Month of the Year Effect: An Empirical Evidence from Muscat Securities Market

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Abstract

This paper explores the existence of a calendar seasonality at Muscat Securities Market (MSM) that is the month-of-the-year effect. It employs Ordinary Least Squares (OLS) and estimates dummy variables for the whole sample period of January 2005 to July 2016. Tests were also repeated using three different models for conditional variance; GARCH, EGARCH and TARCH. This paper confirms the existence of positive and significant returns during April compared to remaining months. Average returns in April are two times higher than average returns during the rest of the year. A possible explanation for April effect is investors' reaction to dividends distributions when returns rise substantially in April that follows the month of earning announcement of March.

The results of this paper are important for investors and researchers alike. Investors can exploit this calendar anomaly through developing a strategy that purchases stocks at the end of November and sell at the end of April. The large spread in returns between April and November and the low transaction costs suggest the feasibility of such strategy. Researchers, on the other hand, need to consider April effect in portfolio construction, the evaluation of fund performance, as well as in asset pricing tests.

Keywords: stock market efficiency, calendar anomaly, April effect, Muscat securities Market.

For the Paper in Arabic Language See the Pages (217).

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Introduction

The Efficient Market Hypothesis of Fama (1965) states that assets prices should reflect all information and no investor can beat the market consistently on risk-adjusted basis. However, the evidence from stock markets suggests the existence of a number of calendar anomalies or seasonalities that constitute challenges to market efficiency. Calendar anomalies include time-of-the-day effect, day-of-the-week effect, week-of-the-month effect, week-of-the-year effect, and month-of-the-year effect. Interestingly, there is neither consensus on their explanations nor on the persistence of those anomalies in different international markets.

The month-of-the-year effect refers to the tendency of stock returns to exhibit large returns in certain month (for example, January) compared to the rest of the months in the year. Consequently, investors can develop profitable strategies based on the observed anomaly and predict stock prices in the certain month.

In recent years, many scholars have investigated month-of-the-year effect in advanced and emerging markets. However, little attention was given to smaller markets such as Muscat Stock Market (MSM). Although international stock markets are correlated and interlinked, the examination of the existence of such anomalies in Muscat stock market provides out-of-sample test of the validity of such seasonality in relatively new and small market in the Arabic Gulf area.

The implications of this paper are twofold. Since I examine the existence of month-of-the-year effect in Muscat stock market, the results of this study will help investors in Muscat stock market recognize the available opportunities and build portfolios in such way to take advantage from the observed anomalies. Second, the performed tests can be considered as tests of the market efficiency for Muscat stock market which will further support or contradict traditional finance theories.

Literature Review

Market anomalies literature identifies various calendar anomalies yielding empirical results that challenge the widely accepted asset pricing models and question the efficient market hypothesis and the major assumption of rational investors. The month-of the-year effect is amongst the most extensively searched anomalies with day-of-the-week and to a lesser extent the week-of-the-year effect.

The month-of-the-year effect includes four anomalies – the January effect, the April effect, the May-to-October effect and the October effect. According to January effect, also called the turn-of-the-year effect, returns in January tend to be significantly higher than returns in other months (Rozeff and Kinney, 1976; Ariel, 1990; Schwert,2003; Starks et al.,2006). For example, Rozeff & Kinney (1976) find that investors in NYSE can achieve abnormal returns through using the month effect where they approve that the return in January is more than other months. After that, similar results found in Canada by Berges et al. (1984). Also, the January effect has been documented in Europe by many researchers (see, Barone, 1990; Canestrelli and Ziemba, 2000; Donnelly, 1991; Gahan, 1993; Lucey, 1994; Van den Berg and Wessels, 1985).

The evidence from other markets suggests different monthly seasonal patterns. The May effect refers to the fact that stock returns tend to be higher in May than returns in other months (Coutts & Sheik, 2000; Mouselli and Al-Samman, 2016) in Johannesburg stock exchange and Damascus Securities Exchange subsequently. Also, the October effect (also called Mark Twain effect) suggests that stock returns in October are lower than in other months in the Canadian stock market (Cadsby, 1989). June effect is found in Jamaica (Ramcharran, 1997) and Bangladesh (Ahsan and Sarkar, 2013). July returns outperform other months in Kuwait (Al-Saad & Moosa, 2005) and Ramadan effect (Holy month of Muslims) is documented for the Saudi market (Seyyed et al. 2005).

According to May-to-October effect (or the Halloween effect) that stock returns tend to be significantly lower during the time from May to October (summer and fall months) than other months (Bouman and Jacobsen, 2002; Kamstra et al., 2003; Maberly and Pierce, 2004; Zarour, 2007; Jacobsen and Marquering, 2009; Lean, 2011; Jacobsen and Zhang, 2012; Andrade et al., 2013, Norvaisiene et al., 2015). For example, Bouman and Jacobsen (2002) test the monthly returns for 37 developed and emerging markets and they proved the existence of Halloween effect in 36 of 37 countries.

Another important strand of literature investigates possible explanations of those calendar anomalies and month-of-the-year effect in particular. For example, Dyl (1977) suggests a tax-loss selling hypothesis where individuals tend to sell stocks that suffer declines in December and reinvest the proceeds in January. Furthermore, Anderson et al., (2007) perform auction experiments in January and December on investors and attribute January effect to investors' psychological factors.

Not only that individuals cause the month-of-the-year effect, but also institutional investing plays a key role in creating such anomaly too. For instance, Haugen & Lakonishok (1988) suggest that institutional investors sell underperforming stocks around the end of the year to make their portfolios look better in their aim to dress up their portfolios prior to mandatory portfolio disclosure dates. However, Ng & Wang (2004) suggest a risk shifting hypothesis at which institutions increase the riskiness of their portfolios by buying small risky stocks in January in order to increase expected returns while avoiding investor screening. Sikes (2008) argues that tax-sensitive institutional investors, on the purpose of realizing paper losses and reduce the tax liabilities of their investors, systematically sell losing stocks in December.

The out-of-sample tests provide mix results on the reasons behind such anomaly and argue that those reasons augment and complement one another. On the one hand, some studies claim that individual investors cannot cause January effect by their individual trading (see, Brown et al., 1983; Reinganum, 1983). Besides, Keim (1983) finds there is a relation between January effect and size effect. On the other hand, Lynch et al. (2014) attempt to separate tax-loss selling hypothesis from window-dressing and risk-shifting hypotheses. Nevertheless, their findings back window-dressing hypothesis against tax-loss or risk-shifting hypothesis. Lately, Easterday & Sen (2016) argue that January effect is primarily caused by potential tax-loss sellers and not a result of noise traders or connected to systematic risk factor explanation.

Many scholars have conducted tests on the existence of calendar anomalies in developing and small markets. However, there is mixed evidence on the month at which stock returns perform better in compared to other months. Moreover, previous research on the existence of stock market seasonalities in Muscat Securities Market centers around day-of-the-week effect (Al-Jafari, 2012). Therefore, this study comes to fill this gap in literature by examining the presence of another important calendar anomaly in Muscat stock market, the month-of-the-year effect.

METHODS AND RESULTS

Muscat Securities Market was established as a public institution in June 1988 and started its operations later in 1989. This paper uses the MSM 30 index to analyse the existence of month-of-the-year effect in returns of Muscat securities market. The data covers approximately twelve years of market performance that spans the period from January 2005 to July 2016.

The study uses monthly returns on MSM 30 index measured as the natural logarithm of the index value at the last trading day at the end of the week (month) t divided by the index value at the last trading day of week (month) t-1,

$$\boldsymbol{R_t} = \ln\left({\boldsymbol{I_t}}/{\boldsymbol{I_{t-1}}}\right) \qquad (1)$$

Where;

R_t is the logarithm return of month t,

I_t is the closing value of MSM index in month t,

I_{t-1} is the closing value of MSM index in month t-1.

Table 1 provides descriptive statistics of monthly returns of MSM for the period January 2005 to July 2016. It can be noticed that month April has the highest average returns of 3.94%. This can be attributed to the fact that that high percentage of companies have their cut-off dividend date in March of the year. The lowest average returns are documented for October and November with -1.76% and -1.68% respectively. The minimum average returns recorded for the sample is in October with -31.32% while the highest average returns during the sample period documented in March with 16.24%. The average return for the entire sample period is 0.4%. The Jarque- Bera normality test of overall returns rejects the normality of returns at the 1% level of significance. Also, the normality assumption is rejected in month March, October, and June at 1%, 5%, and 10% level of significance respectively.

Table 1. Descriptive Statistics for monthly returns for the period Jan 2005 to July 2016

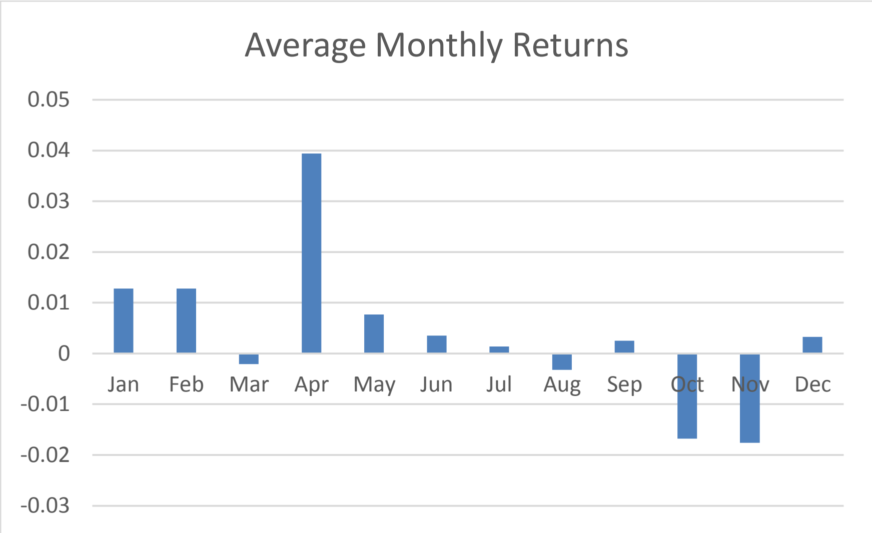
Month	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	Jarque-Bera Test
January	0.0128	0.0202	0.1108	-0.1226	-0.7443	3.9041	1.5166
February	0.0128	0.0127	0.1221	-0.1074	-0.2871	4.3432	1.0670

March	**-0.0021**	**-0.0121**	**0.1624**	**-0.0502**	**2.1189**	**6.9975**	**16.9695 *****
April	**0.0395**	**0.0289**	**0.1041**	**-0.0432**	**-0.0640**	**2.0597**	**0.4503**
May	**0.0077**	**0.0147**	**0.0699**	**-0.0817**	**-0.2611**	**1.8346**	**0.8153**
June	**0.0035**	**-0.0085**	**0.0869**	**-0.0383**	**1.4150**	**4.8845**	**5.7801***
July	**0.0014**	**0.0104**	**0.0470**	**-0.0600**	**-0.3998**	**1.8808**	**0.9460**
August	**-0.0032**	**0.0072**	**0.0819**	**-0.1231**	**-0.6854**	**2.5982**	**0.9354**
September	**0.0025**	**0.0099**	**0.0677**	**-0.1113**	**-0.9811**	**3.8085**	**2.0644**
October	**-0.0168**	**0.0041**	**0.1381**	**-0.3132**	**-1.6522**	**5.8873**	**8.8258****
November	**-0.0176**	**-0.0226**	**0.0512**	**-0.0696**	**0.1801**	**2.3176**	**0.2729**
December	**0.0033**	**0.0160**	**0.0678**	**-0.1409**	**-1.5819**	**5.2185**	**6.8434**
All	**0.0040**	**0.0079**	**0.1624**	**-0.3132**	**-1.2158**	**9.4741**	**276.9974*****

Note: ***,**,* indicates significance at 1%, 5%, and 10% level of significance respectively.

Figure 1 illustrates the average monthly returns for different months in the year. April returns are at least two times higher than a typical month in the MSM. On the other hand, November has the lowest average monthly returns followed by October and August. It can be seen that the second quarter of the year is a good period of the market with positive returns in all three months. However, the fourth quarter of the year is a bad period for investment with a minor recovery in December. A monthly reversal in average returns is witnessed from July to October.

Figure 1. Average Returns of MSM Index on Monthly Basis for the Period Jan 2005 to July 2016



In order to examine the autocorrelation between monthly returns, 36 lags for monthly returns were used in the following Table 2. Q-statistics in Table 2 represents Ljung-Box statistics and illustrates that the null hypothesis of zero autocorrelation is rejected. This indicates that MSM is not weak-form efficient. A closer look at the individual autocorrelation coefficient (AC) indicates the existence of autocorrelation between monthly returns up to 3 lags.

Table 2: Autocorrelation and partial for monthly returns for the period 2005-2016

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.288	0.288	11.779	0.001
.|** |	.|** |	2	0.345	0.286	28.815	0.000
.|* |	.|. |	3	0.193	0.047	34.172	0.000
.|. |	*|. |	4	0.071	-0.089	34.899	0.000
.|. |	.|. |	5	0.017	-0.061	34.942	0.000
*|. |	*|. |	6	-0.130	-0.152	37.425	0.000
*|. |	.|. |	7	-0.085	-0.015	38.489	0.000
*|. |	*|. |	8	-0.171	-0.070	42.888	0.000
.|. |	.|* |	9	-0.033	0.101	43.054	0.000
*|. |	*|. |	10	-0.190	-0.141	48.538	0.000
**|. |	**|. |	11	-0.228	-0.205	56.476	0.000
*|. |	.|. |	12	-0.091	0.048	57.746	0.000
*|. |	.|. |	13	-0.146	-0.000	61.049	0.000
.|. |	.|. |	14	-0.056	0.008	61.539	0.000
.|. |	.|. |	15	-0.061	-0.002	62.130	0.000
.|. |	.|. |	16	0.019	0.014	62.187	0.000
.|. |	.|. |	17	0.021	-0.025	62.255	0.000
.|. |	*|. |	18	-0.034	-0.129	62.439	0.000
.|* |	.|* |	19	0.092	0.103	63.831	0.000
.|. |	.|. |	20	0.027	0.062	63.954	0.000
.|. |	*|. |	21	0.013	-0.125	63.983	0.000
.|. |	*|. |	22	-0.039	-0.116	64.238	0.000
.|. |	.|. |	23	0.004	0.042	64.241	0.000
*|. |	*|. |	24	-0.137	-0.172	67.442	0.000
.|. |	.|. |	25	-0.033	0.034	67.629	0.000
.|. |	.|* |	26	-0.030	0.091	67.787	0.000
.|. |	.|* |	27	0.011	0.110	67.809	0.000
.|* |	.|. |	28	0.131	0.058	70.842	0.000
.|* |	.|. |	29	0.094	-0.020	72.425	0.000
.|* |	.|. |	30	0.075	-0.024	73.425	0.000
.|* |	.|. |	31	0.118	0.058	75.969	0.000
.|* |	.|. |	32	0.153	0.073	80.278	0.000
.|. |	.|. |	33	0.051	0.010	80.760	0.000
.|* |	.|. |	34	0.092	0.029	82.334	0.000
.|* |	.|. |	35	0.111	0.016	84.667	0.000
.|. |	*|. |	36	-0.009	-0.113	84.683	0.000

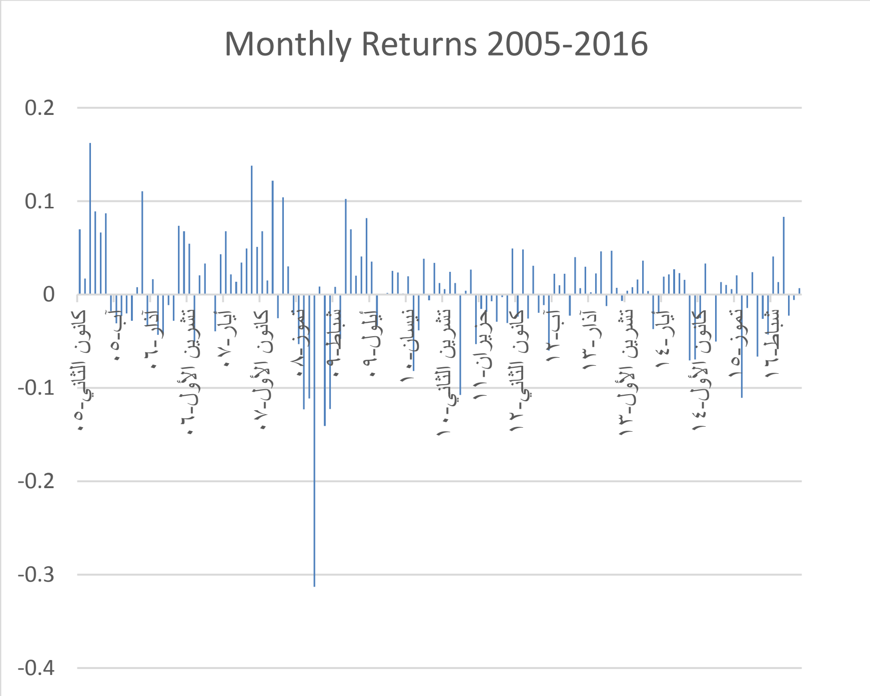
To further examine the validity of previous results, I conduct unit root test using Augmented Dickey-Fuller (ADF) test statistics with intercept, with intercept and trend, and with none of them. The results can be seen in the following table. It can be noticed that the calculated t-statistics is larger in absolute value than the critical t-values at all levels of significance and for all specifications. Hence, the null hypothesis of a unit root can be rejected and therefore the monthly return series is stationary. Therefore, the random walk hypothesis is rejected and the inefficiency of MSM on the weak-form level is confirmed.

Table 3. Results of Augmented Dickey-Fuller (ADF) unit-root test

	Calculated t-Statistics	Critical at 1%	Critical at 5%	Critical at 10%
With intercept	-5.1671	-3.4785	-2.8826	-2.5781
With intercept & trend	-5.2172	-4.0264	-3.4430	-3.1462
None	-5.1733	-2.5820	-1.9432	-1.6152

Figure 2 illustrates the movements in monthly returns during the sample period. It can be seen that the greatest declines in MSM returns took place in October 2008 due to the global financial crisis that drove the market to its worst monthly performance. However, there is no remarkable increase in monthly returns for the remaining periods.

Figure 2. The Movements of Monthly Returns for the Period 2005-2016.



To examine the existence of month-of-the-year effect in MSM returns, I estimate the following regression model using Ordinary Least Squares (OLS) method,

$$\boldsymbol{R_t = \beta_1 D1_t + \beta_2 D2_t + \beta_3 D3_t + \beta_4 D4_t + \beta_5 D5_t + \beta_6 D6_t + \beta_7 D7_t + \beta_8 D8_t + \beta_9 D9_t + \beta_{10} D10_t + \beta_{11} D11_t + \beta_{12} D12_t + e_t} \qquad (2)$$

Where D_i represents dummy variable that takes the value of one if the month is i and zero otherwise, β_i represents the coefficient of the dummy variable D_i and the average of monthly returns of the corresponding month i, e_t is the error term at month t.

Table 4 shows the results from estimating equation (2) for the period January 2005 to July 2016. It can be noticed that the only positive and significant monthly returns are documented in April with average returns of 0.0395 with a p-value of 0.0188. Average monthly returns in January, February, May, June, July, September and December are positive and insignificant. Negative and insignificant returns are observed in all remaining months. This result suggests the existence of April effect and precludes any January effect in MSM.

Table 4. Regression analysis for model (2) for the period Jan 2005 to July 2016

Variable	β_i	t-stats	P-value
D_{Jan}	0.0128	0.773292	0.4408
D_{Feb}	0.0128	0.771021	0.4421
D_{Mar}	-0.0021	-0.126699	0.8994
D_{April}	0.0395**	2.380411	0.0188
D_{May}	0.0077	0.462470	0.6445
D_{June}	0.0035	0.209529	0.8344
D_{July}	0.0014	0.086017	0.9316
D_{Aug}	-0.0032	-0.183160	0.8550
D_{Sep}	0.0025	0.144110	0.8856
D_{Oct}	-0.0168	-0.967907	0.3349
D_{Nov}	-0.0176	-1.016655	0.3113
D_{Dec}	0.0033	0.190454	0.8493

Notes: values and significance of months of the year coefficients estimated from model (2).denotes significance at 5% level of significance.**

In order to test whether the observed differences in average returns between April and other months are statistically significant, I adjust the previous regression model by excluding the dummy variable that is related to April (i.e., D_4) and adding the constant term. That is, I estimate the following regression model (3),

$$R_t = C + \beta_1 D1_t + \beta_2 D2_t + \beta_3 D3_t + \beta_5 D5_t + \beta_6 D6_t + \beta_7 D7_t + \beta_8 D8_t + \beta_9 D9_t + \beta_{10} D10_t + \beta_{11} D11_t + \beta_{12} D12_t + e_t \qquad (3)$$

The constant term will represent now the average returns on April while the coefficients (β_i) will represent now the difference in average returns between month i and April. For example, β_1 will represent now the difference in average returns between month January and April and t-stats for β_1 examines the significance of the difference in average returns between month January and April, and so on.

Table 5 confirms that the average returns in April, represented by the constant term, are positive (3.95%) and statistically significant at 5%. However, all the estimated coefficients, including January, are negative indicating that all months witnessed lower average monthly returns compared to April. November returns are the lowest amongst all months and are less than April returns by 5.71%. Only four months; March, August, October and November, suffer significantly lower returns compared to April with p-values less than 10%. The differences in average returns between the remaining months and April are negative but statistically insignificant. April effect observed in MSM may be attributed to the fact that out of 93 companies that paid dividends on 2016, 67 companies have their cut-off dividend date in March of the year (MSM website).

Table 5. Regression analysis for model (3) for the period Jan 2005 to July 2016

Variable	β_i	t-stats	P-value
C	0.0395**	2.380411	0.0188
D_{Jan}	-0.0267	-1.136405	0.2579
D_{Feb}	-0.0267	-1.138011	0.2573
D_{Mar}	-0.0416*	-1.772795	0.0787
D_{May}	-0.0318	-1.356190	0.1774
D_{June}	-0.0360	-1.535046	0.1273
D_{July}	-0.0381	-1.622382	0.1072
D_{Aug}	-0.0427*	-1.778506	0.0777
D_{Sep}	-0.0370	-1.542114	0.1255
D_{Oct}	-0.0563**	-2.345341	0.0206
D_{Nov}	-0.0571**	-2.380553	0.0188
D_{Dec}	-0.0362	-1.508639	0.1339

Notes: values and significance of the intercept and difference in average returns between other months and April estimated from model (3).,*denotes significance at 5% and 10% level of significance respectively.**

To absorb the possibility of serial correlation observed in Table 2, which may lead to misleading inferences, I also estimate model (3) after including the lagged values of returns as independent variables where Akaike Information Criterion was used to determine the optimal lag length. Also, I address the heteroscedasticity problem by allowing variances of errors to be time dependent through using three different models for conditional variances; GARCH, TARCH, and EGARCH. All those models are estimated using Generalized Error Distribution (GED) because errors are not normally distributed as it was shown by Jarque-Bera test in Table 1. The results from applying those models are shown in Table 6**.**

Table 6. Parameter estimates for the GARCH models with generalized error distribution

	GARCH		**EGARCH**		**TARCH**	
Mean Equation						
Coefficient	**Value**	**Z-stat.**	**Value**	**Z-stat.**	**Value**	**Z-stat.**
C	**0.038090**	**4.798306**	**0.038412**	**4.826275**	**0.038561**	**4.725038**
January	**-0.032726**	**-2.714289**	**-0.032955**	**-2.738905**	**-0.033218**	**-3.078967**
February	**-0.020667**	**-1.752953**	**-0.021006**	**-1.765487**	**-0.021019**	**-2.000362**
March	**-0.062243**	**-5.245132**	**-0.064154**	**-5.406829**	**-0.061947**	**-5.096067**
May	**-0.02660**	**-2.15244**	**-0.02621**	**-2.12676**	**-0.02681**	**-2.27849**

	8	**5**	**8**	**1**	**5**	**5**
June	**-0.046556**	**-4.163686**	**-0.046680**	**-4.126046**	**-0.047396**	**-4.054777**
July	**-0.024641**	**-2.227351**	**-0.024417**	**-2.198333**	**-0.025454**	**-2.210104**
August	**-0.037733**	**-3.235682**	**-0.038503**	**-3.314197**	**-0.038084**	**-3.161515**
September	**-0.030731**	**-2.614219**	**-0.030816**	**-2.852796**	**-0.030844**	**-2.602912**
October	**-0.032398**	**-3.087700**	**-0.032859**	**-3.002652**	**-0.032961**	**-2.891636**
November	**-0.056803**	**-4.749595**	**-0.057433**	**-4.760057**	**-0.057318**	**-5.228817**
December	**-0.019469**	**-1.770212**	**-0.020019**	**-1.782517**	**-0.019945**	**-1.913313**
θ_{-1}	**0.235683**	**3.812129**	**0.236737**	**4.153947**	**0.229696**	**4.244210**
θ_{-2}	**0.210502**	**3.357687**	**0.206334**	**3.296561**	**0.211747**	**3.569000**
θ_{-3}	**-0.003810**	**-0.221444**	**-0.011409**	**-0.283151**	**0.000202**	**0.008110**
Variance Equation						
ω	**0.000773**	**0.888787**	**0.000937**	**1.009939**	**-1.655720**	**-0.720601**
ARCH (α)	**0.239474**	**1.018006**	**0.114519**	**0.330537**	**0.236630**	**0.906744**
GARCH (β)	**0.495924**	**1.044966**	**0.223329**	**0.505324**	**-0.103118**	**-0.544332**

γ			**0.418141**	**0.827143**	**0.753848**	**2.064115**
Adj-R^2	**0.103608**		**0.101209**		**0.104308**	
AIC	**-3.190142**		**-3.180066**		**-3.160092**	
SIC	**-2.783227**		**-2.751734**		**-2.731760**	
LL	**235.9297**		**236.2445**		**234.8862**	
D.W	**2.084207**		**2.086711**		**2.071021**	

Table 6 shows that in the three examined models, the average monthly return of April is approximately 3.8% which is significant at 1 percent level of significance. This is consistent with the results from OLS regressions of 3.95% documented in Table 4. Also, the average monthly returns for all remaining months are negative which confirms the existence of April effect at MSM illustrated in Table 4. Moreover, AR(-1) and AR(-2) coefficients are significant at 1 percent level of significance. The ARCH variable is insignificant in the three models, which means that the returns on a particular day are unaffected by the errors on the previous day. The estimated GARCH term is insignificant implying that news about volatility from the previous period has no explanatory power on current volatility. Furthermore, the asymmetric (leverage) term is positive (0.753848) and significant in the TARCH model which indicates that negative shocks have a larger effect on volatility than positive shocks (Hill et al., 2007).

Discussions and Conclusion

The results of this paper suggest the existence of a calendar anomaly of month-of-the-year effect in MSM, which is April effect. April returns are at least two times higher than the best month in terms of returns in the year. This is consistent with Raj and Kumari (2006) having higher returns in April at the Indian stock exchange. November has the lowest average monthly returns followed by June and October. April effect is neither attributed to small size effect because MSM index is a free-float value-weighted index, nor to institutional investors trading behaviour on the aim of window dressing or tax-loss hypothesis. The existence of April effect can be explained by dividend month premium suggested by (Hartzmark and Solomon, 2013) who argue that dividends are the main cause of positive abnormal returns for firms in months when they are expected to pay dividends and attribute it to price pressure from dividend seeking investors.

The results of this paper are important for investors and researchers alike. Investors can exploit this calendar anomaly through developing a strategy that purchases stocks at the end of November and sell at the end of April. The large spread in returns between April and November and the low transaction costs of 0.0045 of value traded at MSM suggests that applying such strategy is profitable.

Researchers, on the other hand, need to consider April effect in portfolio construction, the evaluation of fund performance, as well as in asset pricing tests. The existence of April effect may be considered as a contradiction to the efficient markets hypothesis. This result is consistent with Jawad (2010) who find the MSM is weak-form inefficient but contradicts Al-Jafari (2012) who finds that MSM does not have day-of-the-week effect. However, Brooks (2014) warns that a calendar anomaly should not be seen as a contradiction to the efficient markets hypothesis unless the time varying nature of returns is explored. Hence, applying those tests on MSM using more recent data and on different time scales would be necessary and could be a venue for future research.

This paper neither explores the existence of April effect on individual stocks level nor does it examine the interaction between April effect and other stock market anomalies such as size effect. Those limitations are important questions that deserve further research.

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