wiley and Sons, New York, USA

[4] Gujarati D. N and Porter D. C (2010). Essentials of Econometrics, McGraw Hill, Boston, USA

[5] Loconsole A (2008). A Correlational Study on Four Measures of Requirements Volatility, 12th International Conference on Evaluation and Assessment in Software Engineering

[6] Pearce D. K (1987), Challenges to the Concept of Stock Market Efficiency, *Economic Review*, pp 16-33

[7] Rachev S, Jasic T, Stoyanov S and Fabozzi F. J (2007).Momentum Strategies Based on Reward-Risk Stock Selection Criteria, *Journal of Banking & Finance*, Vol.31, Issue 8

[8] Raju M. T and Ghosh A (2004). Stock Market Volatility: An International Comparison, Working Paper Series, SEBI Publication

[9] Reilly F. K and Brown K. C (2009). Investment Analysis and Portfolio Management, 9th edition, Thompson one, USA

[10] Rumsey D. J (2016), Statistics for Dummies, 2nd ed., Wiley Publishers, New York, USA

[11] Singh M.P and Vyas R (2012). Requirements Volatility in Software Development Process, *International Journal of Software Computing and Engineering*, Vol.2, No.4

[12] Stefan J (2009), Testing EMH: A Behavioral Approach to the Current Economic Crisis, www.econ.berkeley.edu/sites/default/files/julia_stefan_thesis.pdf

[13] Watkins B (2003). What Makes Investors Overreact in the Short run? Asset Pricing and Valuation e-Journal

APPENDIX- A

Data on Volatility Metrics in the NSE:

NSE companies	Standard Deviation	Proportional Runs Model	Difference between standard deviation and proportional runs
CO1	0.08	0.47	-0.39
CO2	0.08	0.36	-0.29
CO3	0.11	0.36	-0.25
CO4	0.07	0.36	-0.29
CO5	0.07	0.31	-0.23
CO6	0.07	0.25	-0.18
CO7	0.07	0.31	-0.23
CO8	0.07	0.36	-0.29
CO9	0.07	0.36	-0.29
CO10	0.08	0.31	-0.22
CO11	0.11	0.36	-0.25
CO12	0.07	0.25	-0.18
CO13	0.19	0.31	-0.12
CO14	0.13	0.33	-0.20
CO15	0.07	0.36	-0.29
CO16	0.11	0.42	-0.31
CO17	0.11	0.42	-0.31
CO18	0.12	0.42	-0.30
CO19	0.14	0.47	-0.33
CO20	0.07	0.36	-0.29