Monthly Stock Market Seasonality: The Nigerian Evidence

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Abstract
The purpose of this study is to examine monthly stock seasonality in the All Share Index (ASI) returns of the Nigerian Stock Exchange. The study uses monthly returns for the period January 1996 to December 2013. The study specifies a dummy variables regression model with an AR (1) included, and fits a Garch (1, 1) model. Using maximum likelihood estimation method, results obtained provide evidence of monthly stock market seasonality. The study finds evidence of a January effect which is consistent with previous studies that found January effect. However, the finding is not consistent with the tax-loss selling hypothesis explanation in the manner of the December – January seasonality. It could be explained by a tax-loss selling hypothesis of a November – January seasonality.
Keywords: Monthly stock market seasonality, All Share Index, maximum likelihood, January effect, tax-loss selling hypothesis.

1. Introduction

Seasonality is a phenomenon that is characterized by regular and repetitive fluctuation in time series over a span of less than a year. For example the dry season has a seasonality effect on the sales of ice-cream. During the dry season the sales of ice-cream increases. Stock returns, too, demonstrate systematic patterns at certain times of the day, week, or month. The most researched of these is the monthly patterns which suggest that certain months provide better returns as compared to others, i.e. the month of the year effect (Rozeff & Kinney, 1976; Praetz, 1973; Gultekin & Gultekin, 1983; Mehdian & Perry, 2002; Pandey, 2002). Mills & Coutts (1995) noted that one of the most prevalent stock market anomalies that has been researched appear to be the January effect, in which returns are much higher during January than any other month of the year.

The evidence of stock market seasonality violates the efficient market hypothesis (EMH) and capital asset pricing model (CAPM) (Mills & Coutts, 1995). The EMH states that capital markets quickly and accurately react to new information and therefore fully and correctly reflects all relevant information in determining security prices (Fama, 1970; Malkiel, 1992). A violation of the EMH means that traders can earn abnormal returns by applying trading rules to exploit the predictable behaviour of security prices. However, other authors have suggested that the existence of calendar anomalies in equity markets does not necessarily imply market inefficiency. Arsad & Coutts (1997) argued that the implication of the EMH is that when several investors recognize the seasonal patterns, the seasonality disappears and any profitable opportunities would be traded out of existence. There is proof that some anomalies such as the month of the year effect have indeed disappeared in recent years (Maberly & Waggoner, 2000).

Many studies on market anomalies have been criticized on the ground that their findings are merely the result of data mining. Specifically, it is said that many of the calendar anomalies are merely the result of many researchers testing many hypotheses on the same data (Sullivan, Timmermann, & White, 2001). Many reasons have also been advanced for supposing that calendar anomalies are not merely the result of data mining. First, anomalies of stock returns have been found in many stock markets of the world (Hawawini & Keim, 1995). Second, recent stock market return anomalies had occurred throughout much longer periods. Lakonishok & Smidt (1988) found this pattern in the US data.

Most of the empirical studies were conducted in the United States, Australia, and a good number of European countries, with little attention paid to developing countries (e.g. African stock markets). The empirical literature on Nigerian stock market seasonality is very scarce. The objective of this study is to investigate whether the stylized facts as regards month of the year effect that have been observed in stock market returns of developed countries, apply to Nigeria. Specifically the study investigates the existence of the month of the year effect in the monthly returns of the All share index (ASI) returns of the Nigeria stock exchange. Since the tax year in Nigeria runs from January to December, the study attempts to establish whether the popular 'January effect' holds in the case of Nigeria, and explore the possible causes if so.

The rest of the paper is organized as follows: Section 2 reviews the literature on the month of the year effect. Section 3 discusses the data sources and methodology. Section 4 presents the statistical analysis / results and discusses the results. Finally section 5 summarizes and concludes the study.

2. Literature Review

2.1 Theoretical and empirical literature on the month of the year effect

Most of the literatures in this area of study adopt a research – then – theory strategy. They begin by investigating a phenomenon and then giving theoretical explanations for their occurrence. The month of the year effect postulates that stock returns on a particular month are higher than other months of the year.

Many empirical studies in the developed countries have confirmed the month of January as the month where average returns are significantly higher than other months of the year. Thereafter, several theories are advanced for the occurrence of this phenomenon.

2.1.1 Empirical literature

Rozeff & Kinney (1976) in their study of the New York Stock Exchange found that seasonal patterns were present in the New York Stock Exchange Price Index. They found that average returns in January were seven times that of the average returns of the other eleven months. Gultekin & Gultekin (1983), using both parametric and non-parametric methods, found statistical evidence of January effect in thirteen out of the seventeen stock markets of the industrialized countries studied. Keim (1983) in his study of monthly effect for the US stock market, found evidence of January effect, and noted that returns of small firms were significantly larger in January than returns of big firms.

However, other empirical studies show that the January effect was not only found in developed stock markets, but also in emerging stock markets. Bildik (2004) found strong evidence of the January effect in the Istanbul Stock Exchange for the period January 2, 1988 to January 15, 1999. Fountas & Segredakis (2002) in their study of the month of the year effect in eighteen emerging stock markets, found that January returns in Chile, Greece, Korea, Taiwan and Turkey respectively, were significantly higher than returns of the remaining eleven months. However other studies revealed the absence of January effect (Maghayereh, 2003; Flores, 2008).

Other studies documented other months of the year effect besides the January effect. Gultekin & Gultekin (1983) found an April effect in the UK Stock Exchange between the period 1959 and 1979. Kumari & Mahendra (2006) and Alagidede & Panagiotidis (2009) found an April effect in their respective studies.

2.1.2 Theoretical explanations

Many theories have been advanced to explain the aforementioned phenomena. These are the tax-loss selling hypothesis, size of the firm hypothesis, window dressing hypothesis, information release hypothesis, and the herding theory or investors' overreaction hypothesis.

2.1.2.1 The tax-loss selling hypothesis

The tax-loss selling hypothesis was the first and most popular explanation for the January effect. Wachtel (1942), Branch (1977) and Dyl (1977) were among the first to explain the January anomaly based on the tax-loss selling hypothesis. According to this hypothesis, investors wait till the end of the tax year (December) to sell off their non-performing stocks (price-declined stocks) in order to realize capital losses that would be set off against income and consequently reduce tax liability (Thaler, 1987). This selling pressure causes stock returns to decline in December. However, at the beginning of the next-tax year (which usually begins in January in most countries), investors rush to reestablish their portfolios. This creates a buying pressure in January, which results to a January effect (i.e. large returns in January compared to the other months of the year).

2.1.2.2 Size of the firm hypothesis

Roll (1983) combined the tax-loss selling hypothesis with the size effect in explaining the January effect. Roll (1983) posits that small-sized firms are more affected by the tax-loss selling hypothesis than large-size firms. According to Rogalski & Tinic (1986), small-size firms have a higher risk-return trade off in the beginning of the year than in the rest of the year. Consequently investors are attracted more to the stocks of small-size firms than that of large-size firms during the beginning of the year (January). This explains why stock returns are significantly higher in January than in any other month of the year.

2.1.2.3 Window dressing hypothesis

At the turn of the year investors may rebalance their portfolios. This involves reviewing and revising the portfolio composition when relative values of its components change. The high returns in January are caused by systematic shifts in the portfolio holdings at the turn of the year (Haugen & Lakonishok, 1988).

2.1.2.4 The information release hypothesis

The information release hypothesis assumes that for those firms with December year-end financial closing, January represents the beginning of the year when many important financial and non-financial information are released. Informed traders are more likely to trade in January (Williams, 1986; Seyhun, 1988). This creates buying pressure at the turn of the year that leads to the January effect.

2.1.2.5 The herding theory (investors' overreaction hypothesis)

The herding theory is a behavioural explanation for the January effect. It has its roots in Keynes who focused on the motivation to imitate and follow the crowd in a world of uncertainty (Keynes, 1930). Avery & Zemsky (1998) defined herding as a switch in traders' opinion into the direction of the crowd. The literature documents two types of herding: the rational herding, and the irrational herding.

In rational herding, traders are trying to rectify their performances and reputations by abandoning their own analysis of the market and following that of another investor who has more reliable information (Bikchandani & Sharma, 2001). This may have been the cause of the buying pressure noticed in January that led to significantly higher returns in January than in any other month of the year.

In irrational herding, the herding behaviour is likened to a scenario of collective actions taken by individuals in uncertain conditions. The investors adopt such behaviour in order to reduce the uncertainty and to feel confident (Devenow & Welch, 1996). The result is investors' overreaction. Chopra, Lakonishok, & Ritter (1992) argued that the January effect is caused by the investors' overreaction. In the irrational herding, asset returns go beyond the fundamental values with subsequent yields reversal (Puckett & Yan, 2007).

3. Data and Methodology

3.1 Data

The study employs monthly closing observations of the Nigeria All Share Indices over the period 1996 through 2013, giving a total of 216 observations. The Nigeria All Share Index is a value-weighted index composed of all of the industrial equities (The Nigerian Stock Exchange). Market indices are preferred to individual stock prices because market indices are more ideal for detecting seasonal effect (Boudreaux, 1995). The period 1996 to 2013 is chosen because major economic and capital market reforms took place in 1996 and several years between 1996 and 2013 (Egwuatu & Nnorom, 2013; Babalola & Adegbite, 2002).

In line with convention in most anomalies literature (see Mills & Coutts, 1995), we convert the All Share Index to returns as follows: $r_t = l_n(p_t / p_{t-1}) \times 100$ ……..(1), where r_t is the returns in the period t; p_t is the monthly closing All Share Price Index for the period t; and p_{t-1} is the monthly closing All Share Price Index for the previous period.

3.2 Methodology

3.2.1 Preliminary Analysis

We carry out analysis of the variability, normality and stationarity of the return series. If security returns are not stationary and normally distributed this may invalidate the statistical inferences. The study gauges the variability of the return series by plotting a graph of the return series for the period 1996 to 2013. We test for normality of the return series by means of important descriptive statistics such as the skewness, kurtosis and the Jarque-Bera statistic. We determine the stationarity of the return series by means of a correlogram of the returns, and observing the graphical representation of the sample autocorrelation function (ACF) and the sample partial autocorrelation (PACF). We also employ a formal test of stationarity known as the Augmented Dickey-Fuller (ADF) unit root test.

The ADF tests the null hypothesis that the return, r has a unit root, i.e. it is not stationary. This involves running the following regression.

$\Delta r_t = \alpha + \lambda_t + \rho r_{t-1} + \sum_{i=1}^{n} \beta_i \Delta r_{t-1} + \varepsilon_t$ ------------------(3), where Δr_t is the first difference of the return series; α is a constant; λ_t is a time trend; ρr_{t-1} is the series lagged one period; $\sum_{i=1}^{n} \beta_i \Delta r_{t-1}$ is the differenced series at n lags; and ε_t is the error term of the residuals.

3.2.2 Model Specification

Having been satisfied with the results of the preliminary analysis, the study proceeds to investigate the seasonality in the monthly All Share Index (ASI) returns. The study, in line with previous studies (Gultekin & Gultekin, 1983; Fountas & Segredakis, 2002; Wyème & Olfa, 2011), estimates the following dummy variables regression model by ordinary least squares (OLS).

$$y_t = \alpha_1 + \alpha_2 D_{feb} + \alpha_3 D_{mar} + \alpha_4 D_{apr} + \alpha_5 D_{may} + \alpha_6 D_{jun} + \alpha_7 D_{jul} + \alpha_8 D_{aug} + \alpha_9 D_{sep} + \alpha_{10} D_{oct} + \alpha 11 D_{nov} + \alpha_{12} D_{dec} + \varepsilon_t \ldots\ldots(3),$$

where y_t stands for the stock market returns at time t; α_1 is the intercept which indicates the mean return for the month of January, which is chosen as the benchmark; and the coefficients, α_2, α_3, …., α_{12} represent the average differences in returns between January and each month; ε_t is assumed to be a white noise error term, and D_{feb} …., D_{dec} are monthly seasonal dummy variables. Since α_1, the intercept represents the mean return for January (the first month, or the beginning of the tax year), then the dummy variable is equal to zero for January, and equal to unity if otherwise.

3.2.3 Hypothesis

We test the null hypothesis that there is no monthly seasonality effect in the Nigerian stock market. The null hypothesis and its alternative are stated below.

H_0: $\alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10} = \alpha_{11} = \alpha_{12} = 0$

H_1: at least one α is different.

The null hypothesis states that the coefficients should be equal to zero if the returns for each month is the same and if there is no seasonal effect. Indication of a negative value of a dummy coefficient would be proof of a January effect.

3.2.4 Post-Diagnostic Test

After estimating the model in equation 3 by OLS regression, we examine the model fit by means of the R^2 and F-Statistic. We also carry out residual diagnostic for stationarity, serial correlation and Arch effect. We use the ACF and PACF from the correlogram of the residual series to detect serial correlation in the residuals. The Durbin Watson-statistic and the Ljung-Box Q-statistic are used to test for stationarity of the residual series. Next, we test for ARCH effect in the residuals. If the residual series are stationary, but if the tests of serial correlation and ARCH effect in the residuals indicate that the residuals are correlated and that there is ARCH effect, we would then include an AR (1) term on the right hand side of the dummy regression equation (to correct for serial correlation), and then fit a benchmark Garch (1,1) model to take care of the ARCH effect in order to make the disturbance term a white noise.

The following equations would be estimated simultaneously:

$$y_t = \alpha_1 + \alpha_2 D_{feb} + \alpha_3 D_{mar} + \alpha_4 D_{apr} + \alpha_5 D_{may} + \alpha_6 D_{jun} + \alpha_7 D_{jul} + \alpha_8 D_{aug} + \alpha_9 D_{sep} + \alpha_{10} D_{oct} + \alpha_{11} D_{nov} + \alpha_{12} D_{dec} + AR(1) \quad \ldots\ldots (4)$$

$$\delta_t^2 = \alpha_o + \alpha_1 u_{t-1}^2 + \lambda_1 {}_{t-1}^2 \quad \ldots\ldots (5)$$

Where, δ_t^2 is the conditional variance at time t; u_{t-1}^2 is the lagged squared error term at time (t-1); and ${}_{t-1}^2$ is the lagged variance term at time (t-1). α_o, α_1 and λ_1 are parameter coefficients.

The equations 4 and 5 are estimated simultaneously using maximum likelihood. After estimating equations 4 and 5 simultaneously, we test for serial correlation and Arch effect in the residuals using the Ljung-Box Q-Statistic and the Arch heteroskedasticity test respectively. Satisfied that there are no longer patterns in the residuals, we proceed to interpret the results.

4. Results

Table 1 shows the descriptive statistic of the All Share Index (ASI) returns on monthly basis from January to December, and for the whole period 1996 to 2013.

Table 1: Descriptive Statistic of the ASI Returns: January 1996 – December 2013

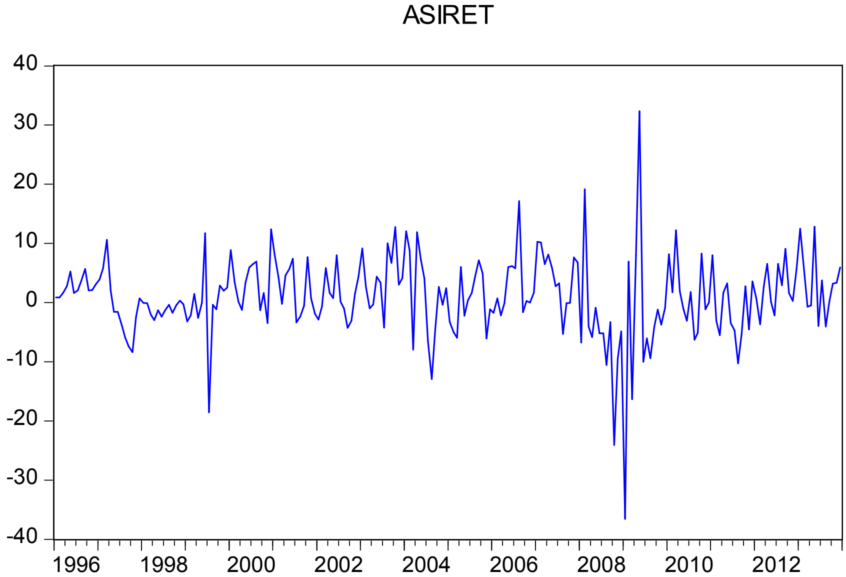
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	1996-2013
Mean	1.556	3.115	-0.280	2.296	4.444	1.087	-1.239	-1.319	-	0.735	-	2.474	0.969
Med	2.356	2.228	-0.475	1.775	3.311	1.014	-0.571	-1.709	0.661	1.811	0.576	2.499	0.692
Max	12.526	19.188	12.196	11.912	32.351	11.740	6.548	17.150	-	12.745	0.103	12.411	32.351
Min	-	-4.996	-	-5.841	-2.208	-	-	-	1.473	-	7.644	-4.886	-
S.	36.588	5.885	16.346	4.520	8.008	10.045	18.577	12.953	9.093	24.080	-	3.933	36.588
Dev	11.259	1.023	6.735	0.328	2.488	5.556	6.154	7.871	-	7.701	9.524	0.545	6.745
Skew.	-2.188	4.139	-0.236	2.576	9.368	0.020	-1.051	0.593	7.445	-1.789	3.950	3.664	-0.530
Kurt.	8.400	4.111	3.452	0.458	48.999	2.398	4.481	2.874	4.793	7.315	-	1.223	9.406
J-	36.241	0.128	0.321	0.795	0.000	0.272	4.958	1.068	0.766	23.569	0.286	0.543	379.47
Bera	0.000	18	0.852	18	18	0.872	0.084	0.586	2.481	0.000	3.282	18	0.000
Prob.	18		18			18	18	18	1.963	18	0.305		216
Obs.									0.375		0.858		
									18		18		

Source: Eviews 7 Output

The mean return for the whole period is 0.969 percent. Returns for January, February, April, May, June and December are higher than for other months. The standard deviation of returns for the whole period is moderately high. January has the highest standard deviation of 11.259 percent, while December has the lowest standard deviation of 3.933. The above shows that volatility is moderately high. This in turn implies that investment in equity in the Nigerian stock market has a moderate risk. Although the Jarque-Bera statistic for the whole period (1996 – 2013) is statistically significant (p = 0.000) indicating non-normality of the data, it is observed that returns for February, March, April, June, July, August, September, November and December are normally distributed. However since 75 percent of the data are normally distributed, the results of our analysis may not be adversely affected.

Figure 1 below is a plot of the ASI returns (ASIRET). It shows variations in the monthly returns of the All Share Returns.

Figure 1 Monthly ASI Returns from January 1996 to December 2013



Source: Eviews 7 Output

A look at figure 1 shows that the ASE return series has a high, stable volatility. Volatility is especially high during the 2008 and 2009 periods. Figure 1 shows an ASE return series that is not drifting upwards but rather fluctuating around its mean. This is an indication that the mean and the variance of this time series are stationary. Table 2, the correlogram of the ASI return series, is used to assess the stationarity of ASI return series.

The graphical representation autocorrelation function (ACF) column shows that the ACF declines or falls very quickly. Except for ACF at lags 1, 2, 3, 5, 10 and 21, all other ACF are statistically insignificant because they are within the 95% confidence bounds. The same goes for the partial autocorrelation function (PACF). The PACF also drops very quickly and many of the PACF are statistically insignificant (inside the 95% confidence bounds) indicating that they are not significantly different from zero. The implication of this is that the ASI return series is stationary.

A more formal test of stationarity is the Augmented Dickey-Fuller (ADF) unit root test. We present the results of the ADF unit root test in table 3.

Table 2 Correlogram of ASI Returns
Date: 04/18/14 Time: 14:33
Sample: 1996M01 2013M12
Included observations: 216

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|* |</td><td>.|* |</td><td>1</td><td>0.154</td><td>0.154</td><td>5.1855</td><td>0.023</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>2</td><td>0.159</td><td>0.139</td><td>10.776</td><td>0.005</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>3</td><td>0.171</td><td>0.134</td><td>17.244</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>4</td><td>-0.052</td><td>-0.118</td><td>17.842</td><td>0.001</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>5</td><td>0.178</td><td>0.169</td><td>24.915</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.026</td><td>-0.022</td><td>25.068</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>0.006</td><td>-0.012</td><td>25.078</td><td>0.001</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>8</td><td>0.081</td><td>0.025</td><td>26.550</td><td>0.001</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>9</td><td>0.088</td><td>0.119</td><td>28.324</td><td>0.001</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>10</td><td>0.134</td><td>0.074</td><td>32.440</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>11</td><td>-0.041</td><td>-0.123</td><td>32.819</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>0.015</td><td>-0.001</td><td>32.868</td><td>0.001</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>13</td><td>-0.142</td><td>-0.169</td><td>37.552</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>-0.045</td><td>0.015</td><td>38.022</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>0.018</td><td>0.009</td><td>38.100</td><td>0.001</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>16</td><td>-0.091</td><td>-0.017</td><td>40.033</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>17</td><td>-0.060</td><td>-0.095</td><td>40.893</td><td>0.001</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>18</td><td>-0.068</td><td>-0.018</td><td>41.981</td><td>0.001</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>19</td><td>-0.080</td><td>-0.044</td><td>43.506</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>20</td><td>-0.023</td><td>-0.005</td><td>43.629</td><td>0.002</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>21</td><td>-0.151</td><td>-0.104</td><td>49.145</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>22</td><td>-0.070</td><td>0.024</td><td>50.339</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>23</td><td>-0.046</td><td>0.036</td><td>50.849</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>24</td><td>-0.037</td><td>-0.000</td><td>51.178</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>25</td><td>0.001</td><td>0.002</td><td>51.178</td><td>0.002</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>26</td><td>-0.076</td><td>-0.047</td><td>52.609</td><td>0.002</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>27</td><td>-0.085</td><td>-0.050</td><td>54.397</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>28</td><td>-0.022</td><td>0.020</td><td>54.516</td><td>0.002</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>29</td><td>-0.100</td><td>-0.064</td><td>57.045</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>30</td><td>-0.025</td><td>-0.002</td><td>57.210</td><td>0.002</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>31</td><td>-0.001</td><td>0.054</td><td>57.210</td><td>0.003</td></tr>
<tr><td>.|. |</td><td>.|* |</td><td>32</td><td>0.059</td><td>0.093</td><td>58.095</td><td>0.003</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>33</td><td>0.029</td><td>-0.028</td><td>58.305</td><td>0.004</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>34</td><td>0.102</td><td>0.070</td><td>60.994</td><td>0.003</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>35</td><td>0.083</td><td>0.050</td><td>62.805</td><td>0.003</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>36</td><td>0.101</td><td>0.111</td><td>65.492</td><td>0.002</td></tr>
</table>

Source: Eviews 7 Output

Table 3: Results of the ADF unit root test in the ASI monthly return series
ADF: With constant and time trend

	t-statistic	Prob*
ADF test-statistic	-12.454	0.000
Test critical values:		
1% level	-4.001	
5% level	-3.431	
10% level	-3.139	

*Mackinnon (1996) one-sided p-values. Maxlag = 14
Eviews 7 Output

The decision rule of the ADF test is that if the ADF test statistic (in absolute terms) is greater than the Mackinnon critical values (in absolute terms) at the 1%, 5%, and 10% levels, reject the null hypothesis of unit root. The ADF test statistic of -12.454 (p = 0.000) is greater in absolute terms than the Mackinnon critical values (in absolute terms) of -4.001, -3.431, and 3.139 at 1%, 5%, and 10% respectively. The ADF test statistic is also highly statistically significant (p = 0.000). Therefore we reject the null hypothesis that the ASI return series has a unit root. The ASI return series is therefore stationary. We can therefore confidently use the monthly ASI return series to carry out analysis of monthly seasonality in the Nigerian stock market.

4. 2 Month of the Year Effect

We estimate equation 3 using OLS dummy variable regression. Table 4 shows the results of the regression.

Table 4: OLS Estimation of the ASI Returns

Source: Eviews 7 output.

Dependent Variable: ASIRET				
Variable	Coefficient	Std. Error	t-Statistic	Prob
C	1.556	1.574	0.988	0.324
DumFeb	1.559	2.226	0.700	0.485
DumMar	-1.835	2.226	-0.824	0.411
DumApr	0.741	2.226	0.333	0.739
DumMay	2.888	2.226	1.297	0.196
DumJun	-0.468	2.226	-0.210	0.834
DumJul	-2.794	2.226	-1.255	0.211
DumAug	-2.875	2.226	-1.291	0.198
DumSep	-2.216	2.226	-0.995	0.321
DumOct	-0.821	2.226	-0.369	0.713
DumNov	-2.132	2.226	-0.958	0.339
DumDec	0.918	2.226	0.412	0.680
R-squared	0.069	F-statistic	1.388	
D.W. Stat.	1.706	Prob.	0.181	

Source: Eviews 7 output.

Table 4 examines monthly seasonality in the ASI returns. The benchmark month is January represented by the intercept, which shows a return of 1.556 percent. None of the coefficients are statistically significant. The R^2 is 0.069 which is very low. The F-statistic is 1.388 with an insignificant p-value of 0.181 indicating that the overall model fit is poor. The Durbin-Watson statistic of 1.706 is not close to 2, indicating that there is positive serial correlation in the residuals.

The following post-diagnostic tests were carried out to test for serial correlation in the residuals, and to detect the presence of arch effect: (1) The correlogram of the residuals, (2) Breusch-Godfrey serial correlation LM test, and (3) ARCH: Heteroskedasticity test.

The Ljung Box-Q statistic as shown in table 5 and the Breusch-Godfrey serial correlation LM test as shown in table 6 were used to test for serial correlation in the residuals. While table 7 shows the result of the ARCH heteroskedasticity test.

Table 5 shows Q-statistics that are statistically significant up to lag 36. This suggests that the residuals of the model (equation 4) estimated with the OLS regression are serially correlated.

The Breusch-Godfrey serial correlation LM test result is shown in table 6.

Table 5 Correlogram of the Residual
Date: 04/18/14 Time: 15:25
Sample: 1996M01 2013M12
Included observations: 216

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	0.146	0.146	4.6861	0.030
.|* |	.|* |	2	0.175	0.157	11.437	0.003
.|* |	.|* |	3	0.198	0.161	20.094	0.000
.|. |	*|. |	4	-0.053	-0.128	20.706	0.000
.|* |	.|* |	5	0.212	0.193	30.780	0.000
.|. |	.|. |	6	0.067	0.015	31.791	0.000
.|. |	.|. |	7	0.027	-0.007	31.955	0.000
.|* |	.|. |	8	0.085	-0.006	33.579	0.000
.|* |	.|* |	9	0.107	0.140	36.171	0.000
.|* |	.|* |	10	0.143	0.079	40.835	0.000
.|. |	*|. |	11	-0.064	-0.173	41.777	0.000
.|. |	*|. |	12	-0.056	-0.101	42.492	0.000
*|. |	*|. |	13	-0.171	-0.164	49.270	0.000
.|. |	.|. |	14	-0.047	0.042	49.788	0.000
.|. |	.|. |	15	0.038	0.040	50.129	0.000
*|. |	.|. |	16	-0.091	-0.031	52.080	0.000
.|. |	.|. |	17	-0.040	-0.055	52.463	0.000
.|. |	.|. |	18	-0.042	0.020	52.874	0.000
*|. |	.|. |	19	-0.067	-0.030	53.949	0.000
.|. |	.|. |	20	-0.028	-0.028	54.137	0.000
*|. |	*|. |	21	-0.147	-0.076	59.337	0.000
*|. |	.|. |	22	-0.070	0.056	60.522	0.000
*|. |	.|. |	23	-0.068	0.002	61.644	0.000
*|. |	*|. |	24	-0.114	-0.128	64.821	0.000
.|. |	.|. |	25	-0.010	-0.017	64.847	0.000
*|. |	.|. |	26	-0.077	0.004	66.332	0.000
*|. |	.|. |	27	-0.075	-0.013	67.752	0.000
.|. |	.|. |	28	-0.022	-0.009	67.868	0.000
*|. |	.|. |	29	-0.087	-0.035	69.796	0.000
.|. |	.|. |	30	-0.000	0.046	69.796	0.000
.|. |	.|* |	31	0.018	0.076	69.878	0.000
.|. |	.|* |	32	0.057	0.075	70.698	0.000
.|. |	.|. |	33	0.045	-0.002	71.212	0.000
.|* |	.|* |	34	0.114	0.118	74.548	0.000
.|. |	.|. |	35	0.070	0.029	75.822	0.000
.|. |	.|. |	36	0.038	-0.013	76.203	0.000

Source: Eviews 7 output

Table 6: The Breusch-Godfrey Serial Correlation LM Test Dependent Variable: Resid.

F-statistic	4.839	Prob. F (2, 202)	0.009
Obs*R-squared	9.876	Prob. Chi-square (2)	0.007

Source: Eviews 7 output.

As these results show, there is strong evidence of (second-order) autocorrelation, for both the F and χ^2 values are highly significant because their p values are so low.

Table 7: Heteroskedasticity Test: ARCH
Dependent variable: Resid^2

F-statistic	9.462	Prob. F (5, 204)	0.000
Obs*R-squared	39.533	Prob. Chi-square (5)	0.000
Lags	5		

Source: Eviews 7 output.

Table 7 shows that there is strong evidence of autocorrelated heteroskedasticity in the residuals, for both the F and χ^2 values are highly significant because their p-values are so low. This is an indication that there is arch effect in the residuals. Under these conditions, the OLS estimation shown in table 4 cannot be relied on for statistical inferences.

We therefore specified a new equation (equation 4) with an AR (1) term added to the right hand side and we also fitted a Garch (1, 1) model (equation 5). These two equations were run simultaneously using the maximum likelihood estimation method, in order to take care of the serial correlation and arch effect in the residuals. We present the results in table 8.

Table 8: Results of ML estimation arrived at after correcting for serial correlation and arch effects in the residuals.
Dependent Variable: ASI Returns

Mean Equation				
Variable	Coefficient	Std. Error	z-statistic	Prob.
C	3.711	1.016	3.651	0.000
DumFeb	-1.969	1.744	-1.129	0.259
DumMar	-2.154	1.728	-1.246	0.213
DumApr	-1.178	1.876	-0.628	0.530
DumMay	0.138	1.685	0.082	0.935
DumJun	-1.795	1.480	-1.213	0.225
DumJul	-3.805	1.311	-2.902	0.004
DumAug	-2.998	1.291	-2.323	0.020
DumSep	-3.045	1.679	-1.814	0.070
DumOct	-1.746	1.522	-1.147	0.251
DumNov	-3.662	1.856	-1.973	0.048
DumDec	-0.441	1.347	-0.327	0.743
AR (1)	0.227	0.095	2.402	0.016
Variance Equation				
C	2.549	1.174	2.170	0.030
Resid(-1)^2	0.291	0.089	3.277	0.001
Garch (-1)	0.687	0.075	9.125	0.000
R-squared	0.048	Adj. R.squared -0.008	Durbin-Watson statistic	2.227

Source: Eviews 7 output

However before interpreting the results in table 8 we checked for patterns in the residuals. Table 9 and 10 were used to check for serial correlation and arch effect in the residuals respectively.

Tables 9 and 10 are shown below.

Table 9 Correlogram of standard residuals squared
Date: 04/18/14 Time: 16:11
Sample: 1996M02 2013M12
Included observations: 215
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.006	0.006	0.0090	
.|. |	.|. |	2	-0.048	-0.048	0.5164	0.472
.|* |	.|* |	3	0.111	0.112	3.2190	0.200
*|. |	*|. |	4	-0.100	-0.106	5.4313	0.143
.|. |	.|. |	5	0.007	0.022	5.4426	0.245
.|. |	.|. |	6	0.001	-0.024	5.4428	0.364
.|. |	.|. |	7	0.002	0.028	5.4438	0.488
.|. |	.|. |	8	0.000	-0.016	5.4439	0.606
.|. |	.|. |	9	-0.037	-0.030	5.7511	0.675
*|. |	*|. |	10	-0.094	-0.102	7.7831	0.556
.|. |	.|* |	11	0.065	0.074	8.7452	0.556
.|. |	.|. |	12	0.067	0.060	9.7619	0.552
*|. |	*|. |	13	-0.086	-0.069	11.480	0.488
.|. |	.|. |	14	0.026	0.001	11.641	0.557
.|. |	.|. |	15	-0.013	-0.021	11.682	0.632
*|. |	*|. |	16	-0.112	-0.085	14.597	0.481
.|* |	.|* |	17	0.137	0.132	19.018	0.268
.|. |	.|. |	18	0.055	0.045	19.740	0.288
.|. |	.|. |	19	-0.027	-0.012	19.912	0.338
*|. |	*|. |	20	-0.090	-0.143	21.831	0.293
.|. |	.|. |	21	0.001	0.044	21.831	0.350
.|. |	.|. |	22	-0.039	-0.045	22.208	0.388
.|. |	.|. |	23	-0.058	-0.045	23.030	0.400
.|. |	.|. |	24	0.019	-0.009	23.119	0.454
.|. |	.|. |	25	-0.053	-0.050	23.804	0.473
.|* |	.|* |	26	0.108	0.108	26.686	0.372
.|. |	.|. |	27	-0.003	0.029	26.688	0.426
.|. |	.|. |	28	0.021	0.046	26.803	0.474
.|* |	.|* |	29	0.166	0.088	33.678	0.212
*|. |	.|. |	30	-0.068	-0.063	34.846	0.210
.|. |	.|. |	31	0.020	0.049	34.944	0.245
.|. |	*|. |	32	-0.051	-0.096	35.612	0.260
.|. |	.|. |	33	-0.038	0.016	35.990	0.287
.|. |	.|. |	34	0.064	0.041	37.043	0.288
.|. |	.|. |	35	-0.048	-0.055	37.643	0.306
.|. |	.|. |	36	0.024	0.019	37.791	0.343

Source: Eviews 7 output.

Table 9 shows strong evidence that there are no longer serial correlations in the residuals, because the Ljung-Box Q-statistics are all insignificant at all the lags. The results of table 10 is used to test arch effect in the residuals.

Table 10: Heteroskedasticity Test: ARCH
Dependent Variable: WGT_RESID^2

F-statistic	1.112	Prob. F (5, 204)	0.355
Obs*R-squared	5.572	Prob. Chi-square (5)	0.350

Source: Eviews 7 output

There is strong evidence that the residuals no longer have arch effect, because both the F-statistic and χ^2 are now insignificant. We can now confidently proceed to interpret the result of our ML estimation in table 8.

4.1 Interpretation of Results and Discussion

Table 8 shows that the coefficients for the intercept (benchmark for January) and for July, August, September and November are statistically significant (p = 0.000; 0.004; 0.020; 0.070; and 0.048 respectively). This is an evidence of monthly seasonality in the Nigeria stock market. The average returns for the intercept (benchmark for January) is 3.710 percent which is the highest comparatively. This is followed by the positive average returns of 0.138 percent for the month of May. However this positive return for May is statistically insignificant. All other monthly average returns are low (negative) when compared to the benchmark for January.

The lowest average return is recorded in the month of July (-3.805 percent). Average monthly returns for the months of July, August, September and November are amongst the lowest compared to January. Since average return for January is the highest and is highly statistically significant while many other average monthly returns are lower (negative returns) compared to the benchmark for January, this is an indication of a January effect. This finding is consistent with the findings of Wachtel (1942), Gultekin & Gultekin (1983), Roll (1983), Reinganum (1983), and Fountas & Segredakis (2002). Fountas & Segredakis (2002) found evidence of a monthly effect for average January return exceeding the average return for some of the rest of the months for five emerging stock markets (Chile, Greece, Korea, Taiwan and Turkey). However our finding is not consistent with the tax-loss selling hypothesis explanation of December-January seasonality. According to the tax-loss selling hypothesis, investors sell off their low performing stocks in December (where December is the end of the tax year) and use the capital losses to offset their tax-liability. As a result of this rush to sell in December stock returns are expected to be low in December. However, at the beginning of the new tax year in January, investors now rush to reestablish their portfolios. This rush leads to upsurge in stock returns in January.

Our results show that average monthly return in December, though very low (negative), is statistically insignificant. This indicates that there is no end of the year effect in December. However average returns in November is very low and statistically significant (return – 3.662; p = 0.048). It may be that investors in Nigeria start selling off all their low performing stocks in November in order to offset their tax liability with their capital losses, and then wait till the beginning of January to reestablish their portfolios. This selling pressure in November may have resulted to the very low returns in November and the buying pressure in January creates the January effect. Other reasons could be adduced for the January effect in the Nigeria stock market. The January effect may be due to the information release hypothesis (Rozeff & Kinney, 1976) or may simply be due to investors' overreaction as found in other studies (Chopra, Lakonishok, & Ritter, 1992).

5. Conclusion

This study investigated the existence of monthly stock market seasonality effect in the Nigerian stock market. The study tested the null hypothesis that there was no monthly stock market seasonality effect in Nigeria. To take care of serial correlation and arch effects in the residuals, the study entered an autoregressive variable AR (1) of order one into the right hand side of the dummy variable regression model and fitted a Garch (1,1). The study employed the maximum likelihood estimation technique in estimating the parameters of the regression. Our findings confirmed the existence of monthly seasonal effect in the ASI returns. The study found that returns in January, July, August, September, and November were statistically significant. The January return, represented by the intercept was positive and was the highest. The months of July, August, September, and November had low returns (negative returns). This is an indication of the January seasonal effect in the Nigerian stock market. In this regard the study is consistent with the January effect found in most studies of stock seasonality of developed countries.

The study was not consistent with the December – January tax-loss selling hypothesis explanation for the January effect. The tax year runs from January to December. It was found that return in December, though low (negative return), was statistically insignificant. However the study found a November – January tax-loss selling hypothesis explanation for the January effect. This was because average stock return in November was low (negative) and statistically significant while average return in January was very high and statistically significant.

The results of the study negate the informational efficiency aspect of the efficient market hypothesis. The implication of this is that stock returns in Nigeria are not entirely random. Investors may be able to make abnormal returns by timing their investments. However investors may not necessarily reap supernormal profits because of borrowing constraints and high transaction costs.

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