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TABLES CONTENTS

Annualized Stock Market Returns Volatility: An Evidence of Dar es Salaam Stock Exchange

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Abstract
Financial market players raise a concern about returns volatility anomalies. Yet, the day effects of stock market return instability in the Dar es Salaam financial market are not known. The present study, investigated the day effects on returns using time series data for the years 1998 through 2020. The return of market stocks was analysed using Win Rat and E-views. The results showed that the day of and the month of the year outcome existed in the return equation only with a constant decay rate $(\alpha + \beta = 0.75)$ *meaning that the unpredictability forecast reverts to its unrestricted mean at the proportion of 0.75 per transaction period. Moreover, it was found that the lowest monthly returns spread were observed for TCC and the highest for the whole market while the maximum and nethermost daily returns occurred on Wednesdays and Tuesdays, respectively. Furthermore, it was found that the positive January effect was observed in the market and monthly mean returns were positive with the lowest returns in December. The study concludes that that day's effects impacted the market stock return caused by the volatility effect on returns. It is therefore recommended that rational investors should invest in the market for their future gains.*

Keywords*: Financial market returns, returns instability, day effects, month effects.*

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1.0 Introduction

The financial market permits the relocation of economic possessions to a broader range of the population. Capital markets ease transaction, hedging, and sharing of risks, easily acquire information about investments, and allocate resources between both economic deficit and surplus sides (Edwards, 2018). Though, ordinary market companies express concern above the level of standard market returns anomalies (Schwert, 2018). Newer theories of disorder and adaptive decision-making explain the dilemma of stock market value explosiveness (Aleke et al. 2022; Khan et al.

2020; Oslen, 2019). Consequently, Christie and Huang (2019) found that daily and monthly routine returns are unreliable with herding during eras of large price drives. Also, the daily price impulsiveness of the typical market is evidenced so that it is not affected by the introduction of futures trading (Edwards, 2018). On the other hand, it is argued that stockholder behaviour bias creates excess stock returns volatility as a result it drives ordinary worth away from fundamentals (Khan et al., 2020; Zhan, 2019). It is further witnessed that the presence of the day-of-the-week effect in both volatility and returns affects the pattern of the market stock exchange (Berument and Kiymaz, 2001).

Moreover, Sewraj et al. (2010) and Hirschey (2019) observed an optimistic January effect at the market level with the non-existence of the first day of the week effect in the normal market returns and confirmed the persistence in both daily and monthly stock returns. Similarly, Kling et al. (2005) observed monthly effects of higher returns in February and November, and Fridays were profitable through the weekdays on the Chines Stock exchange. It is also noted that some anomalies were observed in January, half of the month, weekend, and yearly vacations effect in some market indices (Mills and Coutts, 2006), and the day of the week effect on the routine exchange index (Sutheebanjard and Premchaiswadi, 2010). A similar observation by McConnell and Xu (2018) on the presence of an end-of-the-month effect in typical market returns was caused possibly by month-end buying pressure.

In fact, the instability of routine prices in the financial market and yields remains one of the major problems in the finance literature. One common source of volatility has been thought to be related to the day- of the - week and month–of the – year trends as calendar effects on standard market returns (Christie and Huang, 2019; Sewraj et al., 2010; Hirschey, 2019). This study, therefore, investigated the annualized effects on normal market returns instability in the Dar es Salam stock exchange using time series data of the market index.

2.0 Literature Review

As the financial market enables the allocation of economic reserves to an inclusive continuum of the residents with deficit and surplus behaviour, Oslen (2019) believes that newer theories of confusion and adaptive decision-making in the desire to invest in emerging stock markets explain the mystery of stock price explosiveness. Accordingly, Blasco et al. (2012) confirmed that steering has a direct effect on the annualized instability of stock returns. Furthermore, Edwards (2018) observed that the daily price unpredictability of the stock market is not affected by the introduction of prospects transactions in long as well as short positions.

It has further been explained that monthly effects in November-December in emerging stock markets had high mean returns contrary to March and May on stock market returns (Patel, 2008). Contrary, observations made by Patel & Evans (2003) marked monthly effects in the last month of the year through the fifth month than in the sixth month through the eleventh month which is a unique stock market returns global trend as opposed to Patel's (2013) observations of no monthly effects at all. Paradoxically, Bouazizi et al. (2022); Elhassan (2021); Jebran (2018), and Hung (2018) observed variable instability spill-overs from the oil price volatility, COVID-19, and extraneous exchange market to the financial market and vice versa in the pre-financial crisis period.

Thus, in analysing the puzzle of stock return volatility, Akthar, and Khan (2016) employed both ARCH (1) and GARCH models as stock market volatility models for yearly calendar returns. Accordingly, Dexit and Agrawal (2020) observed that the presence of serial autocorrelation in market returns provides an opportunity for employing the same models to explain the conditional variance of stock market returns instability. As a result, the decaying constant value ($\alpha+\beta$) is close to the unit indicating the stock market volatility clustering in the return series (Dexit and Agrawal, 2020). Consequently, Rastogi et al. (2018) argue that stock explosiveness can be predicted using similar models and be priced for time-varying risk premium so as to create information on the effect of risks associated with volatility. Thus, the present study investigated the annualized market stock returns volatility in infantry emerging markets, the case of the Dar es Salam stock exchange.

3.0 Research Methodology

Stock market returns instability estimation employed daily price and market directory level changes. The returns to market transactions were computed by assuming away operation costs, and the returns to transactions were computed using the formula:

$$r_{it} = \ln\left(\frac{p_{it}}{p_{it-1}}\right) \quad \text{...} \quad (1)$$

Where:

p_{it} = Price level at period t for each company i

p_{it-1} = Price level at period (t - 1) for each company i

r_{it} = Stock return realized at period t for each company i

ln = natural logarithm

The given formula was employed to compute daily and monthly yields for each company and the overall market.

Conditional heteroscedasticity was a specifically designed model, and forecast conditional variances were determined. The stock exchange yield sequence was computed using GARCH models. The study employed longitudinal data from 1998 through 2020 for early listed companies in Dar es Salaam stock exchange; TOL Gases Limited, Tanzania Breweries PLC, Tanzania Cigarette Company (TCC), Tanzania Tea Packers (TATEPA), Tanga Cement PLC(SIMBA), and SWISSPORT Tanzania PLC; which were used to generate calendar effects on stock returns volatility in the market.

The market index was generated by computing the overall average from the sum of individual market indices using MS Excel. Win Rats software was employed in data analysis to determine the persistence of shocks. The analysis technique involved dropping days and months of the calendar one after another so as to test returns volatility using the same GARCH model (Engel, 2018). This employed the GARCH (1, 1) model (Engel, 2018) which introduced a lagged conditional variance to capture long memory to the ARCH (1) (Bollerslev, 1986).

$$h_{it} = \omega + \alpha_{i1} e_{it-1}{}^{2} + \beta_{it} h_{it-1} \ldots\ldots \quad (2)$$

Where:

α_{i1} = Measure of instability clustering, the extent to which volatility today feeds through into the next period's explosiveness.

β_{i1} = Coefficient that arrests the persistence of unpredictability over time. This required that the decaying constant $(\alpha_{i1} + \beta_{i1}) < 1$ satisfies the non-explosiveness of the conditional variances. Furthermore, each of ω, α_{i1} and β_{i1}>0 so as to satisfy the positivity of conditional variance for each given time.

4.0 Results and Discussion

5.0 Market stock returns

The descriptive statistics for monthly and annualized returns report the daily trend of returns for the market. Examinations of the displayed characteristics show that the lowest monthly returns spread were observed for TCC and the highest for the whole market. This indicates the existence of monthly information symmetry and asymmetry for TCC and the whole market, respectively (Figures 1 and 2). The highest annualized spread of returns was observed for TATEPA and the lowest for SIMBA. The spread of returns indicates the costs incurred by investors in market transactions due to information asymmetry. The results show that there is high monthly information asymmetry for the whole market compared to individual firms as returns are inversely related to bad news contrary to good news (Ponziani, 2022).

Furthermore, results in Figures 1 and 2 report on skewness and kurtosis for the yield pattern of equity investigated in the market. The distributions for SWISSPORT, TBL, and the overall market were negatively skewed, but the rest were positively skewed or non-symmetrical. They also exhibited extremely high and low kurtosis, which indicates that spreading led to heavier tails than ordinary scattering. The results display that both annualized and monthly returns were not normally distributed; rather, the returns with SWISSPORT, followed by those with SIMBA, were most skewed and leptokurtic for all equities and skewed, but platykurtic for the market in general. The present findings are similar to observations by Antonopoulou et al. (2022) that fluctuations and discrepancies in the return on stocks cause deviation from the predicted returns.

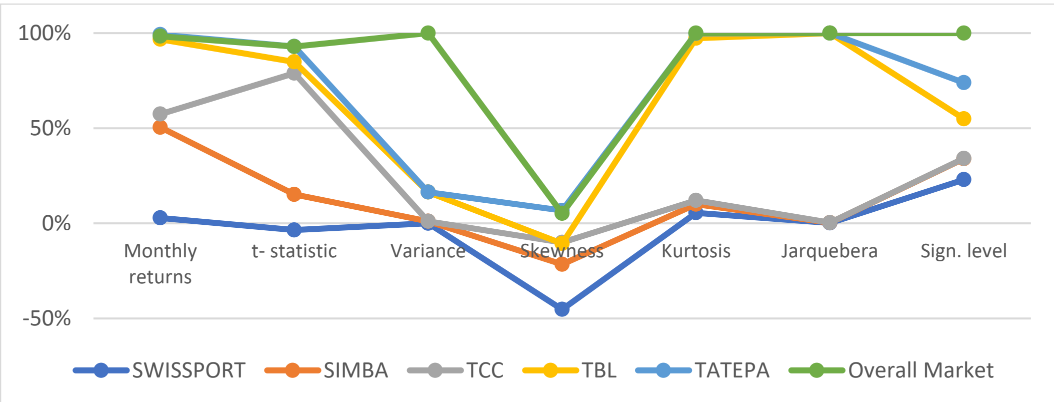

Figure 1: Monthly series of stock returns

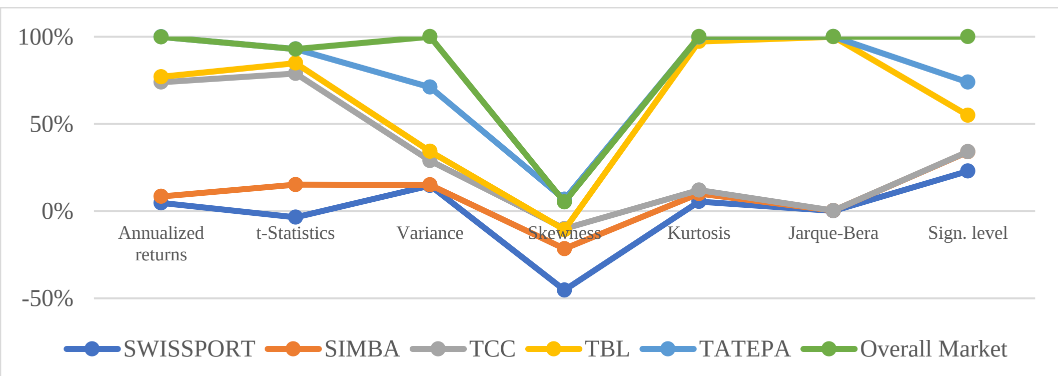

Figure 2: Annualized series of stock returns

5.1 Market returns volatility

The results of the variance equation (Table 1) show that the decay process in the exchange financial market was slow $(\alpha + \beta) < 1$ as it decayed at the rate of 0.75 per transaction period. Furthermore, the findings indicate that explosiveness shocks in the present period tended to feed into volatility in the succeeding periods of volatility, suggesting that liquidity was a high-risk that required a high-risk premium because of holding risky assets. Speculators were likely to dictate in order to reap the profit through short and long-term positions. Therefore, the volatility of asset prices in DSE might be associated with the calendar effects of transactions.

Table 1: GARCH-test for market index stock yields

Variance Equation.

Predictor variable: $\ln\left(\frac{\mathit{Market}\,\text{Index}}{\text{Market Index(-1)}} \right)$

Variables	Coefficient	Std. Error	Z-Statistic	Probability value
Constant	7.97E-06	3.40E-06	2.342764	0.0191
ARCH (1) (α)	0.150006	0.188300	0.796630	0.4257
GARCH (1) (β)	0.600002	0.473212	1.267935	0.2048

Predicted variable: Yields
Method: ML-ARCH

3.3 Market returns and volatility control

Controlling volatility in the DSE market involved four selected representative equities to control calendar effect on stock returns.

3.3.1 Daily returns and volatility control

The findings (Figure 3) show that overall daily returns were positive for those days in the market. However, average returns on Tuesdays were lowest and highest on Wednesdays as indicated by the standard deviation in comparison to other days of the week and a systematic fall in the daily rate of return on stocks between Friday closing and Tuesday opening. This could be attributed to individual and institutional investors' tendency to postpone the announcement of bad news on closing day so that the market absorbs the shock, and those stocks going ex-dividend on Tuesday thereby lowering their prices and thus affecting returns. Moreover, findings on skewness and kurtosis for the average return series for those days were adversely tilted, indicating that they were non-symmetric. They exhibited little altitudes of kurtosis, indicating that the distribution had a thicker left tail than a normal distribution. Findings on daily yields were not ordinarily distributed; they were platykurtic and slanted with a constant decay rate $(\alpha + \beta = 0.75)$ (Table 2).

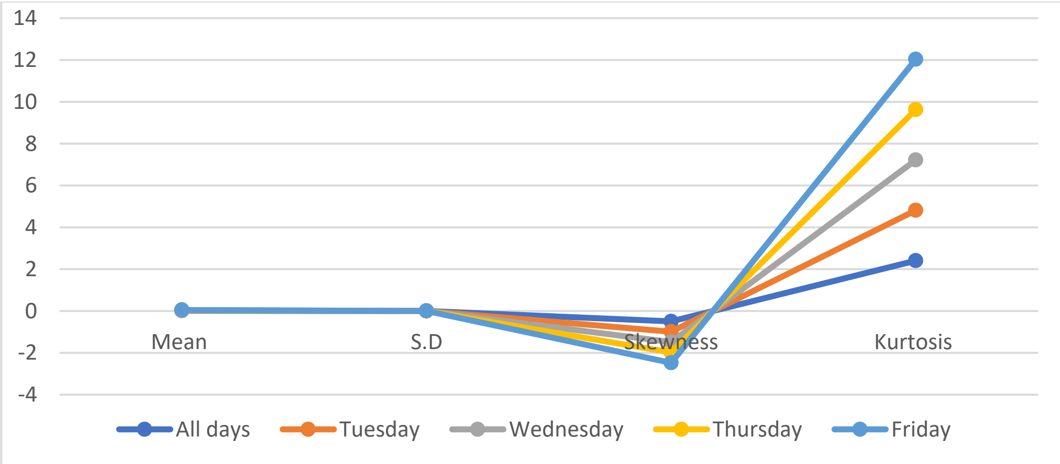

Figure 3: Day of the week effect on stock returns

Table 2: GARCH – testing for daily effect on yields volatility

Variance equation	Predictor variable: $\ln(P_t / P_t(-1))$			
Variable	**Coefficient**	**Std. Error**	**Z-Statistic**	**Prob. value**
Constant	5.86E-10	4.60E-06	0.000127	0.9999
ARCH (1) (α)	0.150000	0.540296	0.277625	0.7813
GARCH(1) (β)	0.600000	0.633176	0.947604	0.3433

Predicted variable: RETURNS
Method: ML-ARCH

3.3.2 Monthly effect on returns

Descriptive statistics for returns in each month of the year were performed by dropping one month after another for the November 2003 - December 2020 period, and then the results were tested for volatility. The findings (Figure 4) show that average controlled monthly returns were positive for those months while the lowest returns were observed in December. The possible explanation for this was that most market participants took precaution to save money for the end of the year by buying pressure on Christmas and New Year days with their families (McConnell and Xu, 2018). The highest returns occurred in January (Haugen and Jorion, 2019) compared to other months' returns. This was attributed to most firms and individual investors forming budgets for their future investments; good news made by the financial managers showing the better end of the year portfolio structure and release of important financial information was a symmetry to both informed and uninformed traders; and tax-loss-selling hypotheses where investors experiencing losses tend to sell-non-profitable stocks for tax reasons and re-investing in January as observed by (Haug and Hirschey, 2019) that persistent January effect has an association with tax-loss selling in the stock market.

Furthermore, even though volatility $(\alpha + \beta = 0.75)$ was constant in the market, the standard deviation (risk) of the mean return in January provided profits to investors due to high- risk premium they demanded as compensation (Haugen and Jorion, 2019; Hirschey, 2019; Sewraj et al., 2010), suggesting a proportionate relationship between average portfolio returns and systematic risk in January compared to other periods.

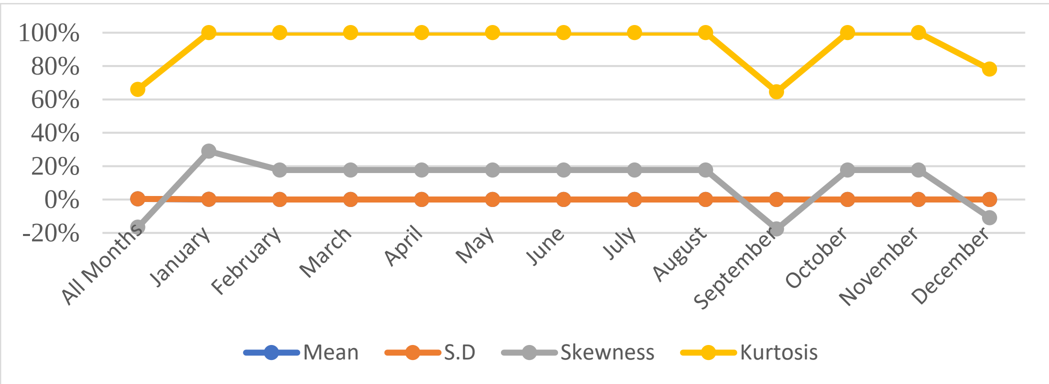

Figure 4: Month of the year effect on stock returns

3.3.3 Monthly returns volatility testing

The number of trading days per week started from Tuesdays through Fridays during this period interval. Only four equities were selected for returns and volatility control: TBL; TCC; SIMBA and SWISSPORT, and returns were tested using GARCH Models (Table 3). The rest of the trading period had constant returns $(\alpha + \beta = 0.75)$ possibly because most of the noise traders depended on agricultural outputs. During these months they used much cash to buy agricultural inputs, according to geographical seasons' variations in the year. People had variable surplus money, which they invested in the market, thus leading to constant demand for stocks associated with low risk (Figure 4) in the market. The GARCH- testing for volatility effect on the controlled month-of-the-year effect shows that shocks to volatility were more persistent and therefore had a slower decaying rate in those transaction months.

Table 3: GARCH –testing for monthly effect on returns volatility

Variance equation Predictor variable: $\ln\left(\frac{P_t}{P_t(-1)}\right)$

Variable	Coefficient	Std. Error	Z-Statistic	Prob. value
Constant	5.87E-10	5.83E-06	0.000101	0.9999
ARCH (1) (α)	0.150000	0.624910	0.240035	0.8103
GARCH (1) (β)	0.600000	1.541118	0.389328	0.6970
Predicted variable: RETURNS Method: ML- ARCH				

6.0 Conclusions and recommendations

The findings showed that the highest daily returns occurred on Wednesdays, and positive January effect was present in the market while the annual and monthly mean yields were both positive. Furthermore, the findings showed that the overall market was characterized by platykurtic and negative skewness. Moreover, the GARCH (1, 1) models revealed that the annualized day of the week and month of the year effect in volatility were constant over time. The study, therefore, concludes that the calendar effects' impact on the market stock return was caused by the variable volatility effect on returns. It is, therefore, recommended that rational investors should invest in the market for their future gains.

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