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EMPIRICAL EVIDENCE OF CALENDAR ANOMALIES FOR THE EGYPTIAN STOCK MARKET

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Abstract *In this paper, we analyse prominent calendar anomalies for the Egyptian stock market. We also evaluate if there is any volatility clustering in the sample market and the reaction of volatility to positive and negative shocks (news) in the Egyptian stock market. The closing prices of ten indices of the Egyptian Stock Exchange have been examined over the period 2012-2019. The calendar anomalies pertaining to the day-of-the-week effect, Halloween effect, trading-month effect, and month-of-the-year effect have been analysed. Dummy variable regression technique is used to test the calendar anomalies. Further, the GARCH family of models, including GARCH-M and T-GARCH techniques have been utilised to test for the nature of volatility clustering. The results validate that day-of-the-week anomaly is strongly observed in the data. However, the other anomalies have not been observed. The results also confirm the presence of volatility clustering. The results finally show that negative shocks result in more volatility clustering than positive shocks. There has been little research pertaining to understanding the nature of volatility clustering for the Egyptian markets. Thus, to enrich the literature for the emerging markets and contribute to the area, we conduct a comprehensive study on calendar anomalies for the Egyptian market.*

Keywords: *Calendar Anomalies, Volatility Clustering, GARCH, T-GARCH, GARCH-M, Egypt, Market Efficiency*

INTRODUCTION

Understanding the behaviour of financial markets has been an area of interest not only for investors, but also for policymakers who can use this information for framing macroeconomic policies. One such aspect of financial markets pertains to studying assets' pricing, which is considered as a barometer for understanding the efficiency of the markets. Much of the asset pricing work emanated after the seminal study of Fama (1970) concerning efficiency of capital markets. Fama (1970) propounded that markets are efficient with regards to information and no one can exploit any historical, publicly published, and private information to obtain abnormal returns. However, post this work, there have been several studies that have questioned the efficiency of markets, and which have come out with various trading strategies that can be exploited to achieve abnormal returns. Such strategies are mostly based on exploiting market anomalies. These anomalies question the basic premise of the efficient market hypothesis. The financial anomalies can be broadly segregated into three categories, including fundamental anomalies, anomalies related to trading rules, and calendar anomalies. Fundamental anomalies are primarily related to fundamentals of a company that include the value anomaly (Stattman, 1980), net stock issues anomaly (Loughran & Ritter, 1995), and size anomaly (Banz, 1981), to name a few. Technical anomalies pertain to trading rules and include anomalies such as the momentum effect (Jegadeesh & Titman, 1993; Barroso et al., 2015). Finally, calendar anomalies are related to time and include several anomalies pertaining to the time in which trading occurs, like the day-of-the-week effect, Halloween effect, trading-month effect, and so on.

Calendar anomaly is an economic anomaly linked to a calendar (Khan et al., 2017; Singh & Yadav, 2019; Alekneviciene, 2021). The occurrence of a calendar anomaly indicates that markets behave differently at different times in a day, on different days of the week, on different months of the year, and various other temporal combinations. Such behaviour provides opportunities to the investors to create trading strategies resulting in abnormal returns. The calendar anomalies can be categorised into five broad categories, including the day-of-the-week effect (Cross, 1973; Kayacetin & Lekpek, 2016), the month-of-the-year effect (Rozeff & Kinney, 1976; Ariss et al., 2011), the mid-year effect (Jaisinghani, 2016), the Halloween effect (Fields, 1934; Guan & Saxena, 2015) and the trading-month effect (Ariel, 1987).

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Initial studies on calendar anomalies were done for the developed markets (Fields, 1934; Gibson & Hess, 1981) that mostly supported the existence of calendar anomalies in various matured markets. Later, research on the issue was extended to the developing markets (Gao & Kling, 2005; Kayacetin & Lekpek, 2016). However, such studies for emerging markets are limited and do not cover all the emerging markets (Tadepalli & Jain, 2018). In a comprehensive literature review, Tadepalli and Jain (2018) study four major calendar anomalies, which were published in 112 noteworthy papers from multiple databases. They find that the anomalies that were persistent in developed markets in yester years have become insignificant in more recent data. Their study suggests that there is a lot of empirical evidence with regards to calendar anomalies for the developed markets; however, very few evidences are found for the emerging markets, including markets in Africa.

There have been very few studies conducted for the Egyptian markets that pertain to calendar anomalies. Besides, a majority of such studies have focused on analysing the day-of-the-week effect (Aly et al., 2004; Khatayebh, 2017) and have focused mainly at the aggregate market level, leaving sufficient scope to test them on sectoral indices. Besides, there has been no systematic study to understand the nature of volatility clustering in the Egyptian markets.

Thus, to enrich the literature for emerging markets and contribute to the area, we conduct a comprehensive study on calendar anomalies for the Egyptian market. The key objective of the present study is to examine four different calendar anomalies, namely the day-of-the-week effect, the month-of-the-year effect, the Halloween effect, and the trading-month effect, for the Egyptian stock markets. The study also aims to observe volatility clustering for the Egyptian markets. Finally, the study analyses whether negative shocks (news) cause more volatility than shocks related to positive news.

The organisation of the study is as follows: Section 2 deals with the review of literature. Estimation techniques are provided in section 3, while in section 4, empirical results are discussed. The last section presents a discussion of the key results, followed by conclusions.

LITERATURE REVIEW

A brief review of literature pertaining to major calendar anomalies frequently tested for both developed and emerging markets is provided in this section.

The Day-of-the-Week Effect

The day-of-the-week effect, popularly termed as the Monday effect or the Weekend effect, is a phenomenon mostly observed in the stock markets of matured economies. The anomaly suggests that, in a week, Monday's returns are significantly lower than the preceding Friday's returns. The effect varies from country to country. The effect was first observed by Cross (1973) for American markets, and later, by many investigators (French, 1980; Lakonishok & Smidt, 1988). In the last one-and-a-half decades, researchers have observed the disappearance of the day-of-the-week effect across various markets (Sullivan & Liano, 2003; Blau et al., 2009; Mensah et al., 2016; Du Toit et al., 2018). They argue that because of short-selling phenomena, release of information, and impact of institutional investors, this effect has disappeared. Some of the prominent reasons given in literature for negative Monday effects have been lack of availability of analysts' reports on Mondays, lack of institutional trading, higher selling pressure on the first trading day of the week to have enough reserves for the remaining days, and the announcement patterns of negative earnings results on Fridays.

The Month-of-the-Year Effect

The month-of-the-year (MOY) anomaly is described as the abnormal behaviour of stock returns mainly in January. It was first officially stated by Rozeff and Kinney (1976). Post that there have been many studies done to understand the monthly seasonality present in stock returns (Branch, 1977; Reinganum, 1983). The prime argument generally provided for MOY is that loss-making securities are sold at year end to offset losses against income, popularly called as Tax Loss Selling Hypothesis. In the new year, investors start buying stocks again, which results in positive January returns. In later studies, many researchers argued that the January effect is mainly found in small stocks (Tinic et al., 1987). Jacob and Levvy (1987) discussed various explanations for the January effect. They stated that the various reasons could be tax loss selling hypothesis, window dressing hypothesis (investors take long positions in profitable shares while taking short positions in non-profitable shares in December, so that loss-making companies can be taken off the financial statements while preparing the final reports), and parking of proceeds hypothesis. The January effect was tested in later studies, either individually or jointly (Ritter, 1988; Haug & Hirschey, 2006). In recent years, there has been literature found outside the US markets for the January effect (Gao & Kling, 2005; Kayacetin & Lekpek, 2016). Instead of the

January effect, different months were observed in different countries; for example, post-February effect was observed in China, as February is the fiscal year-end (Gao & Kling, 2005). Similarly, Ariss et al. (2011) observe the absence of the December effect for Middle-East countries, which is the month of Ramadan. Kayacetin and Lekpel (2016) find the January effect in the Turkish market.

The Halloween Effect

The Halloween effect implies that stock returns in different markets differ not only on different days of the week or months of the year, but also during different climatic conditions. The effect, first recognised by Bouman and Jacobsen (2002), states that returns observed in the winters are higher than those observed in summers. This effect has been observed for several developed markets of the world (Jacobsen & Visaltanachoti, 2009; Swinkles & Van-Vliet, 2012). Bouman and Jacobsen (2002) observed returns in 37 countries to investigate this effect and found the presence of such an effect (also known as "sell in May" effect) mainly in developed markets belonging to the European countries. Jacobsen and Visaltanchoti (2009) observe the presence of Halloween effect for the US markets for a period from 1926-2006. Haggard and Witte (2010) observe that even the January effect control does not diminish the presence of the Halloween effect. Swinkels and Van Vliet (2012) test five calendar anomalies, including the Halloween effect, and observe very strong Halloween effect. Jacobsen and Zhang (2013) find strong presence of the Halloween effect in the UK markets. There have been few studies which claim that this effect is merely a sample phenomenon and profitable trading strategies cannot be formed using it (Maberly & Pierce, 2003; Dichtl & Drobetz, 2014).

The Trading-Month Effect

Apart from the anomalies discussed above, another prominent anomaly being tested in literature is the trading-month effect, also known as the semi-month effect. It was tested first by Ariel (1987), who finds that mean daily returns during the first half of the month exceed those in the second-half of the month. The study also indicates that the strength of the trading month was in line with the day-of-the-week effect. Jacobs and Levy (1988) give economic rationale to the trading-month effect and some of the reasons provided are portfolio rebalancing and the release of earnings reports by various companies. Pettengill and Jordan (1988) acknowledged the presence of trading-month effect both for large and small capitalisation firms.

Volatility Clustering

In addition to knowing the returns patterns, it is important to understand if there are any patterns in volatility as well. Since volatility proxies for risk, it would be interesting to understand these patterns, as portfolio managers tend to understand risk before forming trading strategies on anomalies (Sen, 2014; Wadhwa, 2015; Desai, 2021). So, understanding the nature of volatility clustering would be essential in addition to understanding calendar anomalies. Volatility clustering has been tested in prior literature (Esman-Nyamongo & Misati, 2010; Holden et al., 2005). Tsoukalas (2000) investigates volatility clustering in Japan, the U.S., and the UK by deploying Autoregressive Conditional Heteroscedasticity (ARCH) model and finds strong evidence in support of volatility clustering. Tai (2002) analyses time-varying risk premiums in forex markets of four Asia-Pacific countries by deploying GARCH-M technique and observes the presence of time-varying risk premiums in these countries. Karmakar (2007) finds the presence of volatility clustering. Similarly, there have been studies using the GARCH-M technique to test volatility clustering (Lee & Koray, 1994; Fang et al., 2008; Guidi et al., 2001).

In contrast to the preceding studies, there is limited literature available for calendar anomalies pertaining to the Egyptian markets. Aly et al. (2004) investigate day-of-the-week effect in the Egyptian market and observe no seasonal patterns in day-of-the-week effect. Alagidede (2009) did not find any day-of-the-week effect for the Egyptian markets. Cifuentes and Cordoba (2013) find weak day-of-the-week effect among CIVETS countries, which includes Egypt. Akhter et al. (2015) find Zul-Hijjah[1] effect for markets in six Islamic countries, including the Egyptian market. Khatayebh (2017) investigates the day-of-the-week, month-of-the-year, and the Holy Month of Ramadan effect for Jordan and Egyptian markets. The author finds month-of-the-year effect and Holy Month of Ramadan effect for the Egyptian markets. However, no day-of-the-week effect and volatility effect were observed for the Egyptian markets. Gharaibeh (2017) finds significant January effect in Egyptian markets. Lobao (2018) analyses six African markets and finds positive Friday effect and January effect for the Egyptian markets. However, the author finds weak relationships for half of the months and Halloween effect, and observes half-yearly seasonality patterns.

[1] Zul-Hijjah is the twelfth month according to the Islamic calendar. The month is considered to be very sacred and pious. This is also the month in which the popular pilgrimage of the Hajj takes place.

DATA AND METHODOLOGY

Data

Closing prices of the 11 different indices of the Egyptian Stock Exchange are obtained from the Emerging Market Information Services (EMIS) database. Table 1 presents the indices selected, the type of index, period of the study, and the final tally of observations. Besides, the table also presents the descriptive statistics for the sample indices. Results indicate that the highest daily average returns are generated by the Basic Resources Index and the lowest daily average returns are generated by the Construction and Materials Index.

Calendar Anomalies Analyses

The present study analyses major calendar anomalies for various indices of the Egyptian Stock Exchange. These anomalies have been tested using dummy variable regression analysis. Moreover, it is usually observed that the closing prices are non-stationary in their base forms. Hence, the regression technique has been conducted on the log-differenced price series. Thus, the dummy variables provide differences in returns across different periods. The general form of calculating the return series is provided by the following equation.

$$\Pi_{it} = \ln(P_{it}) - \ln(P_{it-1}) \quad (1)$$

Where, Π_{it} indicates the continuous compounded rate of return for the index 'i' and date 't'. Similarly, P_{it} and $P_{it} - 1$ signify the closing index values on date t and t−1, respectively. The return series has been exposed to various forms of calendar anomalies. These anomalies have been tested using the dummy variable regression technique. The baseline regression is as follows:

$$\Pi_{i,t} = \Phi + \lambda_2 D_2 + \lambda_3 D_3 + \cdots + \lambda_k D_k + \mu \quad (2)$$

In equation (2), $\Pi_{i,t}$ implies the continuous compounded rate of return on series 'i' for the time period 't'. Φ represents

Table 1: Descriptive Statistics

Index	Type	Start Date	End Date	Observations	Mean	Median	Maximum	Minimum	Std. Dev.
EGX Basic Resources	Sectoral	10 January 2012	05 July 2018	1567	0.0012	0.0008	0.1417	−0.1470	0.0228
EGX Construction and Materials	Sectoral	10 January 2012	05 July 2018	1561	0.0000	0.0002	0.0838	−0.0998	0.0150
EGX Food and Beverage	Sectoral	10 January 2012	05 July 2018	1559	0.0007	0.0002	0.0945	−0.1021	0.0161
EGX Financial	Sectoral	10 January 2012	05 July 2018	1564	0.0005	0.0007	0.0886	−0.1095	0.0174
EGX Healthcare	Sectoral	10 January 2012	05 July 2018	1561	0.0009	0.0001	0.0836	−0.1011	0.0162
EGX Industrial	Sectoral	10 January 2012	05 July 2018	1560	0.0008	0.0007	0.0834	−0.0840	0.0159
EGX Personal	Sectoral	10 January 2012	05 July 2018	1565	0.0011	0.0009	0.0690	−0.0756	0.0139
EGX Real Estate	Sectoral	10 January 2012	05 July 2018	1562	0.0010	0.0015	0.1106	−0.1155	0.0198
EGX S&P Quote	Broad Market	10 January 2012	05 July 2018	1553	0.0009	0.0014	0.1042	−0.1923	0.0186
EGX Telecommunications	Sectoral	10 January 2012	05 July 2018	1564	0.0004	0.0002	0.0909	−0.1153	0.0184
EGX Travel and Leisure	Sectoral	10 January 2012	05 July 2018	1556	0.0005	0.0007	0.0976	−0.1180	0.0213

In this table, we present the list of sample indices, the time period, and their descriptive statistics.

mean return obtained for the omitted category, that is, the category for which the dummy variable has not been defined.[2] Moreover, λ_2 denotes the difference between the mean return of the omitted category and the category with the dummy variable D_2.

The generic form of the dummy variable can be modified for testing different calendar anomalies. The following set of equations describe the estimation of the four calendar anomalies that have been tested in the current study.

$$\Pi_{i,t} = \Phi + \lambda_2 Monday_i + \lambda_3 Tuesday_i + \cdots + \lambda_5 Thursday_i + \mu \quad (3)$$

Equation (3) describes the functional form for examining the day-of-the-week effect. The Egyptian Stock Exchange functions from Sunday till Thursday. Here, Sunday has been considered the base category. Thus, Φ represents the mean return obtained on Sundays. Besides, λ_2 to λ_5 describe the difference between the mean return on Sunday and that on other days.

Continuing the same logic, the functional form for the remaining three anomalies, that is, the month-of-the-year effect, the Halloween effect, and the trading-month effect, can be described by the following three equations, respectively.

$$\Pi_{i,t} = \Phi + \lambda_2 February_i + \lambda_3 March_i + \cdots + \lambda_{12} December + \mu \quad (4)$$

$$\Pi_{i,t} = \Phi + \lambda_2 Hallowee_i + \mu \quad (5)$$

$$\Pi_{i,t} = \Phi + \lambda_2 First\_Fortnight_i + \mu \quad (6)$$

January, summer months, and the second fortnight represent the omitted categories for equation (4), equation (5), and equation (6), respectively. Ordinary Least Squares (OLS) technique was deployed to generate the results.

Analysing Volatility Clustering

In addition to studying the different calendar effects, it is also pertinent to analyse how volatility of returns behaves across different periods. This can be achieved through analysing the properties of the error terms contained in a time series. The most widely adopted model is the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model. The GARCH model estimates the variance of the error terms as a function of past variances. The GARCH model is an extension of the basic Autoregressive Conditional Heteroscedasticity (ARCH) model in which the variance of the error terms are modelled as a function of the squared term of the lagged residuals. The generic form of a GARCH model can be expressed in a functional form, as presented in equation (7).

$$\sigma_{it}^2 = \lambda_0 + \sum_{i=1}^{k} \lambda_i e_{t-i}^2 + \sum_{i=1}^{l} \theta_i \sigma_{t-i}^2 \quad (7)$$

Equation (8) presents the variance equation consisting of a GARCH term of order 'l' and an ARCH term of order 'k'. The estimation process in higher-order ARCH and GARCH terms is quite involved, and hence, only the first order of these two terms are estimated in the current study. Thus, the final model adopted is a GARCH (1, 1) model. The final model can be described by the following functional form.

$$\sigma_{it}^2 = \lambda_0 + \lambda_1 e_{t-1}^2 + \theta_1 \sigma_{t-1}^2 \quad (8)$$

The GARCH model presents the influence of past volatility on current volatility. Therefore, the statistical significance of the GARCH term provides empirical evidence supporting volatility clustering. However, evidence supporting volatility clustering is not sufficient to understand what kinds of events cause more volatility. Hence, it becomes essential to analyse volatility clustering across positive and negative shocks. In other words, it is important to understand whether negative news leads to more volatility, compared to positive news. This can be efficiently handled by deploying the Threshold GARCH (T-GARCH) technique. The baseline form of a T-GARCH model is presented in equation (9).

$$\sigma_{it}^2 = \lambda_0 + \lambda_1 e_{t-1}^2 + \gamma_1 e_{t-1}^2 d_{t-1} + \theta_1 \sigma_{t-1}^2 \quad (9)$$

In equation (9), apart from the usual ARCH and GARCH terms, an additional term $e^2_{t-1} d_{t-1}$ has been introduced. This term is the threshold term and contains a multiplicative dummy. The coefficient of the threshold term γ_1 indicates whether positive or negative shocks cause more volatility. Dummy represents an indication function for negative shock. Hence, a positive and significant coefficient of γ_1 indicates that negative shocks lead to more volatility than positive shocks. The following section presents the results of various analyses.

EMPIRICAL RESULTS

Testing Calendar Anomalies

To test the calendar anomalies, we first test for the existence of the day-of-the-week effect for all the 11 sectors of the Egypt economy separately. The day-of-the-week effect is tested using equation (3). Day-of-the-week effect results are reported in Table 2. The coefficient of Sunday shows the average return on Sundays. Similarly, the coefficients of the remaining days show the difference between the average

[2] This is usually done to avoid the problem of perfect multicollinearity that arises, by considering equal number of dummies as there are categories. Hence, the dummy variable is not considered for one of the categories. This category in question is called the omitted category of the base category.

return on Sunday and that day. Table 2 clearly shows that there is a significant day-of-the-week effect in the Egyptian market. Six of the 11 indices report significant negative returns on Sundays. Further, since Sunday is the first day of the trading week in Egypt, it is similar to Monday in other countries. Hence, the results are like the Monday effect generally observed in other countries.

The analysis of the coefficients of other days also highlights certain key points. It is observed that most of the other days have positive coefficients. Hence, it is clear that Sundays have the minimum average returns. Further, it is observed that Tuesdays have the highest positive coefficients. The coefficients of Tuesdays are significant for all the 11 indices. The possible reasons for the negative Sunday effect for the Egypt market could be lack of availability of analysts' reports on Sundays, lack of institutional trading, more selling pressure on Sundays to have enough funds for other days, and the announcement of negative and below-expected results happening on Thursdays, which may cause the Sunday returns to be negative.

Next, we evaluate month-of-the-year effect, Halloween effect, and trading-month effect. These three effects are verified, respectively, by deploying equations (4), (5), and (6). The results for the month-of-the-year effect, Halloween effect, and the trading-month effect are presented in Tables 3, 4, and 5, respectively. We find no significant results for the three anomalies, implying absence of month-of-the-year, Halloween effect, and trading-month effect in the Egyptian markets. Our results conform to previous research

Table 2: Day-of-the-Week Effect Results

Index	Day	Sunday	Monday	Tuesday	Wednesday	Thursday	F-Value
EGX Basic Resources	Coefficient	−0.0010	−0.0001	0.0045	0.0025	0.0038	2.7268
	p-value	0.4608	0.9321	0.0067***	0.1451	0.0304**	0.0130**
EGX Construction and Materials	Coefficient	−0.0017	0.0013	0.0032	0.0021	0.0022	1.9138
	p-value	0.0833*	0.2896	0.0091***	0.0852*	0.0826*	0.0959*
EGX Food and Beverage	Coefficient	−0.0026	0.0023	0.0046	0.0043	0.0050	5.1648
	p-value	0.0079***	0.0826*	0.0004***	0.0004***	0.0001***	0.0003***
EGX Financial	Coefficient	−0.0019	0.0015	0.0037	0.0024	0.0047	3.4653
	p-value	0.079*	0.2749	0.0061***	0.0774*	0.0006***	0.0059***
EGX Healthcare	Coefficient	−0.0033	0.0034	0.0054	0.0046	0.0076	9.3563
	p-value	0.0032***	0.0314**	0.0001***	0.0017***	0.0000***	0.0000***
EGX Industrial	Coefficient	−0.0016	0.0022	0.0033	0.0023	0.0043	3.0805
	p-value	0.1091	0.06*	0.0076***	0.0607*	0.0004***	0.0096***
EGX Personal	Coefficient	−0.0006	0.0001	0.0025	0.0019	0.0039	4.5909
	p-value	0.4926	0.9611	0.0144**	0.0752*	0.0001***	0.0002***
EGX Real Estate	Coefficient	−0.0021	0.0013	0.0052	0.0039	0.0051	4.3368
	p-value	0.0817*	0.3842	0.0006***	0.0144**	0.0006***	0.0017***
EGX S&P Quote	Coefficient	−0.0036	0.0048	0.0062	0.0033	0.0084	8.9742
	p-value	0.004***	0.004***	0.0000***	0.0275**	0.0000***	0.0000***
EGX Telecommunications	Coefficient	−0.0019	0.0014	0.0038	0.0026	0.0038	2.4438
	p-value	0.0788*	0.2973	0.0079***	0.0844*	0.0044***	0.0239**
EGX Travel and Leisure	Coefficient	−0.0003	−0.0014	0.0043	−0.0007	0.0019	3.6772
	p-value	0.8016	0.3967	0.0083***	0.6762	0.2232	0.0005***

Table 2 displays the results of the day-of-the-week effect for all the indices. The constant term represents the mean returns obtained on Sundays. The coefficient of all other days (i.e. Monday to Thursday) represents the difference between the mean returns on Mondays and on that particular day. The F-statistics is used to determine whether the mean returns on all the days are significantly different or not. The Newey-West robust estimates are used to find the results. *, **, and *** are significant at 10, 5, and 1 per cent levels, respectively.

on the Egyptian markets that have observed no significant Halloween effect or trading-month effect (Khatayebh, 2017; Gharaibeh, 2017; Lobao, 2018). However, contrary to many previous studies, we find no significant month-of-the-year effect during the study period. To sum up, we observe that only the day-of-the-week effect is a significant calendar anomaly present.

Testing Volatility Clustering

In the next stage, we evaluate volatility clustering for sample indices. The existence of volatility clustering has been observed in three stages. First, by using the GARCH model, which shows whether there is volatility clustering or not. Second, by deploying the Threshold GARCH (T-GARCH) model, which reveals whether negative and positive shocks

Table 3: Month-of-the-Year Effect Results

Month	January	February	March	April	May	June	July	August	September	October	November	December	F-Value
Coef-ficient	0.0034	−0.0024	−0.0017	−0.0035	−0.0063	−0.0059	−0.0014	0.0000	0.0001	−0.0044	−0.0021	0.0020	1.6462
p-value	0.2735	0.5408	0.6778	0.3100	0.0703*	0.1280	0.7163	0.9907	0.9889	0.2364	0.6577	0.6373	0.2224
Coef-ficient	0.0003	0.0005	0.0001	−0.0002	−0.0017	−0.0008	0.0011	−0.0007	−0.0005	−0.0009	−0.0009	0.0005	0.3505
p-value	0.8192	0.8067	0.9644	0.9163	0.3603	0.7221	0.5331	0.6956	0.7562	0.6564	0.7066	0.8184	0.9439
Coef-ficient	0.0023	−0.0025	−0.0023	−0.0015	−0.0014	−0.0045	−0.0022	−0.0037	−0.0009	−0.0006	−0.0007	0.0017	1.3760
p-value	0.1809	0.3455	0.3136	0.4303	0.5166	0.0562**	0.3426	0.091*	0.6572	0.8097	0.8123	0.4448	0.3098
Coef-ficient	0.0021	−0.0011	−0.0005	−0.0028	−0.0034	−0.0047	0.0004	−0.0030	−0.0006	−0.0001	−0.0024	−0.0001	1.2024
p-value	0.3422	0.7004	0.8669	0.2965	0.1977	0.1295	0.8817	0.2857	0.8286	0.9708	0.4537	0.9756	0.5826
Coef-ficient	−0.0007	0.0026	0.0007	0.0019	−0.0002	0.0022	0.0023	0.0016	0.0002	0.0028	0.0016	0.0037	0.7375
p-value	0.5097	0.0515**	0.6086	0.2164	0.9261	0.1297	0.1900	0.3012	0.8990	0.0737*	0.4564	0.0418**	0.4121
Coef-ficient	0.0025	−0.0025	−0.0007	−0.0029	−0.0036	−0.0042	−0.0014	−0.0022	0.0014	−0.0008	−0.0019	−0.0006	1.3002
p-value	0.2920	0.3543	0.8004	0.2986	0.1641	0.1234	0.6247	0.4598	0.6041	0.7614	0.5908	0.8439	0.1508
Coef-ficient	0.0019	0.0020	−0.0023	−0.0035	−0.0029	−0.0032	0.0002	−0.0014	0.0027	−0.0006	−0.0012	0.0021	3.0850
p-value	0.3323	0.4287	0.3433	0.1057	0.2396	0.1800	0.9324	0.5631	0.2811	0.8105	0.7135	0.3321	0.002208***
Coef-ficient	0.0015	0.0004	0.0005	−0.0011	−0.0021	−0.0035	0.0002	−0.0003	0.0010	−0.0004	−0.0020	0.0015	0.7176
p-value	0.5496	0.9027	0.8832	0.7267	0.4677	0.2881	0.9465	0.9308	0.7477	0.9107	0.5880	0.6254	0.8360
Coef-ficient	0.0025	−0.0014	−0.0006	−0.0030	−0.0028	−0.0043	0.0002	−0.0023	−0.0001	−0.0017	−0.0023	−0.0004	0.7597
p-value	0.2028	0.5797	0.8204	0.2087	0.2413	0.1040	0.9514	0.3694	0.9555	0.5136	0.4822	0.8753	0.5952
Coef-ficient	0.0032	−0.0032	−0.0016	−0.0049	−0.0046	−0.0063	0.0004	−0.0031	−0.0041	−0.0020	−0.0030	0.0000	1.7487
p-value	0.2704	0.3424	0.6286	0.1569	0.1487	0.0725*	0.9065	0.3560	0.1738	0.5431	0.4046	0.9940	0.1676
Coef-ficient	0.0031	−0.0007	−0.0024	−0.0034	−0.0054	−0.0062	0.0007	−0.0034	−0.0010	−0.0035	−0.0047	−0.0008	1.4262
p-value	0.2079	0.8276	0.4801	0.3090	0.0767*	0.1044	0.8485	0.2422	0.7739	0.2958	0.2194	0.8118	0.5166

Table 3 displays the results of the month-of-the-year effect for all the indices. The constant term represents the mean returns obtained on Sundays. The coefficient of all other days (i.e. Monday to Thursday) represents the difference between the mean returns on Mondays and on that particular day. The F-statistics is used to determine whether the mean returns on all the days are significantly different or not. The Newey-West robust estimates are used to find the results. *, **, and *** are significant at 10, 5, and 1 per cent levels, respectively.

cause dissimilar volatility. Finally, the GARCH-in-Mean (GARCH-M) model, which is used to check whether the volatility term is present in the mean equation.

The results for the three volatility clustering tests are presented in Table 6. As shown in Table 6, the GARCH effect is significant for all the 11 indices. This clearly indicates a strong presence of volatility clustering for the Egyptian stock market. The results imply that there are prolonged periods of high volatility which subsequently are followed by periods of low volatility. This signifies that there are asymmetries in the way the investors absorb information.

Table 4: Halloween Effect Results

Index	Month	Constant	Halloween	F-Value
EGX Basic Resources	Coefficient	0.0002	0.0018	2.5533
	p-value	0.8290	0.2138	0.2138
EGX Construction and Materials	Coefficient	−0.0003	0.0006	0.6458
	p-value	0.6184	0.4546	0.4546
EGX Food and Beverage	Coefficient	0.0000	0.0013	2.5840
	p-value	0.9948	0.1650	0.1650
EGX Financial	Coefficient	0.0001	0.0009	1.0383
	p-value	0.9105	0.4096	0.4096
EGX Healthcare	Coefficient	0.0008	0.0003	0.0997
	p-value	0.1294	0.7149	0.7149
EGX Industrial	Coefficient	0.0006	0.0005	0.3742
	p-value	0.3425	0.6106	0.6106
EGX Personal	Coefficient	0.0009	0.0005	0.4532
	p-value	0.1561	0.6179	0.6179
EGX Real Estate	Coefficient	0.0006	0.0009	0.7376
	p-value	0.4952	0.4708	0.4708
EGX S&P Quote	Coefficient	0.0006	0.0007	0.4871
	p-value	0.3532	0.4948	0.4948
EGX Telecommunications	Coefficient	−0.0002	0.0013	1.9338
	p-value	0.7254	0.2409	0.2409
EGX Travel and Leisure	Coefficient	−0.0001	0.0012	1.3363
	p-value	0.8987	0.3687	0.3687

Table 4 displays the results of the mid-year effect for all the indices. The constant term represents the mean returns obtained during the months January to June. The coefficient of the dummy variable D (second_half) represents the difference between the mean returns during the first-half and second-half (July-December) of the year. The F-statistics is used to determine whether the mean returns across the two categories are significantly different or not. The Newey-West robust estimates are used to estimate the results. *, **, and *** are significant at 10, 5, and 1 per cent levels, respectively.

Table 5: Trading-Month Effect Results

Index	Month	Constant	TM	F-Value
EGX Basic Resources	Coefficient	0.0009	0.0004	0.1330
	p-value	0.2882	0.7594	0.7594
EGX Construction and Materials	Coefficient	−0.0002	0.0005	0.4974
	p-value	0.6877	0.4957	0.4957
EGX Food and Beverage	Coefficient	−0.0001	0.0016	4.0181
	p-value	0.8337	0.0769*	0.0769*
EGX Financial	Coefficient	0.0010	−0.0010	1.3036
	p-value	0.1164	0.3096	0.3096

Index	Month	Constant	TM	F-Value
EGX Healthcare	Coefficient	0.0009	−0.0001	0.0076
	p-value	0.0650	0.9226	0.9226
EGX Industrial	Coefficient	0.0006	0.0005	0.3595
	p-value	0.3107	0.6046	0.6046
EGX Personal	Coefficient	0.0009	0.0004	0.2532
	p-value	0.1261	0.6802	0.6802
EGX Real Estate	Coefficient	0.0010	0.0001	0.0030
	p-value	0.1810	0.9599	0.9599
EGX S&P Quote	Coefficient	0.0009	0.0001	0.0208
	p-value	0.1292	0.8815	0.8815
EGX Telecommunications	Coefficient	0.0009	−0.0010	1.0716
	p-value	0.2307	0.3779	0.3779
EGX Travel and Leisure	Coefficient	0.0007	−0.0004	0.1285
	p-value	0.4261	0.7571	0.7571

Table 5 displays the results of the mid-year effect for all the indices. The constant term represents the mean returns obtained during the second fortnight. The coefficient of the dummy variable D (first_fortnight) represents the difference between the mean returns for the first fortnight and the second fortnight. The F-statistics is used to determine whether the mean returns across the two categories are significantly different or not. The Newey-West robust estimates are used to estimate the results. *, **, and *** are significant at 10, 5, and 1 per cent levels, respectively.

Table 6: Volatility Effect Results

Index	Day	ARCH	T-GARCH	GARCH	M-GARCH
EGX Basic Resources	Coefficient	0.1106	0.0482	0.8063	2.4327
	p-value	0.000***	0.0005***	0.000***	0.0426**
EGX Construction and Materials	Coefficient	0.0840	0.0867	0.7002	0.8930
	p-value	0.000***	0.0007*	0.000***	0.5993
EGX Food and Beverage	Coefficient	0.1750	−0.0139	0.7352	2.5219
	p-value	0.000***	0.5536	0.000***	0.1393
EGX Financial	Coefficient	0.0823	0.0955	0.7926	3.5630
	p-value	0.000***	0.000***	0.000***	0.0252**
EGX Healthcare	Coefficient	0.0959	0.0510	0.6988	4.6060
	p-value	0.000***	0.0246**	0.000***	0.0023
EGX Industrial	Coefficient	0.1565	0.0591	0.6495	4.1865
	p-value	0.000***	0.0304**	0.000***	0.013**
EGX Personal	Coefficient	0.1488	0.0058	0.6571	5.5731
	p-value	0.000***	0.8155	0.000***	0.004***
EGX Real Estate	Coefficient	0.0704	0.0883	0.8438	3.6896
	p-value	0.000***	0.000***	0.000***	0.0064*
EGX S&P Quote	Coefficient	0.1868	0.1162	0.6975	4.1209
	p-value	0.000***	0.000***	0.000***	0.0004***
EGX Telecommunications	Coefficient	0.1422	0.0577	0.7955	1.6330
	p-value	0.000***	0.0007***	0.000***	0.2144
EGX Travel and Leisure	Coefficient	0.1081	0.0651	0.7294	2.2212
	p-value	0.000***	0.0069*	0.000***	0.0756*

The table presents the results of three different tests of volatility, including the GARCH effect, the T-GARCH effect, and the GARCH-M effect. *, **, and *** represent significance at 10 per cent, 5 per cent, and 1 per cent levels, respectively.

However, mere knowledge of volatility clustering does not indicate whether that clustering is because of positive or negative news. To differentiate between the impact of positive and negative news, we next apply the T-GARCH model. The T-GARCH coefficients are positive and significant for all the indices except for Food & Beverage and Personal indices. The positive sign of the T-GARCH coefficient indicates that negative shock causes more volatility compared to positive shocks. This implies that Egyptian investors react more to negative news compared to positive news. Thus, negative (positive) news causes higher (lower) volatility. This also implies that the price decline due to negative news is much more than the price rise due to positive news.

Finally, we apply the GARCH-M model to check the presence of volatility in the mean equation. The results of the GARCH-M model reveal that the coefficients of nine out of 11 indices are positive and significant. This proves that positive day-of-the-week returns are accompanied by positive risk premiums. Thus, the results indicate that there are certain investors who are awarded due to the abnormal returns on a few days. However, they demand more returns to counter the excess risk on these particular days. In a nutshell, we observe the presence of strong volatility clustering in the Egyptian markets. We also find that volatility clustering is caused more by negative shocks than by positive news. Finally, we find that the positive risk premiums are being demanded to generate higher expected returns.

DISCUSSION AND CONCLUSION

In recent times, the debate on market efficiency has been extended to studying patterns in returns across different calendar combinations. The study examines the major calendar anomalies of the Egyptian Stock Exchange. The study also evaluates the nature of volatility clustering and the various patterns in volatility. We chose 11 indices of the Egyptian Stock Exchange, from January 2010 to July 2018. The data has been collected from the Emerging Market Information Services Database.

We test the calendar anomalies for various indices using dummy variable regression results. The results divulge significant day-of-the-week effect for the Egyptian indices. Specifically, Sundays provide significant negative returns for most of the indices. The Sunday effect for the Egyptian market is akin to the Monday effect of the other countries, as Sunday is the first trading day of the week in Egypt. We further find positive returns for the next four working days of the week. Next, we evaluate the Halloween effect, trading-month effect, and the month-of-the-year effect for the Egyptian markets. All these effects were found to be insignificant for Egypt.

Next, we check volatility clustering using GARCH, T-GARCH, and GARCH-M models. We observe the presence of significant GARCH effect for all sample indices, which indicates the presence of volatility clustering for the Egyptian stock market. Further, the results of the T-GARCH model reveal that negative news causes more volatility clustering compared to positive news. Finally, we apply the GARCH-M model to check for the presence of volatility terms in the mean equation. We find that nine out of the 11 indices report significant and positive GARCH-M coefficients. This indicates that the higher returns are also coupled with higher risk premiums.

The current study has certain important implications for investors as well as regulators. The finding of significant day-of-the-week effect suggests that investors can devise trading strategies to obtain abnormal returns. Specifically, it is observed that Sundays provide the maximum negative returns and Tuesdays provide the maximum positive returns. Hence, investors can device the trading strategy of buying (going long) on Sundays and selling (going short) on Tuesdays. This can be highly beneficial for high volume and institutional investors who buy and sell in bulk.

Any microstructure issues or regulatory inefficiencies caused by different calendar effects can be examined by the regulators. This knowledge can help regulators frame policies that foster better price discovery on all trading days of the week. Studies that negative news causes more volatility compared to positive news can also be effectively exploited to frame appropriate policies. For instance, the timings of news flow, especially the negative news, can be changed. This can be done by announcing the news during the non-trading hours.

There can be several extensions to the current study. One of the areas could be checking calendar anomalies for several other asset classes, such as commodity or currency. The precise cause of the negative Sunday effect and positive Tuesday effect have not been identified. Further, the results of the current study can be validated for other emerging markets to add to the existing literature.

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