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The January Effect: A South African Perspective

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Abstract: The January effect, and its impact in the financial world, is one of the most researched calendar irregularities. The purpose of this study is to examine if there is a January influence on the South African stock market. Aggregate and sectorial indices of Johannesburg Stock Exchange (JSE) were examined. We analyse the January effect by Generalized Auto Regressive Conditional Heteroskedasticity Model (GARCH), exponential GARCH (EGARCH) and threshold GARCH (TGARCH) models. Findings from the mean equation showed a positive January effect for the Top 40 and Basic materials, whilst for the variance equation, a negative January anomaly was found in the Top 40, Health care, Telecommunications, and Technology indices. The January seasonal investment style is recommended for improving returns in Basic materials sector. Investing in the Telecommunications sector in January will assist an investor in portfolio diversification and reduce risk. The findings show that the January effect has shifted to other months. Given the limits of previous research, this study adds to the body of knowledge on calendar anomalies by bringing a South African viewpoint to the debate of the January anomaly and extending the analytic period to 1995–2018.

Keywords: January anomaly; GARCH; EGARCH; TGARCH; JSE

JEL Classification: C12; C23; D53; G12; G14

1. Introduction

January effect has attracted attention mostly in developed countries and many schools of thought have been propounded to unriddle the January anomaly. Kang

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(2010) examined the relationship between the January effect and probability of information-based trading (PIN) in the US using equity data. Results showed that January returns and PIN were negatively related. For the month of January, the PIN effect was observed to have a seasonal pattern, which was referred to as the January PIN effect. The January PIN effect was attributed to selling pressure from institutional investors that occurs in December. This PIN effect has a greater impact on small equities, which is consistent with the window dressing hypothesis, where institutional investors offload risky and non-performing shares from their portfolios at the end of the year. The results provide insight on the role of institutional investors in influencing the stock market returns.

Mashruwala and Mashruwala (2011) examined whether seasonality in US equity prices incorporated accruals quality (AQ). January solely revealed a positive association for AQ and abnormal equity returns. Therefore, AQ premiums entirely existed because of January. The January AQ was present in all firm sizes, both large and small, with superior performance for large AQ equities. Considering all the findings of the study, it can be established that the AQ premium can be attributed to mispricing around the turn of the year, and not systematic information risk.

Balint and Gica (2012) assessed the impact of January and non-January months on Romanian equity returns. The January anomaly was modelled in both mean and variance equations. A portfolio-wise January effect analysis was conducted which involved constructing 3 portfolios from the cargo handling, development of building projects, extractive, manufacturing, monetary intermediation, and wholesale and retail industries. The pre-crisis period revealed a positive January effect in the return equation, and for the volatility equation, positive January, November and December effects are revealed. During the post-crisis period, positive January, March and July effects are observed in the mean equation, whilst positive May, June and July anomalies are evident in the volatility equation. The January anomaly in the Romanian equity market is explained by investors disposing of small stocks at year end. The authors recommended that knowledge of the January effect provides investors with information on which sector to invest in and the investment timing so as to realise excess returns and reduce risk. The pre-crisis period offered investors abnormal returns in January, whilst for the post-crisis, non-January months provided superior returns. The post-crisis phase showed a January effect only for the lowest capitalised portfolio.

Truong (2012) assessed the effect of January returns on equity options using US stock and derivatives data. There was a negative relationship between January returns and optioned equities, which previous studies could not explain. The findings showed trading optioned equities significantly lowered January returns as compared to non-optioned equities. Positive January returns for non-optioned stocks reduced once the stock is option-listed for trading. The study recommended that investors trading in options are able to devise investment strategies which seem unattainable in the stock market. The authors indicated that establishment and operations of equity and derivatives markets correct market inefficiencies.

Yao (2012) studied how the January effect impacts on the momentum and contrarian strategies in the US equity market. The study results provided evidence suggesting that the January size effect was purely the cause of long-term contrarian strategies. Economically and statistically unprofitable results outside the January contrarian strategy were found compared to abnormal profits in the January contrarian strategy. Therefore, no long-term contrarian strategy existed in non-January months. Findings highlighted that intermediate-term momentum produced superior results from the January seasonality strategy. Abnormal profits realised during the sample study period had no clear cause.

Compton *et al.* (2013) analysed the effect of January and non-January months on returns for Russian equity and bond markets. February and March have a positive impact on equity returns, whilst September has a negative impact. The equity market showed no evidence of the January effect, but a positive February effect was found. For the bond market, January, February, March, April, May, August, November and December have a positive effect on bond returns. Positive January, February and December effects were present in the bond market. The authors highlighted that the Russian equity and bonds markets were inefficient.

Dbouk *et al*. (2013) examined the US bond market to establish the relationship between the dependent variable represented by returns, and independent variables depicted by January month, book to market, size, term and default premium. Additionally, the determinants of the January anomaly were modelled using December frequency coupon, coupon, tax loss, junk bond rating, bond issued by financial companies, bond with covenant attached, bond duration and geometric return of a bond in December. January, book to market, term and default premium have a positive impact on bond returns. The January effect was present in the US bond market. The returns in December and tax loss negatively influenced January excess returns. The authors recommended that tax loss and reversal December returns were the major drivers of the January effect for the US bond market.

Lynch *et al.* (2014) assessed whether institutional investors influenced the turn of the year (TOY) returns in the US. TOY effect determinants were examined in the light of risk shifting, window dressing and tax loss selling hypotheses. Abnormal selling of pension plans of small entities performing poorly in December`s last trading days were found. This justifies that window dressing contributes to the TOY effect. However, no risk shifting or tax loss selling strategies of trading was supported by study evidence. The TOY effect was smaller for institutional trading equities than those without. Equities without institutional trading showed returns of about double that of the sample chosen overall. Individual investors were suggested as the main influencer of the TOY returns. The study provides an important contribution on the reasons for the January effect.

This study investigated the January anomaly in the South African stock market using aggregate and sectorial indices. The rest of the article is outlined as follows: literature review is presented in section 2 and research methodology is provided in section 3. We display and discuss empirical findings in section 4 and final highlights conclusions and recommendations in section 5.

2. Literature Review

Norvaisiene *et al*. (2015) researched on monthly seasonality in the Estonia, Latvia and Lithuania equity markets. The results showed a positive impact of January, August and November on returns. October month depicted a negative effect on returns. Evidence in the studied markets resembles the January effect. Therefore, in the Baltic countries, the study provided evidence of the market inefficiencies. The study recommended that investors can benefit from anomalies and increase their profits through incorporating January seasonality in their investment strategies.

Vasileiou and Samitas (2015) investigated monthly seasonality in the Greek equity market. The study revealed that the January effect was associated with the pre-crisis period and disappeared in the post-crisis period, indicating that a change in the macroeconomic environment affects January seasonality. The Greek market was inefficient because of the existence of seasonality in monthly returns, both in growth and recession periods. The study recommended that investors can benefit from monthly seasonality in different economic phases when their investment decisions incorporate calendar anomalies.

Beladi *et al*. (2016) analysed the effect of the January anomaly on stock split announcements in the US equity market. The analysis was divided into surprised and small firm stock splits. For the logistic regression, the January, Halloween, price, return on assets, and asset turnover are positively significant, whilst size, book to market ratio, sales, returned earnings adjusted for equity, and total assets are negative. The January effect suggests that there is a high likelihood of a stock split in the month of January. The impact of a January effect on an equity split announcement is greater in smaller entities as compared to surprised equity splits. Negative factors were found for size, price, sales and retained earnings adjusted for common equity. The findings revealed that the January effect has a positive impact on abnormal returns of equity splits, especially for small stocks. The study highlighted how equity announcement are related to the January effect.

Podgorski (2018) examined the relationship between returns and January anomaly in European Union (EU) economies. The stock equity markets from the Czech

Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia were covered in the study. A positive January effect was evident in the EU stock markets that fades over time. The author acknowledged that there was need for further studies in January anomaly.

Past studies such as Kang (2010), He and He (2011), Truong (2012) and Compton *et al.* (2013) of the January anomaly focussed on OLS, which suffered from methodological challenges of failing to account for autocorrelation and heteroscedasticity. The January seasonality analysis was based on the overall or aggregate equity market indices and did not include sectoral indices. Vasileiou and Samitas (2015) modelled the January effect using the TGARCH, but discarded the fact that seasonality may be present in the volatility of returns. Another limitation of Vasileiou and Samitas's study is that it focused on aggregate equity indices and no sectoral analyses were conducted. Podgorski (2018) employed a dynamic panel model for the January effect; the focus was on aggregate equity indices from EU countries. Podgorski's study, although it gives information on equity markets with January anomalies, it does not provide the investor which sectors to invest in, hence the need to expand the study to sectors and use robust GARCH family models.

3. Data and Methodology

We analysed JSE financial data sourced from IRESS database, a financial data firm covering the period 1995 to 2018. Data comprises of the top 40 (J200), all shares (J203), basic materials (J510), industrials (J520), consumer goods (J530), health care (J540), consumer services (J550), telecommunications (J560), financials (J580) and technology (J590). Eviews 10 integrated with R software was used to analyse the data. The optimum order GARCH, EGARCH and TGARCH models were employed and interpreted though for specification purposes we use the order (1,1). The January effect is analysed by looking at the monthly dummy variables in the mean and variance equations. The GARCH model specification for the January effect is adopted from Alagidede (2013) and is given as follows:

$$R_t = \sum_{i=1}^{12} \alpha_i M_{it} + \epsilon_t \quad (1)$$

$$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1} + \sum_{i=2}^{12} d_i M_{it} \quad (2)$$

Where R_t is the monthly log returns and $\alpha_i$are mean equation coefficients. M_{it} is a dummy variable equal to one where returns occur in month i defined from January to December otherwise its zero. ϵ_t follows a specified density function with mean zero. $a$in the volatility equation denotes the January effect. d_i represents volatility coefficients corresponding to month i.

The EGARCH model specification for the January effect is adapted from Caporale and Zakirova (2017). This study extends the dummy variables in the EGARCH model to take into account the effects that other months have apart from January.

$$In(h_t) = a + cIn(h_{t-1}) + f_1\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} + f_2\frac{|\epsilon_{t-1}|}{\sqrt{h_{t-1}}} + \sum_{i=2}^{12} d_i M_{it} \tag{3}$$

Where $\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}$ denotes leverage and asymmetry effects. $\frac{|\epsilon_{t-1}|}{\sqrt{h_{t-1}}}$is information at time $t-1$ regarding previous volatility.

A specification of the TGARCH model for January effect also includes dummy variables for non-January months and is given by:

$$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1} + \gamma\epsilon_{t-1}^2 I_{t-1} + \sum_{i=2}^{12} d_i M_{it} \tag{4}$$

4. Empirical Findings and Discussions

The GARCH, EGARCH and TGARCH models results of the JSE indices for January effect are explained. Only the Financials sector was modelled by the GARCH specification, 6 JSE indices assumed EGARCH models and 3 indices utilised the TGARCH models. No sign bias, and estimated parameters significant and stable based on the Nyblom test suggest structural independence. For GARCH and TGARCH models, the AIC, SC and LL revealed that Student-t distribution provided a general better fit than the normal distribution assumption, which supports the leptokurtic behaviour of stock returns (Brooks, 2014). However, for the EGARCH model, the normal distribution was better for the Consumer goods and Health care sectors, whilst the Top 40, Basic materials, Telecommunications and Technology indices assumed Student-t distributed errors.

Examining the mean equation in Table 1, it is noted that there is no January effect for the Financials sector, suggesting that investors cannot improve their returns by trading in that month. However, positive and significant July, November and December effects are observed. The December effect is stronger with a coefficient of 0.036569; this indicates that an investor committing a unit of investment in the Financials sector earns 0.036569 units, holding other things constant. There is no evidence of a January effect in the volatility equation, and a disappearance of the July, November and December effects is noted when risk in the form of volatility is considered.

Table 1. GARCH Model Results for January

R_t	J580
Mean equation	
α_1	0.003537
α_2	0.002315
α_3	0.012979
α_4	0.016102
α_5	-0.014096
α_6	-0.002296
α_7	0.021384**
α_8	0.004099
α_9	-0.003865
α_{10}	0.01855
α_{11}	0.014283*
α_{12}	0.036569**
Variance equation	
a	0.002729
b_1	0.209137
b_2	0.22206
b_3	
c_1	0.426685
c_2	0.039897
c_3	0.029891
d_2	-0.004286
d_3	-0.002142
d_4	-0.002784
d_5	-0.002542
d_6	-0.002082
d_7	-0.002696
d_8	-0.002491
d_9	-0.001773
d_{10}	-0.001306
d_{11}	-0.003432
d_{12}	-0.002212
AIC	-3.100389
SC	-2.710948
LL	464.0545
SB	0.4507
NEGSB	0.4787
POSSB	0.6540
JE	0.7870

+ indicates significant Nyblom test at 5% level. * and ** indicate significance at 5% and 1% level respectively. n* denotes that normal distributed error is assumed in the model. J580=Financials.

Table 2 reports the EGARCH results for January effect of the JSE indices. The mean equation shows positive and significant January effects for the Top 40 and Basic materials indices, with coefficients of 0.030579 and 0.035219 respectively. An investor who invests a unit of capital in January in the Top 40 and Basic materials indices increases returns by 0.030579 and 0.035219 units respectively. A significant and negative January effect is illustrated in the Telecommunications sector, highlighting that the returns will decrease by 0.025302 units when a unit of capital is invested, holding other things constant. A negative and significant January effect is observed in the variance equation for the Top 40, Health care, Telecommunications and Technology indices. The greatest reduction in volatility is exhibited in the Telecommunications sector, with a negative coefficient of 2.78712; this means that, all other things being constant, a unit of capital invested in the month of January reduces volatility of returns by 2.78712. Apart from the January effect, the findings unveil other months effect in the mean and variance equations.

In the mean equation for Table 2, there is a negatively significant February effect in the Industrials sector that implies a depletion of returns by 0.013241 following a unit of capital invested. Analysis of February seasonality in the volatility equation confirm a negative and significant effect for the Consumer goods and Telecommunications sectors. The maximum reduction in volatility is found in the Consumer goods sector, with a negative significant coefficient of 1.517717, which explains a fall in risk on investing a unit amount in February. There is a positively significant March effect in the mean equation for the Telecommunications sector, which suggests that investment of a unit amount increases returns by 0.021034, all other things being constant. By contrast, the March effect in the volatility equation is negatively significant and only appears in the Consumer goods sector, expounding the fact that volatility is reduced by 1.417877 units if an investor trades one unit of capital, holding other variables constant. April effects for the mean equation are pronounced in the Consumer goods and Health care sectors, with positive and significant impact on returns. The highest coefficient for the April effect is 0.039665, which defines an increase in returns to an investor who invests a unit of capital in Consumer goods, holding other variables constant. Incorporating volatility, it is observed that the April effect for the Health care sector disappears, whilst for Consumer goods, the effect is negatively significant, showing that trading in April reduces risk of returns by 0.880025 for every unit of capital invested. There are no May and June effects in the variance equation, but only in the mean equation. For May, the seasonality effects are apparent in the Telecommunications sector, with a significantly negative impact of 0.030823, and Technology has a positive significant effect of 0.034946. An investor’s decision to trade a unit of capital in the

Telecommunications and Technology sectors in the month of May decreases and increases returns by 0.030823 and 0.034946 respectively, all other things being constant. A negative and significant June effect is noted, which implies that trading in June decreases returns by 0.01171 for every unit of investment committed by the investor. The Consumer goods sector has negative and significant July, August, October, November and December effects in the variance equation, signifying that an investor can reduce volatility of returns by trading in the respective months a unit of capital, holding other things constant. However, volatility of returns increases on trading a unit of amount in August for the Telecommunications sector and September for the Top 40 index, because the associated coefficients are positively significant. In the mean equation, a positive and significant July effect is found in the Consumer goods, Telecommunications and Technology sectors. A significantly positive August effect is apparent in the Consumer goods and Health care sectors. October effects are positive and significant in the Top 40, Consumer goods, Health care and Technology indices. A positive and significant November effect in the Consumer goods index is observed, whilst December effects are found in all JSE indices except Technology. A highly positive significance in July, August, October, November and December suggests that returns increase by the associated coefficients' values on subsequent investment of a unit of capital, holding other things constant.

Table 2 also reports leverage effects in the Top 40, Consumer goods and Technology indices, suggesting that bad news increases volatility of returns more than good news of equal magnitude (Brooks, 2014). For the previous month there is a positive impact on current volatility for the Top 40, Consumer goods, Telecommunications and Technology indices. The news from the previous 2 months has a significant negative impact on current volatility for Consumer goods and a positive impact for the Top 40, Basic materials, Telecommunications and Technology indices. The negative news from the past 3 months has a negative and significant influence on current volatility for the Basic materials sector. The sum of the GARCH effect terms suggests that information from past months on volatility generally influences current volatility for the JSE indices represented. The combined ARCH and GARCH terms in the EGARCH models indicate that volatility is persistent (Brooks, 2014).

Table 2. EGARCH Models Results for January

R_t	J200	J510	J530 n*	J540 n*	J560	J590
Mean equation						
α_1	0.030579**	0.035219**	0.007393	-0.00086	-0.025302**	0.015643
α_2	0.010411	-0.013855	-0.013241*	-0.00082	-0.010479	0.02011
α_3	0.006957	-0.011249	0.010618	0.022604	0.021034*	0.011625
α_4	0.006276	0.024697	0.039665**	0.02238**	0.011864	0.010534
α_5	-0.0035	-0.00099	0.000943	0.01006	-0.030823**	0.034946**
α_6	-0.01171*	-0.003141	-0.003997	0.006824	-0.006863	-0.00686
α_7	0.004545	-0.008792	0.028974**	0.013157	0.022448*	0.050415*
α_8	0.011867	0.007822	0.009615*	0.021864**	0.003775	0.01547
α_9	-5.42E-06	-0.002218	0.001334	0.01134	-0.006584	-0.00183
α_{10}	0.021157**	0.027318	0.020626**	0.033277**	0.019051	0.031032*
α_{11}	-0.00328	-0.009864	0.022395**	0.013653	-0.01193	0.004964
α_{12}	0.016339**	0.023779**	0.035765**	0.032264**	0.049711**	0.015083
Variance equation						
a	-1.676127*	-0.791683	-0.605903	-1.457334**	-2.78712**	-1.070499**
f_1	-0.196454**	-0.107432	-0.198422**	0.016513	0.086093	-0.067005*
f_2	0.485961**	-0.142117	0.810066**	0.259042	0.747096**	0.42017**
f_3	0.667455**	1.058709**	-0.34242*	0.397599	0.686068**	0.560785**
f_4	-0.103154	-0.674319**		0.331911	-0.009964	-0.019516
c_1	0.190111**	0.936727**	0.092846	0.166749	0.062988	-0.45931**
c_2	-0.136354*		0.706253**	0.90259**	-0.10772*	0.438871**
c_3	0.816377**			-0.273316	0.743024**	0.914242**
d_2	0.149664	1.435485	-1.517717**	-0.597665	-0.71519**	0.363563
d_3	-0.020219	-0.104894	-1.417877**	-0.801063	-0.2296	-0.09024
d_4	-0.559643	0.646492	-0.880025*	-0.773766	-0.14825	-0.52147
d_5	0.545186	-0.291699	-0.759502	-0.37477	0.13223	-0.37391
d_6	-0.685724	0.22963	-0.679657	-0.16614	-0.2425	-0.84405
d_7	0.714215	0.477155	-1.57396**	-0.774729	-0.29352	-0.07026

d_8	-0.201878	-0.211435	-1.034925**	-0.483212	0.479833**	-0.16253
d_9	0.67518*	0.727298	-0.232394	-0.313367	-0.20038	-0.49552
d_{10}	0.071398	0.146705	-0.967545**	-0.21998	0.335232	-0.65206
d_{11}	-0.747862**	0.106008	-1.813097**	-0.932117**	-0.00319	0.055808
d_{12}	-0.049284	-0.135918	-1.001708**	-0.886948	0.514097	-0.63441
AIC	-3.098423	-2.377284	-2.803298	-2.871697	-2.260662	-2.02101
SC	-2.683019	-1.987842	-2.426838	-2.469274	-1.845258	-1.6056
LL	465.7793	362.8198	421.4617	433.0376	348.4927	314.9407
SB	1.0017	0.2259	0.7964	1.1504	0.06257	0.01733
NEGSB	0.8332	0.7271	0.8018	1.2322	0.78103	0.07624
POSSB	0.9268	1.1779	0.2118	0.2013	0.50844	0.64744
JE	4.4931	1.9225	0.8880	2.0101	0.92397	0.64175

+ indicates significant Nyblom test at 5% level. * and ** indicate significance at 5% and 1% level respectively. n* denotes that normal distributed error is assumed in the model. J200=Top 40, J510= Basic materials, J530=Consumer goods, J540=Health care, J560=Telecommunication and J590=Technology.

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Consumer goods sector, with a negative significant coefficient of 1.517717, which explains a fall in risk on investing a unit amount in February. There is a positively significant March effect in the mean equation for the Telecommunications sector, which suggests that investment of a unit amount increases returns by 0.021034, all other things being constant. By contrast, the March effect in the volatility equation is negatively significant and only appears in the Consumer goods sector, expounding the fact that volatility is reduced by 1.417877 units if an investor trades one unit of capital, holding other variables constant. April effects for the mean equation are pronounced in the Consumer goods and Health care sectors, with positive and significant impact on returns. The highest coefficient for the April effect is 0.039665, which defines an increase in returns to an investor who invests a unit of capital in Consumer goods, holding other variables constant. Incorporating volatility, it is observed that the April effect for the Health care sector disappears, whilst for Consumer goods, the effect is negatively significant, showing that trading in April reduces risk of returns by 0.880025 for every unit of capital invested. There are no May and June effects in the variance equation, but only in the mean equation. For May, the seasonality effects are apparent in the Telecommunications sector, with a significantly negative impact of 0.030823, and Technology has a positive significant effect of 0.034946. An investor's decision to trade a unit of capital in the Telecommunications and Technology sectors in the month of May decreases and increases returns by 0.030823 and 0.034946 respectively, all other things being constant. A negative and significant June effect is noted, which implies that trading in June decreases returns by 0.01171 for every unit of investment committed by the investor. The Consumer goods sector has negative and significant July, August, October, November and December effects in the variance equation, signifying that an investor can reduce volatility of returns by trading in the respective months a unit of capital, holding other things constant. However, volatility of returns increases on trading a unit of amount in August for the Telecommunications sector and September for the Top 40 index, because the associated coefficients are positively significant. In the mean equation, a positive and significant July effect is found in the Consumer goods, Telecommunications and Technology sectors. A significantly positive August effect is apparent in the Consumer goods and Health care sectors. October effects are positive and significant in the Top 40, Consumer goods, Health care and Technology indices. A positive and significant November effect in the Consumer goods index is observed, whilst December effects are found in all JSE indices except Technology. A highly positive significance in July, August, October, November and December suggests that returns increase by the associated coefficients' values on subsequent investment of a unit of capital, holding other things constant.

Table 2 also reports leverage effects in the Top 40, Consumer goods and Technology indices, suggesting that bad news increases volatility of returns more than good news of equal magnitude (Brooks, 2014). For the previous month there is a positive impact on current volatility for the Top 40, Consumer goods, Telecommunications and Technology indices. The news from the previous 2 months has a significant negative impact on current volatility for Consumer goods and a positive impact for the Top 40, Basic materials, Telecommunications and Technology indices. The negative news from the past 3 months has a negative and significant influence on current volatility for the Basic materials sector. The sum of the GARCH effect terms suggests that information from past months on volatility generally influences current volatility for the JSE indices represented. The combined ARCH and GARCH terms in the EGARCH models indicate that volatility is persistent (Brooks, 2014).

Table 3. TGARCH Models Results for January

R_t	J203	J520	J550
Mean equation			
α_1	0.014383	-0.00707	0.008615
α_2	0.009709	0.005669	0.003437
α_3	0.008349	0.00414	0.011982
α_4	0.019873	0.020615**	0.023669**
α_5	-0.005315	-0.00621	0.003691
α_6	0.008117	-0.00394	0.002998
α_7	0.007731	0.018939**	0.025256*
α_8	0.014213*	0.014498	0.015838**
α_9	0.006014	-0.00087	-0.00159
α_{10}	0.023228**	0.026463*	0.04065**
α_{11}	0.00896	0.005324	0.024128
α_{12}	0.0278**	0.035403**	0.032975**
Variance equation			
a	0.002271**	0.002678**	0.003347*
b_1	0.1054	0.069765	-0.04814
γ	0.560706*	-0.02792	0.454614*
b_2	0.230698	0.249853*	
b_3	-0.15082		
c_1	0.415953	0.517801	0.557906
c_2	0.047613	0.099689	0.01863
c_3	0.073304		0.018093
d_2	-0.00281*	-0.00411**	-0.00546**
d_3	-0.00191	-0.00253	-0.00175
d_4	-0.00249*	-0.0033	-0.0038*
d_5	-0.00238**	-0.00218	-0.0008
d_6	-0.00125	-0.00235**	-0.00295
d_7	-0.00256*	-0.00322**	-0.00222
d_8	-0.00225**	-0.002	-0.00427*
d_9	-0.00172	-0.00136	-0.0009
d_{10}	-0.00254**	-0.00255*	-0.00212

d_{11}	-0.00202*	-0.00249	-0.00179
d_{12}	-0.00226*	-0.00249	-0.00407
AIC	-3.18842	-3.03775	-2.73538
SC	-2.77301	-2.64831	-2.34594
LL	478.3786	455.2853	412.9529
SB	0.8685	0.4179	1.2745
NEGSB	1.2100	0.1835	0.8964
POSSB	0.2758	0.3196	0.1532
JE	1.9803	0.7304	3.4927

+ indicates significant Nyblom test at 5% level. * and ** indicate significance at 5% and 1% level respectively. n* denotes that normal distributed error is assumed in the model. J203=All shares, J520=Industrials and J550=Consumer services.

The TGARCH models results for January are illustrated in Table 3 for the All Shares, Industrials and Consumer services indices. There are no January, February, March, May, June, September and November effects in the mean equation. However, significant and positive April, July, October and December effects for the Industrials and Consumer services sectors are noted. A positive and significant August effect is evidenced in the All Shares and Consumer services indices. In addition, the All Shares index shows positive significance in October and December. Despite having no January effect, an investor can transact a unit amount in the positive and significant months and earn units of returns corresponding to the coefficient values, holding other things constant. A positive and significant January effect was found in the variance equation for the All Shares, Industrials and Consumer services indices, suggesting that volatility increases by the associated coefficient value for each unit of investment traded in that month, assuming other variables remain constant. Moreover, a negative and significant February anomaly is found in the All Shares, Industrials and Consumer services indices. An April effect in the All Shares and Consumer services indices, and May, November and December effects are found in the All Shares index, whilst there is a June effect in the Industrials sector. A July effect is observed in the All Shares and Industrials indices, an August effect in the All Shares and Consumer services indices, and an October effect in the All Shares and Industrials. This suggests that an investor transacting a unit of capital in the non-January negatively significant months reduces the volatility of returns by the respective coefficient unit values, holding other things constant. The leverage coefficient is positively significant for the All Shares and Consumer services indices, highlighting that negative news increases risk in the JSE indices more than positive news of equal weight (Brooks, 2014). Only past information for the past 2 months increases volatility of returns for the Industrials sector. The GARCH coefficients are insignificant for the JSE indices, presenting the notion that information on volatility from the past does not influence current volatility.

The Islamic equity market appears to mimic the findings on the JSE, as unveiled by the positive and significant January, March, April and July coefficients in the mean equation, and negative January, February, March, April, May, June, July, October and November coefficients in the variance equation (Jebran & Chen, 2017). The negative February and June in the Consumer goods and Top 40 indices respectively suggest that recession may have influenced the effects (Vasileiou & Samitas, 2015). The January effect was exposed in the Greek stock market, which is in sync with the JSE (Vasileiou & Samitas, 2015). Examining the variance equation, Halari *et al.* (2018) showed positive and significant January effects for Turkey and Indonesia's stock markets, which agreed with the findings for the All Shares, Industrials and Consumer services indices on the JSE. Prior studies on the JSE provide contradictory results, with Coutts and Sheikh (2002), Darrat *et al.* (2013), and Auret and Cline (2011) finding no evidence of a January effect. In addition, Alagidede (2013) found evidence of a positive February effect whereas current evidence showed negative effects; the difference is methodology, Alagidede's results are based on the OLS while the present study employed the GARCH family of models. There is a note of similarity for January effects findings with Mahlophe's (2015) results, who found seasonality in January returns.

The January effect can be explained by the liquidity effect of the December bonus and window dressing of the portfolio (Ritter, 1988; Athanassakos, 1992). The awarding of bonuses in December increases liquidity, which drive prices of securities up, resulting in excess returns to investors in January (Ritter, 1988). Moreover, the demand by institutional investors for securities in order to balance their investment mix may entail making using of the available cash balances at the end of the year to purchase securities in January, exerting pressure on the stock prices and consequently high returns in January (Athanassakos, 1992). The existence of January, April, October, July and December effects on the JSE debunk the EMH. Investors can use monthly seasonal strategies to invest their capital and earn abnormal returns on the JSE.

5. Conclusion and Recommendations

The GARCH, EGARCH, TGARCH models were employed in modelling of the January anomaly. The GARCH with Student-t error assumption fitted better for the Financials sector. The EGARCH with normal error innovations was optimum for the Consumer goods and Health care sectors. The Top 40, Basic materials, Telecommunications, and Technology indices employed EGARCH with Student-*t* distributed error for the January effect. The All Shares, Industrials and Consumer services indices utilised TGARCH with Student-*t* errors. Analysis of the mean equation shows a positive January effect for the Top 40, and a positive December effect for the All Shares. The sectoral indices confirmed a positive January effect for

Basic materials, positive April for Consumer goods, positive July effect for Technology, positive October effect for Health care and Consumer services, and positive December effect for Financials, Telecommunications, and Industrials. The Basic Materials sector provided the highest January effect. The Consumer goods sector offered the largest April effect whilst the Technology sector had the highest July effect. The largest October effect is revealed in the Consumer services sector, whilst for the December effect, the highest impact is in the Telecommunications sector.

For the variance equation, the aggregate indices results show a negative January effect for the Top 40 and a negative February effect for the All Shares. An examination of the sectors indicated a negative January effect for Health care, Telecommunications, and Technology, a negative February effect for Industrials and Consumer services, and a negative November effect for Consumer goods. The Telecommunications sector had the lowest January impact on variance. The lowest February effect is depicted in the Consumer services sector, whilst for the November effect, the minimum impact is observed in Consumer goods.

The January seasonal investment style is recommended for improving returns when an investor puts money in the Basic materials sector. Diversification in the Telecommunications sector by investing in January will reduce risk for an investor. Investors can make use of other monthly investment strategies to attain positive returns on their capital. It is recommended to invest in the Consumer goods sector for the month of April, in the Technology sector for July, in the Consumer services sector for October, and in the Telecommunications sector for December. Traders can reduce risk by investing in Consumer services and Consumer goods for the months of February and November respectively.

References

Alagidede, P. (2013). Month of the year and pre-holiday effects in African stock markets. *South African Journal of Economics and Management Sciences*, 16(1), pp. 64-74.

Athanassakos, G. (1992). Portfolio rebalancing and the January effect in Canada. *Financial Analysis Journal*, 48(6), pp. 67-78.

Auret, C. & Cline, R. (2011). Do the value, size and January effects exist on the JSE? *Investment Analysts Journal*, 40(74), pp. 29-37.

Balint, C. & Gica, O. (2012). Is the January effect present on the Romanian capital market? *Procedia-Social and Behavioural Sciences*, 58(2012), pp. 523-532.

Beladi, H.; Chao, C.C. & Hu, M. (2016). Another January effect: Evidence from stock split announcements. *International Review of Financial Analysis*, 44(C), pp. 123-138.

Brooks, C. (2014). *Introductory econometrics for finance*. 3rd ed. Cambridge: Cambridge University Press.

Caporale, G. M. & Zakirova, V. (2017). Calendar anomalies in the Russian stock market. *Russian Journal of Economics*, 3(2017), pp. 101–108.

Compton, W.; Kunkel, R. A. & Kuhlemeyer, G. (2013). Calendar anomalies in the Russian stocks and bonds. *Managerial Finance,* 39(2), pp. 1138-1154.

Coutts, J. A. & Sheikh, M. A. (2002). The anomalies that aren't there: the weekend, January and pre-holiday effects on the all gold index on the Johannesburg stock exchange 1987-1997. *Applied Financial Economics,* 12(12), pp. 863-871.

Darrat, A. F.; Li, B. & Chung, R. (2013). Seasonal anomalies: A closer look at the Johannesburg stock exchange. *Contemporary Management Research*, 9(2), pp. 155-168.

Dbouk, W.; Jamali, I. & Kryzanowski, L. (2013). The January effect for individual corporate bonds. *International Review of Financial Analysis,* 30(C), pp. 69-77.

Halaria, A.; Helliar, C.; Power, D. M. & Tantisantiwong, N. (2018). Taking advantage of Ramadan and January in Muslim countries. *The Quarterly Review of Economics and Finance* xxx (2018):xxx–xxx.

Jebran, K. & Chen, S. (2017). Examining anomalies in Islamic equity market of Pakistan. *Journal of Sustainable Finance & Investment*, 7(3), pp. 275-289.

Kang, M. (2010). Probability of information-based trading and the January effect. *Journal of Banking and Finance,* 34(12), pp. 2985-2994.

Lynch, A.; Puckett, A. & Yan, X.S. (2014). Institutional and turn of the year effect: Evidence from actual institutional trades. *Journal of Banking and Finance,* 49(2014), PP. 56-68.

Mahlophe, M. I. (2015). *Effect of market anomalies on expected returns on the JSE: A cross-sector analysis.* Vaal Triangle: North-West University (Thesis-Masters).

Mashruwala, C. A. & Mashruwala, S. D. (2011). The pricing of accruals quality: January versus the rest of the year. *The Accounting Review,* 86(4), pp. 1349-1381.

Norvaisiene, R.; Stankeviciene, J. & Lakstutiene, A. (2015). Seasonality in the Baltic stock markets. *Procedia-Social and Behavioural Sciences,* 213(2015), pp. 468-473.

Podgorski, B. (2018). Impact of the January effect on return rates in the markets of the 2004 EU enlargement. *Journal of Management and Business Administration: Central Europe,* 26(1), pp. 27-48.

Ritter, J.R. (1988). The buying and selling behavior of individual investors at the turn of the year. *Journal of Finance,* 43(3), pp. 28-30.

Truong, C. (2012). The January effect, does options trading matter? *Australian Journal of Management,* 38(1), pp. 31-48.

Vasileiou, E. & Samitas, A. (2015). Does the financial crisis influence the month and the trading month effects? Evidence from the Athens stock exchange. *Studies in Economics and Finance,* 32(2), pp. 181-203.

Yao, Y. (2012). Momentum, contrarian, and the January seasonality. *Journal of Banking and Finance,* 36(10), pp. 2757-2769.