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Do seasonal anomalies still persist? Empirical evidence post-global financial crisis

Muskan Kaur
Faculty of Management Studies, University of Delhi, New Delhi, India
Email: Muskankaur1306@gmail.com

Dinesh Jaisinghani
Fortune Institute of International Business, New Delhi, India

Mahesh Ramalingam
Institute of Management Technology (IMT), Hyderabad, India

Abstract

The present study examines the presence of seasonal anomalies and volatility clustering in the Malaysian securities market in the post-global financial crisis period. An analysis has been performed for 11 different broad and sectoral indices of the Bursa Malaysia stock exchange. The time frame of one decade post the global financial crisis, that is, from 2009 to 2018, has been chosen for the empirical analysis. The results provide strong support for the existence of the presence of the day-of-the-week effect and the trading-month effect for the Malaysian market. However, there is weak evidence supporting the month-of-the-year effect. The results further highlight significant volatility clustering for the Malaysian market. Moreover, it is also observed that negative shocks generate higher volatility in the Malaysian market, as compared to positive shocks. The overall results confirm that the Malaysian market is not weak-form efficient in the post-global financial crisis period.

Keywords: *Seasonal Anomalies; Malaysia; Emerging Economies; Volatility Clustering; T-GARCH; GARCH-M*

Introduction

Efficiency of the financial markets is one of the most researched topics in the field of finance (Fama, 1965; Tuyon & Ahmad, 2016). Efficiency can be studied from various angles such as operational efficiency (Dimson & Mussavian, 1998; Seddighi & Nian, 2004), transaction efficiency (Gay & Jung, 1999; Liu, 2007), and information efficiency (Fama, 1965; Summers, 1986; Jaisinghani, 2016). Information efficiency is also often termed price efficiency. The proponents of information efficiency claim that markets are efficient when the prices incorporate all available public information. Fama (1965), in his seminal study, argues that markets are efficient in terms of price- and hence no trading strategy can generate abnormal returns in the long run. Many researchers define abnormal returns in terms of "excess" returns, over and above some anticipated benchmark return, generated by a particular stock or an index over a particular period of time (Brav et al., 2000; Truong, 2011).

Fama (1970) classified three types of efficiency based on the nature of information reflected in security prices. These forms include the weak, the semi-strong y, and the strong form of efficiency. The weak form of efficiency argues that current security prices incorporate all publicly available historical information. Therefore, trading strategies based on past prices will not provide abnormal returns. The semi-strong form of efficiency argues that any new public information is quickly reflected in prices, and there are no arbitrage opportunities. The strong form of efficiency suggests that prices reflect all kinds of information, including public and private information. Thus, efficiency of markets indicates that investors cannot obtain abnormal returns on an ongoing basis (Rossi, 2015).

Earlier studies on market efficiency focused on testing one or more of the three forms of information efficiency for various markets (Barone, 1990; Jegadeesh & Titman, 1993). The later work on the topic focused on finding patterns and events that may create market inefficiencies. These studies focused on three broad domains including analysis of various patterns (Barber & Lyon, 1997), examining time-based anomalies (Redman et al., 1997; Kling & Gao, 2005), and analysing event studies related to corporate announcements (De Bondt & Thaler, 1985; Henry et al., 2017). The studies about anomalies focussed on finding patterns of returns based on certain calendar events such as returns during different days, months, and holiday periods. Similarly, the research on event concentrated on the reaction of prices to various corporate announcements such as dividend announcements, mergers and acquisitions, and share buyback.

Studies analysing various seasonal anomalies in international stock markets have been proliferating in the financial economics literature (Kuria & Riro, 2013; Jaisinghani, 2016). Analysing seasonal anomalies represents a vast area of research in corporate finance (Latif et al., 2011). The presence of seasonal anomalies contradicts the concept of market efficiency as it implies that investors adopting a specific strategy can earn abnormal returns by exploiting seasonal patterns (Muhammad & Rahman, 2010). The global financial crisis in 2008, followed by the stock market crash, has aroused the interests of academicians, investors and policy makers in terms of analysing various seasonal anomalies (Al-Rjoub and Alwaked, 2010). Moreover, in the post crisis period, a drastic fall in stock prices for most companies could be observed. The falling prices were accompanied by a rapid rise in volatility clustering[1] (Al-Rjoub & Alwaked, 2010). Many analyst and researchers expected market returns to behave differently post

[1] Volatility clustering refers to a phenomenon wherein a fluctuation in the returns is followed by even higher fluctuations in the following periods. This usually happens when there is a sudden inflow of some new and unexpected information.

the crisis period, leading to reversal or disappearance of various documented calendar anomalies (Chakrabarti & Sen, 2011; Adam et al., 2016).

There have been many studies that analyse the presence of different seasonal anomalies in the pre-global financial crisis period (Wong et al. 1992; Ibrahim, 1997; Berument & Kiymaz, 2001; Kok & Wong, 2004; Niu & Wang, 2013; Hong et al., 2017). However, very few studies have conducted an in-depth analysis in the post-global financial crisis period. Therefore, the present study aims at analysing the behaviour of seasonal anomalies and volatility patterns for the decade following the global financial crisis. There is a need to conduct such as study because the periods immediately following the financial crisis year have been characterized by noteworthy changes in stock prices across the globe. Moreover, the risk-return relationships, which existed during the pre-crisis period, changed considerably in the post-crisis periods. In addition, there is evidence of large volatility clustering in the periods immediately following the financial crisis (Al-Rjoub & Alwaked, 2010). These changes have led many analyst and researchers to expect market returns to react in a different way post the global financial crisis (Chakrabarti & Sen, 2011; Adam et al., 2016). Thus, there is a need to study the behaviour of calendar anomalies and volatility clustering in the post-global financial crisis period. Moreover, the structural reforms and bailout packages provided by various governments require a closer examination of the efficiency of different markets in the post-crisis period. Thus, the present study adds to the existing literature on market efficiency in general and seasonal anomalies and volatility clustering in particular.

This research focuses on analysing various seasonal anomalies for and volatility clustering in the securities market in Malaysia. The primary rationale here is that the earlier studies conducted on calendar anomalies have mostly focused on countries with advanced capital markets (Roll, 1984; Alagidede & Panagiotidis, 2009). There has been significant development in the stock markets of emerging countries in recent decades. This is especially true for Asian markets. There have been studies that have analysed calendar anomalies for Asian economies in general (Lean et al., 2007; Lim & Chia, 2010) and the Malaysian economy in particular (Lim et al., 2010; Yat et al., 2011). However, not much comprehensive research has been done on the Malaysian market, specifically in the post-global financial crisis period (Muhammad & Rahman, 2010). Malaysia is one of the rapidly growing economies in Asia. Since the 1960s, the Bursa Malaysia market is one of the significant components of the Malaysian capital market (Butler et al., 1990).

Malaysia achieved independence in 1957 and since then it has successfully transformed from an agriculture and commodity-based economy to a manufacturing and services-oriented economy. Besides, in the recent past, Malaysia has become a leading exporter of electrical appliances, electronic parts, and other electrical components. Since 2010, Malaysia is regarded as one of the most open economies, with trade to GDP ratio averaging over 130 percent. Investments and openness to trade have been significant in employment generation and income growth. Post Asian financial crisis, the Malaysian economy has shown an upward trajectory. The GDP growth has averaged 5.4 percent since 2010, and Malaysia is expected to transition from upper middle-income to a high-income economy by 2024.[2] Thus, Malaysia represents an important setting, especially among the emerging markets, for the study of nature of market efficiency and various seasonal anomalies.

The present study analyses different calendar anomalies for 11 different, broad and sectoral, indices listed on the Bursa Malaysia exchange. The time period from 2009 to 2018 has been selected for the

[2] Source: World Bank country report. Available online at: https://www.worldbank.org/en/country/malaysia

empirical analysis. The data has been obtained from the Emerging Market Information Services (EMIS) database. The results show that the day of the week effect and the trading month effect are highly significant for the Malaysian market. However, there is weak evidence supporting the month of the year effect. The overall results counter the theory of market efficiency for the Malaysian market in the post-global financial crisis period.

The present study also analyses different patterns of volatility for various indices of the Malaysian market. Analysing volatility patterns is an important objective as it provides valuable information to potential investors (French et al., 1987; Lux & Marchesi, 2000). An understanding of volatility patterns facilitates formulation of trading strategies according to the perceived risk levels (Bentes et al., 2008; Chou et al., 2015). Moreover, volatility can be symmetric as well as asymmetric across different types of shocks (or news). Thus, there are possibilities that markets may react differentially to good and bad news (Antoniou et al., 1998; Ning et al., 2015). This kind of information can further help investors in deciding their trading strategies. Therefore, it is highly relevant to study the nature of volatility clustering for different markets especially those of emerging economies. The present results show that there is significant volatility clustering in the Malaysian market. Moreover, it is also observed that negative shocks generate more volatility in the Malaysian market compared to positive shocks.

The present study offers several useful contributions to the overall knowledge on market efficiency. The present research focuses on analysing different effects, namely, the day of the week effect, the month of the year effect, the Halloween effect, and the trading month effect. The study specifically tests for the post-global financial crisis era. Therefore, the present research work examines whether the well documented seasonal anomalies still persist in the post crisis period. The study also analyses the nature of volatility clustering in the Malaysian market. This has been done using three advanced techniques, that is generalized autoregressive conditional heteroscedasticity (GARCH), threshold GARCH (T-GARCH), and GARCH-in-Mean (GARCH-M) models. Earlier studies in this area have either concentrated on individual stocks or broad indices. The present research, however, considers two broad indices and nine sectoral indices for the analysis. This kind of analysis provides better insights into different patterns observed in the sectoral indices. To the best of our knowledge, such holistic analysis has not been performed for the Malaysian market before.

The paper is constructed as follows: Section 2 presents the literature review, section 3 describes data and methodology, and section 4 presents the empirical results. The last section concludes the study and sets out the scope for future research.

Literature Review

Analysing efficiency of markets and various seasonal anomalies has been a topic of great interest among researchers and practitioners (Rozeff & Kinney, 1976; Haug & Hirschey, 2006; Soon & Rahim, 2017). Fama (1970) present a comprehensive assessment of various paradigms of market efficiency. Efficiency of markets signifies that current prices incorporate all available public information (Rossi, 2015). Stock markets are said to be efficient if the prices reflect all available information and there is no possibility of making any abnormal profits. Urquhart and McGroarty (2014) argue that efficiency of markets is not a true condition and markets fluctuate over time because of the presence of seasonal anomalies. Several studies have analysed the existence of various seasonal anomalies for different securities and indices (Latif et al., 2011; Kuria & Riro, 2013). The most prominent calendar anomalies studied include the day of the week effect (also called the weekend effect), the month of the year effect (also popularly known as the January effect), the Halloween effect (also called the winter effect) and the trading month effect (also popularly referred to as the turn of the month effect). The following sections provide a review of literature related to seasonal anomalies and volatility clustering.

Calendar anomalies

Several studies have documented the presence of various seasonal anomalies which violate the theories of asset pricing models (Kumar, 2017). Rozeff and Kinney (1976) proposed "the January effect" which highlights that returns achieved in the month of January are, on average, higher than those achieved in other months. Similar results have been observed for certain other markets (Wong et al., 2006; Haug & Hirschey, 2006; Rendon & Ziemba, 2007). Many researchers also propose the "the day of the week effect" as a variation in the returns across different days of the week. Specifically, the returns on Mondays are found to be lowest, whereas those on Fridays are found to be highest (Abraham & Ikenberry, 1994; Wang et al., 1997; Wong et al., 2006). Other researchers have also proposed the "trading month effect" which states that returns obtained over the first fortnight of a month are significantly higher than those obtained over the second fortnight (Wong et al., 2006; Floros, 2008). The "Halloween effect" was first presented by Bouman and Jacobsen (2002), who observe lower returns for the months from May to October as compared to returns for November to April.

Some studies have been conducted to analyse the presence of different calendar anomalies for the Malaysian stock market (Nassir & Mohammad, 1987; Wong et al., 1992). The studies by Nassir and Mohammad (1987) and Wong et al. (1992) examine the day of the week effect for the Malaysian stock market. These studies find lowest returns on Mondays compared to other days. Nassir and Mohamad (1987) also report significantly higher returns in the month of January. However, the empirical results associated with various seasonal anomalies for the Malaysian market have mostly been inconclusive (Soon & Rahim, 2017). Hamid et al. (2010) in their analysis of the weak form of market efficiency in the Asia Pacific region, including Malaysia, for find evidence against the weak form efficiency. Thus, there remains a lot to be studied in terms of the existence of various seasonal anomalies for the Malaysian market. Based upon the detailed review of the literature, the following hypotheses are being tested for the Malaysian market.

Hypothesis 1 (Day of the Week Effect): In the post-global financial crisis period, the returns obtained for different days of the week are significantly different for the Malaysian equity market.

Hypothesis 2 (Month of the Year Effect): In the post-global financial crisis period, the returns obtained for different months of the year are significantly different, for the Malaysian equity market.

Hypothesis 3 (Halloween Effect): In the post-global financial crisis period, the returns obtained during the winter season are significantly higher than those obtained during the summer season for the Malaysian equity market.

Hypothesis 4 (Trading Month Effect): In the post-global financial crisis period, the returns obtained during the first fortnight of a month are significantly higher than those obtained during the second fortnight for the Malaysian equity market.

Volatility clustering

Many studies have examined the nature of volatility clustering for different variables (Tsoukalas, 2000; Tai, 2002; Karmakar, 2007). Tai (2002) assesses the presence of a time-varying risk premium for different Asia-Pacific markets. The findings show that a time-varying risk premium can be earned in the foreign exchange series. Tsoukalas (2000) examines the pattern of volatility clustering for the stock markets of the US, Japan and the UK. The study provides substantial evidence supporting volatility clustering for the selected markets. Grier and Perry (2000) assess the effect of output uncertainty on the current inflation rate for the US. The study did not support any systematic relationship between output uncertainty and inflation. Karmakar (2007) analyses the nature of volatility clustering and finds evidence supporting volatility clustering and its persistence. The author also finds that risk does not systematically vary with returns for the Indian stock markets. Numerous studies employ GARCH-M and related methods for assessing the time series behaviour of different variables (Lee & Koray, 1994; Chancharoenchai & Dibooglu, 2006; Fang & Miller, 2008; Guidi et al., 2011). Lim and Sek (2013) examine volatility patterns for the Malaysian market. The authors deploy different forms of volatility models for different sub-periods considered. The results reveal that different models have differential explanatory power during different sub-periods.

The preceding discussion highlights that, apart from understanding the patterns in returns series, it is also important to understand the patterns in the volatility behaviour. This understanding will help investors understand whether differences in returns are also accompanied by differences in the risk level. The analysis of volatility clustering will also help investors understanding whether the nature of volatility clustering differs across “good” and “bad” news. These insights can help investors frame differential trading strategies based on the nature of risk-return relationships. Thus, it is important to conduct an in-depth analysis of volatility clustering for the Malaysian market. The present study analyses differential volatility patterns for various indices of the Malaysian market. In accordance with the literature review, the present study proposes the following alternative hypotheses for the volatility patterns of the selected indices.

Hypothesis 5: In the post-global financial crisis period, there is significant volatility clustering for the Malaysian equity market.

Hypothesis 6: In the post-global financial crisis period, the pattern of volatility clustering is asymmetric across positive and negative shocks for the Malaysian equity market.

Hypothesis 7: In the post-global financial crisis period, the return series of different indices incorporate the existing levels of volatility clustering for the Malaysian equity market.

Data and methodology

Data and descriptive statistics

The data for the present work comprises the closing index values of 11 different indices of the Malaysia Stock Exchange. The data has been obtained from the Emerging Market Information Services (EMIS) database. The time frame from 2009 to 2017 has been considered for various empirical analyses. The rationale for selection of this time frame is to analyse the existence of market anomalies in the post-global financial crisis period. The indices names, the time period, and the number of observations are reported in Table 1. It is evident from Table 1 that out of the 11 indices, two are broad market indices, and the remaining nine are sectoral indices. The table also reports the descriptive statistics for the selected 11 indices. The table clearly shows that there is large variation among different indices in terms of the behaviour of their returns.

Table 1: Descriptive statistics

Index Name	Type	Start Date	End Date	N	Mean Return (%)	Median Return (%)	Maximum Return (%)	Minimum Return (%)
Construction	Sectoral	31-Dec-08	5-Jul-18	2323	0.009	0.028	6.671	-14.407
Consumer Product	Sectoral	31-Dec-08	5-Jul-18	2324	0.041	0.059	4.783	-3.257
Finance	Sectoral	31-Dec-08	5-Jul-18	2324	0.039	0.052	3.904	-3.971
EMAS	Broad	31-Dec-08	5-Jul-18	2324	0.032	0.044	3.597	-3.440
KLCI	Broad	8-Jul-09	5-Jul-18	2199	0.021	0.039	3.322	-3.237
Industrial Product	Sectoral	31-Dec-08	5-Jul-18	2324	0.039	0.066	3.154	-5.932
Mining	Sectoral	31-Dec-08	5-Jul-18	2319	0.057	0.000	25.886	-14.443
Plantation	Sectoral	31-Dec-08	5-Jul-18	2324	0.026	0.019	7.662	-5.760
Property	Sectoral	31-Dec-08	5-Jul-18	2323	0.029	0.031	6.210	-4.961
Technology	Sectoral	31-Dec-08	5-Jul-18	2324	0.041	0.056	8.805	-9.154
Trade & Services	Sectoral	31-Dec-08	5-Jul-18	2324	0.025	0.045	3.675	-3.335

Note: The table presents the descriptive statistics for the selected indices of the Malaysian stock market. The time frame selected is from 2009 to 2018. Continuous compounded rate of return has been estimated from the daily closing value of the indices.

Analysing calendar anomalies

The present study examines different calendar anomalies for the Malaysian stock market. For testing the presence of calendar anomalies, application of dummy variable regression analysis has been performed. The results of regression analysis are considered to be valid only if the underlying series is stationary. The results of stationarity for the closing prices and stock returns for all the selected 11 indices show that the closing prices are non-stationary, but the return series of all the indices are stationary in the base form.[3] Hence, regression analysis can be applied to the returns series. The continuously compounded returns (CCR) have been determined by differencing the log values of successive daily closing stock values. The following equation explains this calculation.

$$CCR_{it} = \ln\left(\frac{Close_{it}}{Close_{it-1}}\right) \qquad (1)$$

Analysing volatility clustering

Several methodologies have been proposed to analyse the nature of volatility in returns. However, the most prominent is the generalized autoregressive conditional heteroscedasticity (GARCH) model. The GARCH model, introduced by Bollerslev (1986), was an extension of the basic autoregressive conditional heteroscedasticity (ARCH) model introduced by Engle (1982). This model requires estimation of two equations. The first equation is employed for modelling the mean, and the second equation is employed for modelling the volatility.

[3] The results of the test of stationarity are not presented to conserve space. These results are available upon request.

$$CCR_{it} = X_t^{'}\beta + e_t \quad (2)$$

$$\sigma_{it}^2 = \lambda_0 + \sum_{i=1}^{g} \lambda_i e_{t-i}^2 + \sum_{i=1}^{h} \Phi_i \sigma_{t-i}^2 + \eta_t \quad (3)$$

In Equation (2), which is the mean equation, CCR_{it} represents the continuous compounded rate of return series of various indices and e_t represents the noise term. Equation (3) describes the variance equation that consists of an ARCH term of the order "g" and a GARCH term of the order "h". However, in empirical estimations it is often very difficult to interpret results for order terms greater than 1. Therefore, in the present analysis, the empirical estimation has been conducted for the GARCH (1, 1) model only. The model is suitable for long series that are stationary in their base form. The present study considers daily returns of various indices for a long period of time. Thus, the method of GARCH (1, 1) is suitable for the present dataset. Besides, several past studies have applied GARCH (1, 1) based models in the return series of various securities and indices (Hansen & Lunde, 2005; Basher & Sadorsky, 2016). Thus, the final model that has been estimated for all indices takes the following form.

$$\sigma_{it}^2 = \lambda_0 + \lambda_1 e_{t-1}^2 + \Phi_1 \sigma_{t-1}^2 \quad (4)$$

The GARCH model describes the relation between present and past volatility. Thus, the significance of the GARCH model provides evidence in favour of volatility clustering. In the assessment of volatility clustering, it is also essential to study the presence of a systematic pattern in volatility for positive and negative shocks. This is achieved by the application of the threshold generalized autoregressive conditional heteroscedasticity (T-GARCH) model. The model comprises of a further term, in addition to ARCH and GARCH terms, that represents the threshold parameter. This can be represented by the following equation.

$$\sigma_{it}^2 = \lambda_0 + \lambda_1 e_{t-1}^2 + \theta_1 e_{t-1}^2 d_{t-1} + \Phi_1 \sigma_{t-1}^2 \quad (5)$$

Equation (5) shows that an additional term $\theta_1 e_{t-1}^2 d_{t-1}$ has been added to the base volatility equation. This term represents a slope dummy for the negative error terms. Thus, the slope dummy d_{t-1} takes the value of 1 if the error term has a negative sign and 0 if the error term has a positive sign. Therefore, the significance and sign of the coefficient θ_1 indicates whether volatility clustering is higher or lower due to different kinds of shocks. If the coefficient is positive (negative), it indicates that volatility clustering is higher (lower) during the negative shocks. Thus, a positive and significant coefficient of the threshold term indicates that negative news causes more volatility than positive news. This is generally the case when the majority of investors are risk averse and demand a premium for every unit increase in the riskiness of returns.

The final model to be applied represents the GARCH-in-Mean model. The proponents of the model contend that the heteroscedasticity term affects not just the variance equation but also the mean equation. Thus, the model proposes that the mean equation also contains a GARCH term. Therefore, the mean model, as represented by equation (2), takes the following functional form.

$$CCR_{it} = X_t^{'}\beta + \gamma\sigma_t + e_t^{'} \quad (6)$$

In equation (6) an additional term has been added to the basic mean equation. Thus, the equation suggests that investors explicitly consider risk while setting their expectations about the returns.

Therefore, the significance of the heteroscedasticity term in the mean equation signifies that investors set the expected price of the securities differentially based on the anticipated risk. This can also be understood as an extension of the basic capital assets pricing model (CAPM) presented by Sharpe (1964).

The following section presents the results of the tests for calendar anomalies and volatility clustering for different indices of the Malaysian stock market.

Results

The day of the week effect

The study begins with an assessment of differential returns over different days of the week. This is accomplished by regressing the returns series of 11 Malaysian indices on four different dummies beginning from Tuesday to Friday.

$$CCR_{it} = \mathrm{C} + \Pi_2(Tuesday) + \Pi_3(Wednesday) + \Pi_4(Thursday) + \Pi_5(Friday) + \xi_t \quad (7)$$

Where, CCR_{it} represents the continuously compounded rate of return for the index "i" over the time period "t". The dummies are represented by their respective days from Tuesday to Friday. Monday has been considered as the omitted category, and therefore, its impact is reflected in the coefficient of the constant term "C". The coefficient of a particular dummy "Π" indicates the difference between mean returns on Mondays and on that particular day. For instance, the coefficient of dummy "Friday" represents the difference between the mean return on Mondays and the mean return on Fridays. The significance of the coefficient of a particular dummy presents evidence that the returns on different days are different.

Table 2 presents the output for the day of the week effect for all 11 indices. It is evident from the table that the returns over different days of the week are not similar. The coefficients of a majority of dummy variables (representing days from Tuesday to Friday) are positive. This indicates that returns on Mondays are the lowest in absolute numbers form. Moreover, the coefficient for some of the days is highly significant. For instance, the Wednesday dummy is significant for the Industrial Product Index, Property Index, and Trade & Services Index. Similarly, the coefficient of the Thursday dummy is positive and significant for the Construction Index, Industrial Product Index, and Property Index. Finally, the coefficient of the Friday dummy is positive and significant for the EMAS Index, Property Index, and Trade & Services Index. The magnitude of the coefficients also reveals that returns on Thursdays, on average, are the highest compared to other days of the week. Thus, it is evident that the day of the week effect is present in the Malaysian market. The findings contradict the weak form of efficiency for Malaysia.

The month of the year effect

This study assesses the month of the year effect anomaly for the Malaysian stock market. Numerous research studies hypothesize that returns achieved differ significantly across different months (Choudhry, 2001; Giovanis, 2014; Jaisinghani, 2016). The primary reasoning behind this hypothesis is tax saving benefits. This is because investors "sell" their loss-making securities in December to show lower income and reduce their tax obligations. The investors then "buy" in January to rebalance their portfolios. If the hypothesis stands true, then December should display the lowest returns and the month of January should show the highest returns.

Table 2: Results of the Day of the week effect

Index Name		Constant	Tuesday	Wednesday	Thursday	Friday	F-statistics
Construction Index	Coefficient	-0.0008	0.0008	0.0013	0.0016**	0.0009	1.5502
	p-value	0.1837	0.2953	0.1076	0.0277	0.1679	0.2561
Consumer Product Index	Coefficient	0.0001	0.0002	0.0003	0.0006	0.0004	0.8052
	p-value	0.6656	0.6394	0.4921	0.1230	0.2108	0.5263
Finance Index	Coefficient	0.0001	0.0003	0.0002	0.0005	0.0006	0.5907
	p-value	0.8663	0.5602	0.6407	0.2831	0.1415	0.6321
EMAS Index	Coefficient	-0.0002	0.0004	0.0006	0.0007	0.0008**	1.2165
	p-value	0.5676	0.3445	0.1308	0.1013	0.0311	0.2570
KLCI Index	Coefficient	-0.0002	0.0006	0.0004	0.0005	0.0004	0.7784
	p-value	0.5385	0.1211	0.2977	0.1778	0.2831	0.6130
Industrial Product Index	Coefficient	-0.0002	0.0004	0.0012**	0.0008*	0.0007	1.7958
	p-value	0.5825	0.4794	0.0166	0.0955	0.1380	0.1278
Mining Index	Coefficient	0.0008	-0.0008	-0.0013	0.0002	0.0009	0.6399
	p-value	0.5080	0.6317	0.4150	0.9072	0.5849	0.6140
Plantation Index	Coefficient	-0.0001	0.0003	0.0004	0.0007	0.0003	0.4407
	p-value	0.8387	0.5649	0.4781	0.2339	0.5101	0.8297
Property Index	Coefficient	-0.0008	0.0003	0.0015**	0.0018***	0.0020***	4.7286***
	p-value	0.1102	0.6120	0.0182	0.0045	0.0002	0.0003
Technology Index	Coefficient	-0.0007	0.0003	0.0020**	0.0012	0.0019**	2.0042*
	p-value	0.3559	0.7723	0.0274	0.1843	0.0257	0.0765
Trade & Services Index	Coefficient	-0.0004	0.0004	0.0008*	0.0008*	0.0010***	1.7920*
	p-value	0.2849	0.3060	0.0597	0.0840	0.0081	0.0828

Note: The table describes the results of the day of the week effect for all selected stock market indices for the Malaysian market. The constant term represents the mean returns obtained on Mondays. The coefficient of all other days (i.e. for days from Tuesday to Friday) 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 days are significantly different or not. The Newey-West robust estimates are used to find the results. *, **, ***Significant at 10, 5, and 1 percent levels, respectively.

The output for the month of the year effect is achieved by regressing the returns achieved for the selected 11 indices on different dummies representing the months from February to December. The month of January is omitted, and its impact is captured by the constant term. The following regression equation is estimated.

$$CCR_{it} = C + \Pi_2(February) + \Pi_3(March) + \cdots + \Pi_{12}(December) + \varepsilon_t \quad (8)$$

The results of the examination of the month of the year effect are presented in Table 3. The results, as presented in Table 3, clearly show that the coefficients of the dummies for December are positive for most of the indices. The only exceptions are the Construction Index, Mining Index, and the Technology Index. Moreover, the negative coefficients for these three indices are not significant at the conventional levels. This shows that the January effect, which is generally reported for other markets, is not observed for the Malaysian market. Table 3 also highlights that the coefficients of the dummy variables, representing the months of August and November, are negative and highly significant. The overall F-statistics is also significant for a majority of the indices. Thus, the Malaysian market observes the lowest returns during August and November. The overall results indicate significant presence of the month of the year effect in Malaysia. However, the findings contradict the tax loss selling hypothesis. This is because December returns are not significantly different from the January returns.

Halloween effect

The Halloween effect hypothesizes significant higher returns during the winter season (November to April) compared to the summer season (May to October). The results have been obtained by regressing the returns series of selected indices on the winter dummy. The dummy variable equals 1 if an occurrence can be observed in the months of winter season; it is 0 otherwise. The Halloween effect is considered to be present if the value of the coefficient of the dummy variable is significant and positive. The following is the regression form, which is empirically estimated.

$$CCR_{it} = C + \Pi(Winter) + \varepsilon_t \qquad (9)$$

In equation (9), the constant term denotes the mean returns obtained during the summer season. Similarly, the coefficient of the dummy variable represents the difference between the mean returns obtained during the summer season and the mean returns achieved during the winter season. The results for the Halloween effect are reported in Table 4. The coefficients of the winter dummies, for all indices, are insignificant at the conventional levels. Hence, there is no evidence in support of the presence of the Halloween effect for the Malaysian market.

Trading month effect

The last calendar anomaly examined for the Malaysian market relates to the trading month effect. The supporters of the trading month anomaly argue that the returns achieved during the first fortnight are significantly higher than the returns achieved during the second fortnight. The main reasoning behind this anomaly is the purchasing power of individuals which is higher in the first half of the month. The results of the trading month effect are estimated by regressing the returns of the trading month dummy. The dummy variable equals 1 if an occurrence is observed in the days falling in first fortnight; it is 0 otherwise. The following equation depicts the functional form:

$$CCR_{it} = C + \Pi(Trading\_Month) + \varepsilon_t \qquad (10)$$

The output for the examination of the month of the year effect is represented in Table 5. The table shows that the coefficients of the first fortnight are positive for all indices. The coefficients are also significant for the Mining Index, Plantation Index, Property Index, and Technology Index. Thus, the overall results show that the trading month effect is present in Malaysia. The results also indicate that the purchasing power of Malaysian investors is higher in the first fortnight compared to that in the second fortnight. Hence, the study finds significant support for the trading month effect for the Malaysian market.

Table 3: Results of the Month of the year effect

Index Name		Constant	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec	F-value
Construction	Coefficient	0.0009	-0.0013	0.0001	0.0001	-0.0024	-0.0007	0.0001	-0.0029**	-0.0009	0.0010	-0.0021**	-0.0009	2.5743***
	p-value	0.2124	0.1844	0.8864	0.9429	0.1510	0.4857	0.9546	0.0115	0.4278	0.3211	0.0147	0.3949	0.0026
Consumer Product	Coefficient	0.0002	0.0005	0.0008	0.0002	0.0000	0.0003	0.0010*	-0.0008	-0.0003	0.0007	-0.0008	0.0003	2.3554**
	p-value	0.5834	0.3439	0.1613	0.6653	0.9973	0.5805	0.0986	0.2320	0.6235	0.2397	0.1377	0.6142	0.0140
Finance	Coefficient	0.0000	0.0008	0.0009	0.0011	0.0001	0.0004	0.0008	-0.0006	-0.0004	0.0011	-0.0006	0.0010	1.7194
	p-value	0.9713	0.3087	0.3480	0.1992	0.9325	0.6032	0.3289	0.5202	0.7103	0.1915	0.4526	0.2495	0.1221
EMAS	Coefficient	0.0001	0.0003	0.0006	0.0007	-0.0004	0.0002	0.0007	-0.0008	0.0000	0.0011	-0.0008	0.0009	2.0006**
	p-value	0.8846	0.6828	0.3942	0.3599	0.6654	0.7831	0.3187	0.3436	0.9791	0.1389	0.2575	0.2563	0.0317
KLCI	Coefficient	-0.0002	0.0006	0.0012*	0.0003	-0.0006	0.0003	0.0009	-0.0003	0.0002	0.0013*	-0.0004	0.0012	2.4021**
	p-value	0.7202	0.3717	0.0702	0.6183	0.4687	0.6653	0.1944	0.7303	0.8239	0.0614	0.5028	0.1038	0.0177
Industrial Product	Coefficient	0.0004	0.0000	0.0003	0.0001	-0.0001	0.0000	0.0004	-0.0014	-0.0001	0.0014	-0.0014*	0.0008	2.1768**
	p-value	0.5739	0.9916	0.7029	0.9257	0.9485	0.9540	0.5869	0.1493	0.8831	0.1002	0.0781	0.3642	0.0174
Mining	Coefficient	0.0035	-0.0036	-0.0031	-0.0031	-0.0033	-0.0040	-0.0014	-0.0041	-0.0037	-0.0002	-0.0043*	-0.0040	0.8386
	p-value	0.1482	0.2179	0.2225	0.2563	0.2145	0.1240	0.6161	0.1465	0.1561	0.9559	0.0833	0.1328	0.7033
Plantation	Coefficient	0.0004	-0.0005	0.0001	-0.0002	-0.0010	0.0000	-0.0001	-0.0011	-0.0002	0.0013	-0.0005	0.0004	1.3567
	p-value	0.6605	0.6467	0.8846	0.8534	0.3511	0.9838	0.9492	0.2973	0.8568	0.2286	0.6195	0.7268	0.3769
Property	Coefficient	0.0003	0.0003	0.0004	0.0008	0.0002	-0.0004	0.0004	-0.0016	0.0002	0.0009	-0.0017*	0.0001	1.6234**
	p-value	0.7013	0.7611	0.6768	0.4896	0.8687	0.7056	0.6653	0.1634	0.8884	0.4426	0.0666	0.9298	0.0306
Technology	Coefficient	0.0019	-0.0024	-0.0016	-0.0008	-0.0003	-0.0018	0.0000	-0.0054***	-0.0023	-0.0001	-0.0030	-0.0007	2.4841**
	p-value	0.2444	0.2118	0.4291	0.6869	0.8915	0.3225	0.9795	0.0078	0.2222	0.9588	0.1051	0.7018	0.0299
Trade & Services	Coefficient	0.0000	0.0003	0.0007	0.0008	-0.0006	0.0001	0.0007	-0.0006	0.0002	0.0010	-0.0006	0.0006	1.6050*
	p-value	0.9785	0.6713	0.3118	0.2855	0.4760	0.8931	0.2667	0.4695	0.7412	0.1455	0.3364	0.3816	0.0853

Note: The above table displays the results achieved for the month of the year effect for all selected stock market indices of the Malaysian market. The constant term represents the mean returns obtained in January. The coefficient of all other months (i.e. for months from February to December) represents the difference between the mean returns on January and on that particular month. The F-statistics is used to determine whether the mean returns on all the months are significantly different or not. The Newey-West robust estimates are used to estimate the results. *, **, *** Significant at 10, 5, and 1 percent levels, respectively.

Table 4: Results of the Halloween effect

Index Name		Constant	D (Halloween)	F-statistics
Construction Index	Coefficient	-0.0001	0.0003	0.6365
	p-value	0.8403	0.4702	0.4702
Consumer Product Index	Coefficient	0.0004	0.0000	0.0156
	p-value	0.0373	0.9118	0.9118
Finance Index	Coefficient	0.0002	0.0003	0.9416
	p-value	0.3080	0.4031	0.4031
EMAS Index	Coefficient	0.0002	0.0002	0.3457
	p-value	0.2689	0.6069	0.6069
KLCI Index	Coefficient	0.0001	0.0002	0.4463
	p-value	0.5420	0.5431	0.5431
Industrial Product Index	Coefficient	0.0004	-0.0001	0.0668
	p-value	0.0779	0.8169	0.8169
Mining Index	Coefficient	0.0007	-0.0002	0.0472
	p-value	0.3159	0.8171	0.8171
Plantation Index	Coefficient	0.0002	0.0001	0.0613
	p-value	0.3626	0.8124	0.8124
Property Index	Coefficient	0.0003	0.0001	0.0299
	p-value	0.4451	0.8845	0.8845
Technology Index	Coefficient	0.0003	0.0002	0.1771
	p-value	0.5295	0.7168	0.7168
Trade & Services Index	Coefficient	0.0002	0.0002	0.3456
	p-value	0.4355	0.5892	0.5892

Note: The table above presents the results for the Halloween effect for all selected stock indices for the Malaysian stock market. The constant term represents the mean returns obtained from May to October. The coefficient of the dummy variable D (Halloween) represents the difference between the mean returns for the two periods, that is May-October (summer months) and November-April (winter months). 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. *, **, ***Significant at 10, 5, and 1 percent levels, respectively.

Evidence on volatility clustering

The next examination pertains to the testing of the incidence of volatility clustering for the Malaysian market. Many authors argue that volatility tends to follow patterns of clustering (Franses & Van Dijk, 1996; Marcucci, 2005; Dyhrberg, 2016). Several studies also show that clustering is asymmetric in relation to positive news and negative news (Rabemananjara & Zakoian, 1993; Chan & Maheu, 2002). This asymmetry is assessed with the help of the Threshold Generalized Autoregressive Conditional Heteroscedasticity (T-GARCH) model. The final analysis explores whether the volatility term also explicitly impacts the mean equation. This is done by estimating the GARCH-in-Mean (GARCH-M) model.

The results for the volatility clustering tests are presented in Table 6. The table clearly shows that there is significant volatility clustering for the Malaysian stock market. This is evidenced by the p-values of the ARCH and the GARCH terms. Moreover, the T-GARCH terms are positive and significant for almost all indices except for the Mining Index. This indicates that the volatility induced by negative news is significantly higher than the volatility induced by positive news. This indicates that Malaysian investors are risk-averse and react more strongly to negative news. The results of the GARCH-M analysis show that the variance term is explicitly represented in the mean model. This proves that investors explicitly factor in risk while setting their expectations about future returns.

Table 5: Results of the Trading month effect

Index Name		Constant	D (Turn of the Month)	F-statistics
Construction Index	Coefficient	-0.0003	0.0008*	3.3333*
	p-value	0.3624	0.0961	0.0961
Consumer Product Index	Coefficient	0.0003*	0.0002	0.8302
	p-value	0.0559	0.4066	0.4066
Finance Index	Coefficient	0.0002	0.0004	2.2379
	p-value	0.4191	0.2027	0.2027
EMAS Index	Coefficient	0.0002	0.0003	1.4787
	p-value	0.4017	0.2813	0.2813
KLCI Index	Coefficient	0.0002	0.0001	0.0699
	p-value	0.3610	0.8129	0.8129
Industrial Product Index	Coefficient	0.0002	0.0004	2.0172
	p-value	0.4162	0.1981	0.1981
Mining Index	Coefficient	-0.0003	0.0018*	3.6133*
	p-value	0.6140	0.0540	0.0540
Plantation Index	Coefficient	-0.0001	0.0007*	4.2747*
	p-value	0.7533	0.0560	0.0560
Property Index	Coefficient	-0.0001	0.0009**	5.5758**
	p-value	0.6203	0.0424	0.0424
Technology Index	Coefficient	-0.0005	0.0018***	10.0834***
	p-value	0.2764	0.0072	0.0072
Trade & Services Index	Coefficient	0.0002	0.0001	0.2641
	p-value	0.3595	0.6312	0.6312

Note: The table presents the results of the trading-month effect for all selected stock market indices for the Malaysian stock market. The constant term represents the mean returns obtained during the second fortnight. The coefficient of the dummy variable D (Turn of the Month) 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. The Newey-West robust estimates are used to estimate the results. *, **, ***Significant at 10, 5, and 1 percent levels, respectively.

Discussion and Conclusion

This research aimed to advance the literature on market efficiency and calendar anomalies. The study analyses various calendar anomalies for the Malaysian securities market. The analysis comprises the closing values of 11 different indices of the Malaysian Stock Exchange for the period 2009 to 2018. Four different anomalies including the day of the week effect, the month of the year effect, the Halloween effect, and the trading month effect have been tested for the selected indices. This is followed by an examination of the volatility behaviour of various indices.

The results of the day of the week analysis show that the weekend effect, primarily observed for advanced markets, is significant for the Malaysian market. These results are similar to the results of several previous studies; e.g., Gibbons and Hess (1981) who found negative Monday returns for stocks and T-bills; Boudreaux et al. (2010) who found the presence of weekend effect as well as the day of the week effect for several US indices. Moreover, the results provide support to the claims of several other authors who have found significant day of the week effects for ASEAN and other emerging markets (Zhang et. al., 2017). These results are in contrast to the findings of Raj and Kumari (2006) who found the absence of a negative Monday effect for the Indian markets.

Table 6: Results of Volatility Clustering

Index Name		ARCH	GARCH	T-GARCH	GARCH-M
Construction Index	Coefficient	0.1020***	0.8911***	0.1144***	4.2358**
	p-value	0.0000	0.0000	0.0000	0.0352
Consumer Product Index	Coefficient	0.1221***	0.8278***	0.0939***	18.3342***
	p-value	0.0000	0.0000	0.0000	0.0000
Finance Index	Coefficient	0.1237***	0.8214***	0.0735***	11.7566***
	p-value	0.0000	0.0000	0.0000	0.0001
EMAS Index	Coefficient	0.1109***	0.8588***	0.1025***	13.7987***
	p-value	0.0000	0.0000	0.0000	0.0001
KLCI	Coefficient	0.1091***	0.8481***	0.0863***	11.4797***
	p-value	0.0000	0.0000	0.0000	0.0023
Industrial Product Index	Coefficient	0.0978***	0.8703***	0.0586***	9.7175***
	p-value	0.0000	0.0000	0.0000	0.0011
Mining Index	Coefficient	0.1196***	0.8346***	-0.0388***	0.4890
	p-value	0.0000	0.0000	0.0002	0.5795
Plantation Index	Coefficient	0.1007***	0.8529***	0.0379***	4.9188*
	p-value	0.0000	0.0000	0.0021	0.0867
Property Index	Coefficient	0.0904***	0.8960***	0.0388***	5.8021**
	p-value	0.0000	0.0000	0.0000	0.0159
Technology Index	Coefficient	0.1352***	0.8062***	0.0706***	3.7803***
	p-value	0.0000	0.0000	0.0000	0.0096
Trade & Services Index	Coefficient	0.1096***	0.8562***	0.1086***	11.5157***
	p-value	0.0000	0.0000	0.0000	0.0006

Note: The above table displays the results of GARCH (1, 1) and T-GARCH, and GARCH-M analyses for the selected stock market indices of the Malaysian stock market. *, **, *** Significant at 10, 5, and 1 percent levels, respectively.

The results of the month of the year analysis indicate that the January effect is not significant for the Malaysian market. The results also show that the returns obtained for the months of August and November are significantly negative. These results contradict the usually observed January effect (Choudhry, 2001; Al-Rjoub & Alwaked, 2010). Hence, it can be concluded that the tax loss selling hypothesis is not valid for the Malaysian market. The results also contradict the findings of Yat et al. (2011) who observe a positive January effect for the Malaysian market during the period from 1998 to 2008. Thus, the present results show that nature of calendar anomalies has undergone changes in the post-global financial crisis.

The results further show that the Halloween effect is insignificant for the Malaysian market. These results are in contrast to the findings of some previous studies that observe a significant Halloween effect for developed markets (Jacobsen & Visaltanachoti, 2009) and emerging markets including Malaysia (Lean, 2011). This finding is in sharp contrast to the findings of Bouman and Jacobsen (2002) who found the presence of a Halloween effect for 36 different countries around the world including the Malaysian market. These results further support the claim that the nature of calendar anomalies has changed in the post financial crisis era. The results for the trading month effect are significant and confirm Floros' findings (2008) who found a positive trading month effect for a few indices of Greek stock market. The results are also similar to those observed by Boudreaux (1995) who found a positive trading month effect for Malaysia and Singapore for the period 1978 to 1992. The results are also similar to those of Kunkel et al. (2003) who observed a significant trading month effect for developed markets but no significant trading month effect for the Malaysian market.

The next stage of analysis involved testing for evidence of volatility clustering. This analysis was performed using a GARCH based models. The results indicate the presence of volatility clustering among several indices. Moreover, the coefficients of the T-GARCH terms are positive and significant for all indices. This shows that volatility caused by negative news is much higher than volatility caused by positive news, indicating that Malaysian investors are risk averse and attach more importance to negative news. The results are similar to Tsoukalas' (2000), who found positive volatility clustering for three advanced markets –Japan, the UK, and the US. The results are in contrast to those of Glosten et al. (1993) who, by utilizing a modified GARCH-M model, found a negative relationship between conditional mean and the conditional variance of positive abnormal returns.

This study has several implications. The most important implications are for traders who can devise strategies based on the anomalies observed in the present study. Investors can also select portfolios by combining various indices that behave differently during different calendar events. This will lead to a more diversified portfolio and hence will help investors minimize their risks. Investors with access to intraday price information can also devise strategies based on the intraday patterns identified using a similar kind of analysis that has been carried out in the present study.

The study also has useful implications for regulators. Regulators should investigate if there are microstructures or regulatory inefficiencies causing different calendar effects by analysing existing trading rules and the priority given to individual investors over institutional investors in executing trades. This is because institutional investors can impact the movement of prices if they get priority in the execution of trades (O'Hara, 2015). Moreover, regulators should analyse whether there are any asymmetries in information dissemination among various market participants. This is because asymmetries in information dissemination usually lead to barriers in asset price discovery (Wang, 1993; Billett & Yu, 2016). If indeed there are certain inefficiencies, regulators should create regulations that prohibit a small set of market players from exploiting other investors who are relatively small and don't possess all the information. Moreover, securities exchanges should devise strategies to promote a healthy trading atmosphere throughout the year. These strategies may involve different trading platforms for individual and institutional traders; temporary halting of trading during the flow of critical information; and designated platforms for reporting certain types of corporate announcements such as mergers, dividends, and share buyback. These strategies can reduce asymmetries in the flow of information. They can also lead to maximization of revenues for the exchanges and hence will help in making the markets more efficient and more conducive for trading.

The present study has certain limitations: the study considers only the indices that represent the broad market and several sectors. The study did not consider individual stocks that can also follow different patterns. Moreover, the study did not consider anomalies in the intraday price movements. Investigation into calendar anomaly for trades in different assets classes (such as gold, forex, and crude oil) has also not been conducted.

Future research in this area can be focussed on a similar analysis for another asset class such as gold, silver, crude oil, and forex. It can also attempt to identify the causes of these monthly anomalies, which may pertain to taxation structure; relative role of individual and institutional investors; behaviour of investors during different holidays; and other factors related to market microstructure. Similarly, the factors causing a significant trading-month effect, as reported for different indices, can be studied further. Last but not least, the present analysis can be repeated for other emerging economies that have similar institutional and financial settings.

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