THE HALLOWEEN EFFECT AND OTHER SEASONAL ANOMALIES IN THE ENERGY SECTOR OF THE STOCK EXCHANGE OF THAILAND

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Abstract

This research aims to explore the existence of three well-known seasonal anomalies – the January Effect, the April Effect, and the Halloween Effect – as pertains to monthly returns as well as to volatility. Effects on returns and volatility will further be studied within the SET Energy index as well as 9 selected energy stocks from the period April 2005 to July 2016. The objective of this study is to find seasonality hidden within the above Index and stocks, and establish a simple trading strategy to benefit investors. As in preceding studies, our methodology uses the dummy regression technique and the EGARCH model is employed to investigate the impact of these seasonal anomalies on the volatility of returns. The result found that Halloween Effect and the January Effect have a statistically negligible effect on returns within the smaller SET Energy Index. The April Effect does have statistical significance on returns within the SET Energy Index. Buying the SET Energy index before April is likely to yield positive returns at the end of the month. Investors should accumulate positions during these seasonal anomalies – in light of low volatility – and take profit once volatility returns to normal.

Keywords: Seasonal Anomalies, Halloween Effect, January Effect, April Effect

บทคัดย่อ

การวิจัยครั้งนี้มีจุดมุ่งหมายเพื่อศึกษาถึงความผิดปกติตามฤดูกาลสามแบบที่รู้จักกันดี ได้แก่ 1) ผลกระทบในเดือนมกราคม 2) ผลกระทบในเดือนเมษายน และ 3) ผลกระทบฮาโลวีน ในรูปของผลตอบแทนรายเดือนรวมถึงความผันผวนด้วย ระยะเวลาการศึกษา จะศึกษาในช่วงตั้งแต่ช่วงเมษายน 2548 ถึงเดือนกรกฎาคมปี 2559 โดยจะสำรวจจากผลกระทบต่อผลตอบแทนและความผันผวนในดัชนีของกลุ่มพลังงาน (SET Energy) โดยเฉพาะ หุ้น 9 ตัวในกลุ่มพลังงานที่ถูกเลือก วัตถุประสงค์ของการศึกษานี้คือเพื่อศึกษาถึงผลกระทบของฤดูกาลที่ซ่อนอยู่ในดัชนีและราคาหุ้นข้างต้น รวมถึงการสร้างกลยุทธ์การซื้อขายแบบง่ายๆเพื่อเป็นประโยชน์แก่นักลงทุน การศึกษานี้ใช้สมการการถดถอยแบบสุ่ม (dummy regression) และใช้แบบจำลอง EGARCH เช่นเดียวกับในการศึกษาอื่นๆในอดีต เพื่อสำรวจความผิดปกติของผลตอบแทนตามฤดูกาล จากค่าความผันผวนของผลตอบแทน ผลของการศึกษา พบว่าผลกระทบของฮาโลวีนและผลกระทบเดือนมกราคมมีผลเล็กน้อยต่อผลตอบแทนของดัชนีกลุ่มพลังงาน ในขณะที่ผลกระทบในเดือนเมษายนมีผลกระทบอย่างมีนัยสำคัญทางสถิติต่อผลตอบแทนในดัชนีกลุ่มพลังงาน การซื้อหุ้นในกลุ่มพลังงานในช่วงก่อนเดือนเมษายนมีแนวโน้มที่จะให้ผลตอบแทนที่ดี ดังนั้น นักลงทุนควรทยอยสะสมหุ้นในช่วงเดือนเมษายนนี้ ขณะที่ค่าความผันผวนอยู่ในระดับค่อนข้างต่ำ และ ขายทำกำไรในช่วงที่ค่าความผันผวนเพิ่มขึ้นกลับสู่ช่วงปกติ

คำสำคัญ: ความผิดปกติตามฤดูกาล ผลกระทบฮาโลวีน ผลกระทบในเดือนมกราคม ผลกระทบในเดือนเมษายน

1. INTRODUCTION

A common saying among seasoned investors in equity markets is “Sell in May, and go away.” The month of May signals the beginning of the bear market, and investors benefit more from selling their stocks and holding cash from May onward. Another common ending to this saying is: “But, come back in November,” which refers to the time investors should return to holding stocks in their portfolios in order to earn profits from the bull market which begin from November onward.

This market timing strategy has persisted in equity markets around the global for decades. The oldest mention of the Sell-in-May effect appeared in an issue of the Financial Times in 1964. Over the years, the saying has subsequently (and frequently) been cited by the press, analysts, and strategists. It was more specifically labeled “the Halloween effect” by Boumen and Jacobsen (2002). Boumen and Jacobsen concluded that stock returns are significantly lower during the May-October periods versus the November-April periods, and therefore, a trading strategy to exploit this seasonal anomaly was proposed. The strategy suggested investing in a value-weighted index during the November-April periods and in a risk-free investment, such as U.S. Treasury bills or bonds, during the May-October periods.

Interestingly, the Halloween Effect, unlike other anomalies, does not suffer from Murphy’s Law, as explained by Elroy Dimson and Paul March (1999). This means that after the discovery of the Halloween effect, this anomaly does not seem to vanish or reverse itself. Moreover, the economic significance of this calendar anomaly is considerable and can simplify trading strategies in many countries, particularly in Europe, as Boumen and Jacobsen (2002) found.

Testing of the Halloween Effect in Thailand has been documented in the work of Boumen and Jacobsen (2002) and Friday and Bo (2015). With the increasing participation of foreign investors in the Thai Stock market along with the increasing level of capital market integration, researchers attempted to identify whether international market anomalies are present in Thailand. Specifically, Boumen and Jacobsen (2002), concluded that the SET index showed slightly higher average monthly returns in the period of November-April than in the other six months of the year because of the combination of the Halloween Effect and the January Effect. They found that the January Effect resulted in an average monthly return of 6% in the month of January from 1988 to 1998, compared to an average annual return of 0.0%, while the Halloween Effect did not have a significant impact on the returns of the SET index over the same period.

A similar study was conducted in Thailand by Friday and Bo (2005), after discovering the Halloween effect in the Vietnam Stock Index. They found that the stock return was relatively higher in December and January during the study period. Although they found evidence of Halloween effect in both SET Index and SET 50, the results were not statistically significant.

The fact that the Sell-in-May Effect has remained valid even after the discovery has interested a wide range of market participants, such as portfolio managers, investors, and listed companies. A trading strategy would reduce both risks and investment costs in an environment. The study of monthly market anomalies can benefit especially new firms to conduct IPOs. Management would optimize a capital raising. Investors can implement much simpler trading strategy based on monthly anomalies to gain profits.

Despite extensive research on international equity markets, the reasons behind the Halloween Effect remain unclear. Yet, much empirical evidence has been found in various stock markets – both developed and emerging markets. This study applied the work of Boumen and Jacobsen into the energy sector of the SET index to find the existence of the Halloween Effect and other monthly anomalies in the energy sector, as well as selected individual energy stocks.

Energy sector has been selected for the study for two main reasons. Firstly, the market value of the energy sector accounts for over 15% of SET index's market value on average - the most among any sectors. Secondly, energy stocks are generally correlated with global market indicator, in particular the crude oil price. The selection of energy stock to test for the Halloween anomaly might be more pronounced, compared to the overall index. Accordingly, this study mainly focuses on anomalies in large-cap stocks, and consequently provide trading strategies. The finding shows that not only does the April Effect exist on the SET Energy Index, but it also has a statistically significant impact on monthly returns, whereas previous works found the April Effect largely insignificant on the SET Index. The anomalies have a significant effect on the volatility of various energy stocks.

2. LITERNATURE REVIEW

Most researchers described "Anomaly" as an event or strategy that contradicts the idea that changes in stock prices occur randomly. In other words, the concept of anomaly in stock prices counters the Efficient-Market Hypothesis, which states that asset prices fully reflect all available information and implies that it is impossible to beat the market consistently on a risk-adjusted basis, as markets tend to adjust to new information or changes in discounted rates (Fama, 1970). The most recognized market anomalies are calendar-related anomalies, which represent apparently different behaviors of stock markets and, consequently, unusually higher stock returns, during certain periods. Such calendar anomalies include the January effect, the Sell-in-May effect, the Monday effect, and the Turn-of-the-Month effect. This seasonality of stock returns has been a topic of debate in academic research and even the public press for over three decades. Earlier studies focused on seasonal anomalies in U.S. and other developed markets. Rozeff and Kinney (1976) discovered seasonal patterns in an equally-weighted index of the New York Stock Exchange (NYSE) over the period of 1904-1974. Lakonishok and Smidt (1988) found a holiday effect in the Dow Jones Industrial Average index. Ariel (1990) found that the average pre-holiday returns of large-cap NYSE stocks are 23 times larger than average-day returns. Anup Agrawal and Kishore Tandon (1994) reported extensive evidence of various seasonal effects across 18 countries. Yakob et al. (2005) examined the existence of monthly seasonality in 10 Asia Pacific markets.

Given that seasonal anomalies have long been circulated in the stock markets, one might assume that once the market perceived that certain seasonal anomalies exist, market participants attempt to exploit these anomalies until the unusually high returns vanished. Yet, current empirical evidence demonstrates that several seasonal anomalies still persist despite public awareness of their occurrences. Bouman and Jacobsen (2002) cited a written reference to the Sell-in-May Effect in an issue of the *Financial Times* in 1964. Bouman and Jacobsen then submitted statistical evidences of the Sell-in-May Effect in multiple countries during the period of 1970-1988, and highlighted that the effect is particularly strong in European countries. Among the most recent studies is the work of Dzhabarov and Ziemba (2010) which examines data from 1993 to 2009. Their study investigates whether or not traditional seasonal anomalies, such as the January effect, the Monthly Effect, and the Sell-in-May Effect, still exist in the turbulent markets of the early part of the 21st century. The evidence indicates that some of these anomalies still have high prediction accuracy and can produce higher returns than a buy-and-hold strategy. They also found that the effects tend to be stronger in small-cap stocks.

Despite a plethora of evidence of seasonal anomalies, some researchers strongly deny the existence of anomalies. Jensen (1978) highlights the importance of trading profitability when assessing market efficiency. He argues that if a trading rule is not strong enough to produce superior returns, such a trading rule is not economically significant, and therefore, a buy and hold strategy on a risk-adjusted basis should be used instead. Sullivan, Timmermann, and White (1999) argue that such calendar effects might be spurious and the result of data snooping. Grant McQueen and Steven Thorley (1999) also think that data mining is among the explanations of seasonal anomalies. Burton G. Malkiel urges in a *Wall Street Journal* commentary that his own personal investment using seasonal anomalies has not been profitable. Therefore, in his opinion, calendar time anomalies are not evidence of market inefficiency as there is not exploitable opportunity (Malkiel 2000).

Boumen and Jacobsen (2002) argue that, while data snooping may cause the January Effect and Monday Effect, the Sell-in-May effect is, on the other hand, not data-driven inference, but based on an old market wisdom – the characteristic that reduces the likelihood of data-mining. In addition, the data mining hypothesis suggests that seasonal anomalies caused by these reasons would hold in specific countries and over short periods of time, while the Sell-in-May Effect can be dated back several decades ago and occurs in both developed and emerging markets. To counter the claim of Malkiel (2000), the study of Boumen and Jacobsen (2002) reveals that the average returns from the period November-May are large and economically significant when compared with the average returns from the other half of the year. In addition, arguments that calendar anomalies do not provide exploitable opportunities are rejected by empirical evidences of significant stock returns induced by anomalies, as shown in the work of Lakonishok and Smidt (1988), Ariel (1990), and Dzhabarov and Ziemba (2010).

Undoubtedly, the persistence and economic significance of seasonal anomalies encourage further examination in other countries beyond the U.S. Gultekin and Gultekin (1983) found the January Effect - in which the average stock returns are significantly higher in January than in other months of the year – in 16 other developed countries across Europe and Asia, namely, Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway. Singapore, Spain, Sweden, Switzerland, and the United Kingdom. Following the work of Anup Agrawal and Kishore Tandon (1994), Bouman and Jacobsen (2002), and Yakob et al. (2005), the subsequent literature on developed equity markets outside the U.S. has produced results that are supportive of the U.S. findings, under different time frames from the preceding studies. Canestrelli and Ziemba (2000) found similar anomalies for stocks traded in the Milan Stock Exchange for the 1974-1993 period. Darrat et al. (2011) explore monthly seasonality in 34 international equity markets over the period from 1988 to 2010 and found the existence of the December Effect and the April Effect in the vast majority of these markets. They also found significant negative anomalies for the three months of June, August, and September compared to other months of the year in almost all global markets in the sample. Hence, they conclude that such persistent seasonal patterns across different markets may suggest market inefficiency and consequently offer exploitable opportunity. It should be noted that the result obtained from the work of Darrat et al. (2011) shows patterns of seasonal anomalies and average returns that are consistent with the Halloween Effect.

In the Thai market, the study of Bouman and Jacobsen (2002) concludes that the Halloween Effect, together with the January Effect, drive moderately significant (statistically speaking) average returns in the period November-April, when compared with average returns during the period May-October. The study covers the period of 1988 to 1998. Darrat et al. (2011) examined the occurrence of seasonal anomalies in international stock markets, including that of Thailand, from the period of January 1988 to December 2010; their work confirmed the results of Bouman and Jacobsen (2002): Darrat et al. (2011) concluded that the mean returns of the Thai stock market was significantly higher than zero in January and December, at 4.256% and 4.256% at the confidence level of 10% and 5%, respectively. Darret et al. (2011) also extended their study into sensitivity tests of empirical results using GARCH (1, 1) model, which confirms that December remained the month that produced the highest returns in the Thai stock market. Unlike other international markets, however, Darrat et al. (2011) did not find a significant April Effect in the Thai stock market. Meanwhile, the study of Haggard, Jones, and Witte (2014) used two different econometric techniques, which are median regression and influence vectors, to examine the role of outliers (extreme observations) on the Halloween Effect in the period of 1970-2012, the sample period studied by Bouman and Jacobsen (2002). While Haggard et al. (2014) did not find evidence that outliers significantly augment the Halloween Effect in the Thai stock market; they found that the difference between the distribution of returns in the Halloween period and non-Halloween period was significantly positively-skewed. The three studies provide evidence of the Halloween Effect and January Effect in the SET index.

Some countries exhibit other cultural holiday effects in addition to western calendar effects. The work of Chan, Khanthavit, and Thomas (1996) identified seasonality and cultural influences on 4 Asian stock markets using daily returns from the period of 1975-1991. As for the case of Thailand, their results showed that the SET index also experiences significant positive holiday returns prior to the Chakri Day – the commemoration of the founding of the current Chakri dynasty by King Rama I in 1982, which falls on April 6th. Other cultural holidays, namely Chinese New Year, Songkran (i.e. Thai New Year, which falls on April 13th), do not have significant impact on the performance of the SET index. Note that, this day-of-the-week study is to be compared with the month-of-the-year study of Darrat et al. (2011) which rejects the existence of the April Effect on the stock market. One possible explanation for this difference is that, while the daily returns of the SET show Chakri Day effect, the occurrence is not large enough to impact the average monthly returns for all of April in the SET index. Another important point to note from the study of Chan et al. (1996) is that Chakri Day has more prominent impact on the large-cap stocks than small-cap stock, whereas, when examined by firm-sized quartiles, companies that fall in the smallest company quartile experience significant impact from the Chinese New Year holiday.

Another question surrounding the study of seasonality is whether these seasonal anomalies are influenced by the size of firms (underlying the stocks). Several researchers report that based on daily returns, small firms generate higher stock returns during the first few days of January, in comparison to larger firms (Keim, 1983; Reinganum, 1983). Arguing against this firm-size bias, Kohers and Kohli (1991) provide evidence that suggests that the S&P indexes – namely, the S&P Composite, the S&P Industrials, the S&P Transportation, the S&P Utilities, and the S&P Financial Index – exhibit the highest mean returns and lowest coefficient of variation in January relative to other months. Therefore, Kohers and Kohli (1991) conclude that the January effect is independent of the sizes of the firms in question.

The discovery of the Halloween Effect, January Effect, and April (Chakri Day) effect in the SET index, as shown in the previous studies, suggests that seasonal anomalies may exist in some sectors of the SET index. This paper investigates the existence of seasonal anomalies in the energy sector of the SET index. It is expected that this sector, which accounts for over 15% of the SET index, would be impacted by more “global” (versus local) seasonal anomalies, given the sector’s greater sensitivity to global factors, such as oil prices, politics, and peers in other countries.

3. RESEARCH DESIGN

3.1 Sample

The data is obtained from Bloomberg and collected for the period from April 2005 to July 2016, for a total of 136 observations. This paper uses the monthly data of the SET Energy index and the sector’s individual stocks, namely BCP, BANPU, EGCO, GLOW, IRPC, PTT, PTTEP, RATCH, and TOP. Daily data was avoided since that could have contributed to an unusually high January Effect, as mentioned by Kohers and Kohli (1991).

3.2 Measurement and Hypotheses

The rates of return on the index and each stock for month t were calculated using the natural logarithm of the price relative as followed: -

$$R_{s,t} = \log(P_{s,t}/P_{s,t-1}) \quad (1)$$

where:

$R_{s,t}$ = The return on a specific index or stock in month *t;*
$P_{s,t}$ = The value of a specific index or stock in month *t;* and
$P_{s,t-1}$ = The value of a specific index or stock in month *t-1*.

Table 1 presents a statistical summary of monthly returns, consisting of the sample means, standard deviations, medians, minimums, maximums, skewness, and kurtosis. The mean monthly returns vary, with the SET Energy index having 0.29% of mean monthly returns from April 2005 to July 2016. GLOW poses the largest mean monthly return of 0.98%, with TOP having the smallest return of -0.04%. IRPC has the highest risk, as gauged by standard deviation, and the second smallest return of 0.05%. Most of the returns are negatively skewed and exhibit leptokurtic shape (with excess kurtosis over 0).

Table 1
Statistics Summary of Monthly Returns

Index/ Stock	Mean (x100)	Std.Dev. (x100)	Median (x100)	Min (x100)	Max (x100)	Skewness	Kurtosis
SET Energy	0.29	7.56	0.79	-39.80	17.49	-1.17	8.34
BANPU	0.18	11.33	1.18	-60.23	27.84	-1.10	8.17
BCP	0.80	9.75	0.65	-51.26	30.78	-0.82	8.95
EGCO	0.71	5.64	0.39	-16.09	24.72	0.46	5.82
GLOW	0.98	7.69	1.57	-33.65	23.98	-0.60	5.28
IRPC	0.05	12.19	0.69	-58.58	41.48	-0.26	7.83
PTT	0.37	8.55	0.63	-36.04	21.72	-0.60	5.09
PTTEP	0.14	9.32	0.92	-38.98	23.18	-0.64	4.66
RATCH	0.21	5.30	0.00	-12.14	32.95	1.83	13.09
TOP	-0.04	11.20	0.47	-70.04	23.81	-1.66	13.15

Note: The values of the index and stocks are sourced from Bloomberg for the period from April 2005 to July 2016.

In order to test for the existence of seasonal anomalies – namely, the Halloween Effect, January Effect, and April Effect – in the SET Energy index, and some of the sector's stocks, this paper uses the usual dummy regression technique, also used by Boumen and Jaconsen (2002) and Maberly and Pierce (2004). The equation is represented as:

$$R_{s,t} = \mu + \alpha_{s,t} D_{s,t} + \varepsilon_t \quad (2)$$

where:

$R_{s,t}$ = Natural logarithm of a specific index or stock price relative in month *t;*
μ = A constant;
$\alpha_{s,t}$ = A regression coefficient to be estimated;
$D_{s,t}$ = Seasonal dummy variable; and
ε_t = An error term.

To test for the Halloween Effect, the dummy variable $D_{s,t}$ is assigned 1 if month t falls on the period of November to April, and 0 if otherwise. For the January Effect, the dummy variable is assigned 1 if month t is January, and 0 if otherwise. For the April Effect, the dummy variable is assigned 1 if month t is April, and 0 if otherwise. When the dummy variable $D_{s,t}$ is 0, the monthly mean returns over the non-anomaly periods equal the constant term μ.

This paper tests whether the coefficient $\alpha_{s,t}$ is significantly different to zero. The null hypothesis of no seasonal anomaly is rejected when the coefficient $\alpha_{s,t}$ is significant and positive.

In order to better understand, and perhaps, predict the future values in the time series data, we subject mean monthly return of the SET Energy Index and individual stocks to autoregressive-moving-average (ARMA) model. The ARMA model describes a weakly stochastic process in terms of two lines of thinking. First, the autoregressive (AR) part describes that the current level of the mean monthly returns $R_{s,t}$ depends on the level of its lagged observations. The notation *AR(p)* refers to the AR model of order *p*. The *AR(p)* model is written as:

$$R_t = c + \sum_{i=1}^{p} \alpha_i R_{t-i} + \varepsilon_t \tag{3}$$

where:

R_t = Mean monthly return in month *t;*
c = A constant;
α_i = A parameter;
R_{t-i} = Mean monthly return in month t with a lag of i times; and
ε_t = An error term.

The moving-average (MA) model is then used to test whether the error term is dependent of its lagged values. The notation *MA(q)* refers to the MA model of order *q*. The *MA(q)* model is written as:

$$R_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{4}$$

where:

R_t = Mean monthly return in month *t;*
μ = An expectation of R_t ;
ε_t = An error term.
θ_i = A parameter; and
ε_{t-1} = An error term with a lag of i times

The generalized form of the ARMA model is *ARMA(p,q)*, which refers to refers to the model with p autoregressive terms and q moving-average terms. The goal is to find the model that provides an acceptable fit to the data. The *ARMA(p,q)* model is written as:

$$R_t = c + \varepsilon_t + \sum_{i=1}^{p} \alpha_i R_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{5}$$

Finally, the mean monthly returns are subjected to a sensitivity test. Unlike the use of generalized autoregressive conditional heteroskedastic (GARCH) model in the work of Darrat et al. (2011), this paper uses exponential generalized autoregressive conditional heteroskedastic (EGARCH) model, created by Nelson (1991). The nonnegativity constraint in the EGARCH model is less restrictive than those counterparts in the GARCH model. The notation *EGARCH(p,q)* is described as:

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \log \sigma_{t-k}^2 \tag{6}$$

where: $g(Z_t) = \theta Z_t + \lambda\big(|Z_t| - E(|Z_t|)\big)$

While the standardized *GARCH(1,1)* model was used in the work of Darrat et al. (2011), this paper selects tailoring the *EGARCH(p,q)* model to best fit each index and stock. In order to identify and better select the model that is the most fitted to the dependent variable, this paper relies on Akaike Information Criterion (AIC) over Schwarz Criterion, as the AIC penalizes less parameters than Schwarz Criterion. The values of p and q in the *EGARCH(p,q)* model are selected when the pair produces the smallest AIC.

4. EMPIRICAL RESULTS AND DISCUSSION

Based on testing for the impact of seasonal anomalies – namely, the Halloween Effect, the January Effect, and the April Effect – on the returns of the SET Energy Index as well as 9 specific stocks, this finding shows that only the April Effect had a significant impact on the mean returns of the SET Energy Index. In other words, from April 2005 to July 2016, the mean returns of the SET Energy index was 4.22% in the month of April, with a p-value of 0.0074 at a 5% level in a 2-tail test. The seasonal anomalies do not have any significant impact on means monthly returns of other 9 stocks: BCP, BANPU, EGCO, GLOW, IRPC, PTT, PTTEP, RATCH, and TOP. The results of the regression of SET Energy index returns on a set of dummy variables are shown in Table 2.

Table 2

Seasonal Anomalies Effect on the SET Energy Index

Variable	Coefficient	Std. Error	t-Stat	Prob.
January Effect	-0.0191	0.0257	-0.7429	0.4589
April Effect	0.0422	0.0155	2.7209	0.0074*
Halloween Effect	-0.0124	0.0161	-0.7701	0.4426

* Significantly different from zero at the 1% level in a 2-tail test

This paper finds that seasonal anomalies, however, had significant impact on the volatility of the SET energy index and the selected 9 energy stocks, as shown in Table 3. The January Effect has a highly significant impact on the volatility of monthly returns of RATCH and shows a positive trend towards significance on the volatility of BANPU's returns, depicted by p-value of 0.009 and 0.0959, respectively. In terms of the direction of the impact, the January Effect resulted in a decrease in volatility of monthly returns of BANPU and RATCH.

Table 3

Anomalies Effect on the Volatility of the Index and Stocks

Index/ Stock	ARMA	EGARCH	January Effect			April Effect			Halloween Effect		
			Coef.	Prob.		Coef.	Prob.		Coef.	Prob.	
SET Energy	MA (3)	EGARCH (1,1)	-0.0012	0.2979		-0.0016	0.4146		0.0010	0.0674	*
BANPU	MA (1)	EGARCH (1,1)	-0.7829	0.0959	*	-0.0214	0.9650		0.3072	0.0402	**
BCP	ARMA (2,2)	EGARCH (1,2)	-0.2735	0.6542		0.3456	0.4496		0.0688	0.8082	
EGCO	ARMA (3,3)	EGARCH (2,2)	-0.5173	0.2593		-1.3107	0.0007	***	0.7598	0.0040	***
GLOW	ARMA (1,1)	EGARCH (1,2)	-0.1933	0.5678		0.0585	0.8753		0.0516	0.8555	
IRPC	AR (2)	EGARCH (1,2)	-0.1181	0.4474		0.0511	0.8145		-0.2511	0.4399	
PTT	ARMA (3,3)	EGARCH (1,2)	0.1801	0.1959		-0.3700	0.0389	**	0.2112	0.4767	
PTTEP	ARMA (5,5)	EGARCH (2,1)	-0.5395	0.2037		-1.0663	0.0240	**	0.2491	0.1196	
RATCH	ARMA (4,4)	EGARCH (1,1)	-1.5525	0.0009	***	-0.9056	0.2618		-0.4012	0.3100	
TOP	ARMA (2,2)	EGARCH (1,1)	0.1179	0.1384		-0.2520	0.0042	***	0.2875	0.5873	

* Significantly different from zero at the 10% level in a 2-tail test
** Significantly different from zero at the 5% level in a 2-tail test
*** Significantly different from zero at the 1% level in a 2-tail test

The April Effect significantly impacts a larger number of stocks, namely EGCO, PTT, PTTEP, and TOP. The significance seems more prominent on EGCO and TOP, with p-values of 0.0007 and 0.0042, respectively. Again, like the January Effect, the April Effect reduces the volatility of monthly returns of these stocks.

Lastly, the Halloween Effect significantly impacts with regards to increasing the volatility of monthly returns on BANPU and EGCO, with p-values of 0.0402 and 0.0040, respectively. This anomaly also showed a favorable trend towards significance on increasing the volatility of the SET Energy Index's monthly returns.

The empirical results in this paper show that the mean monthly returns of the SET Energy Index are significantly impacted by the April Effect, while the selected 9 energy stocks do not receive any significant impact from the seasonal anomalies. The effect of seasonal anomalies is more profound and significant on the volatility of mean monthly returns. Several stocks experience lower volatility during the anomaly periods.

The April Effect on the SET Energy Index is an extension of the work of Chan et al. (1996) which discovered significance in the April effect on the SET index as a part of their study on seasonality and cultural influences on stock markets. Chan et al. (1996), in addition, examined the effect of cultural holidays on the mean daily returns of the index and concluded that the SET index was significantly impacted by Chakri Day, which falls on the 6^{th} of April, and not by the Thai New Year Day, which falls on the 13^{th} of April. Our paper leaves out the study of daily returns for future research. Subsequent work may examine the mean daily returns of the SET Energy index and energy stocks to find whether they are impacted by Chakri Day, Thai New Year day, or both.

The sensitivity test, on the other hand, does not have a large previous body of research. Darrat et al. (2011) used the *GARCH (1,1)* model to explore seasonality and found that December has significant positive impact on the volatility of the SET Index. Our paper differs in that it examines the SET Energy Index and energy stocks, instead of the Thai stock market alone, and also combines the December Effect and the Halloween Effect. Yet, our results are partially consistent with the results of Darrat et al. (2011). The Halloween effect, which includes the month of December, shows significant positive impact on the SET Energy Index, and 2 stocks, namely BANPU and EGCO, implying that the volatility of these index/stocks significantly increase during the Halloween Effect period. The month of April, again, also has negative anomalies on 4 energy stocks: EGCO, PTT, PTTEP, TOP, while the month of January shows negative anomalies on BANPU and RATCH.

The explanations for the seasonal anomalies remain a topic of debate. Grant McQueen and Steven Thorley (1999) suggest data mining or risk differences as possible causes of seasonal anomalies. Data mining suggests that seasonal anomalies would hold in specific countries and over short periods of time; however, our paper also shows that seasonal anomalies extend to emerging markets like the SET Index (including its Energy sector), effects that are observable over a decade, from April 2005 to July 2016. While one may argue that an 11-year period is perhaps a bit short, this time horizon was selected for its availability of data on some stocks. However, future studies could explore individual energy stocks like EGCO or PTTEP, whose data is available to as far back as 1995 and 1993, respectively.

Risk difference hypothesis suggests that higher returns caused by seasonal anomalies are a compensation for a higher risk during the period. Yet, this paper found that seasonality like the January Effect and the April Effect resulted a reduction of volatility. A look back on the performance of some energy stocks during the month of April from the year 2005 to 2016 revealed positive returns. A strategy to buy stocks such as PTT, PTTEP, EGCO, and TOP at the beginning of March and sell at the end of April would have yielded average returns of 5.20%, 6.82%, 2.24%, and 1.30%, respectively. Therefore, in light of such data we suggest that the risk difference hypothesis is not a valid explanation for the unusually high returns during seasonal anomalies.

One possible explanation for seasonality effects on volatility is the effect of holiday's periods. Noticeably, the April Effect, January Effect, and the Halloween Effect occur during when official holidays are plenty and travelling is in peak season. A drop in volatility during the January Effect and April Effect probably indicates lower liquidity and lower trading activity; therefore, stock prices are more likely to be manipulated, resulting in higher returns during the anomalies. Chan et al. (1996) also suggests that the need for cash prior to major holidays may encourage investors to liquidate a part of portfolio. This explanation seems to fit the practice of cash bonuses among Chinese enterprises during the Chinese New Year. As for the case of the SET Energy Index, the need for cash prior to holidays and the fact that investors may be off for vacation during holiday periods may loosely explain the absence of trading volume and low volatility during the anomalies.

5. CONCLUSIONS AND RECOMMENDATIONS

The old market saying "Sell in May, and Go Away", also known as the Halloween Effect, has long persisted in global stock markets. Its persistence over time encourages researchers to study and examine its relevance in various markets in addition to the U.S. and other developed markets. Likewise, other famous seasonal anomalies, namely the January Effect, have been widely studied both individually and as an amplifier of the Halloween Effect. The extensive work on the seasonality of stock markets subsequently led to the discovery of new, more localized or regionalized anomalies, such as the April Effect, and the cultural holiday's effect.

Inspired by the preceding studies of seasonality in the Thai stock market, this study investigated the existence of seasonal anomalies in the SET Energy Index and selected stocks. Interestingly, only the April Effect had significant positive impact on the mean monthly returns of the SET Energy index, while the famous Halloween effect and January effect had no significant impact on returns. The three anomalies, however, exhibited significance on the volatility of returns. The possible explanation for this seasonal phenomenon is, perhaps, the absence of heavy trading activity and the reduction in liquidity prior to the anomaly periods, which also fall on peak travel periods. The liquidation of portfolios prior to holidays may depress stock prices, allowing for buying opportunity. After the holidays, when trading activities resume to normal, stock prices tend to recover, allowing for profit-taking opportunity.

For further research, the sample data for only energy stocks could be extended as far back as 1993 to confirm the persistence of seasonal anomalies over a longer period of time on the returns or volatility of returns on the stocks. Another area to explore is the monthly seasonality of oil prices and their impact on energy stocks, given that oil prices have played a key role in the performance of energy companies and oil price movement likely influence stock prices movement. In addition, similar methodologies could be extended to other key sectors in the SET index, such as the Banking sector or the Construction and Materials sector, in order to examine the existence of seasonal anomalies.

6. REFERENCES

Agrawal, A., & Tandon, K. (1994). Anomalies or illusions? Evidence from stock markets in eighteen countries. *Journal of international Money and Finance, 13*(1), 83-106.

Ariel, R. A. (1990). High stock returns before holidays: Existence and evidence on possible causes. *The Journal of Finance, 45*(5), 1611-1626.

Bouman, S., & Jacobsen, B. (2002). The Halloween indicator," Sell in May and go away": Another puzzle. *The American Economic Review, 92*(5), 1618-1635.

Canestrelli, E., & Ziemba, W. T. (2000). Seasonal Anomalies in the Italian Stock Market, 1973-1993r. *Security Market Imperfections in Worldwide Equity Markets, 9*, 337.

Chan, M. L., Khanthavit, A., & Thomas, H. (1996). Seasonality and cultural influences on four Asian stock markets. *Asia Pacific Journal of Management, 13*(2), 1-24.

Darrat, A. F., Li, B., Liu, B., & Su, J. J. (2011). A fresh look at seasonal anomalies: An international perspective. *International Journal of Business and Economics, 10*(2), 93.

Dzhabarov, C., & Ziemba, W. T. (2010). Do seasonal anomalies still work?. *The Journal of Portfolio Management, 36*(3), 93-104.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance, 25*(2), 383-417.Grant McQueen and Steven Thorley (1999)

Friday, H.S., & Bo, No. (2015). Seasonality in the Thai Stock Index. *Global Economy and Finance Journal, 8*(1), 112 – 120.

Gultekin, M. N., & Gultekin, N. B. (1983). Stock market seasonality: International evidence. *Journal of financial economics, 12*(4), 469-481.

Haggard, K. S., Jones, J. S., & Witte, H. D. (2015). Black cats or black swans? Outliers, seasonality in return distribution properties, and the Halloween effect. *Managerial Finance, 41*(7), 642-657.

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of financial economics, 6*(2-3), 95-101.Keim, 1983

Kohers, T., & Kohli, R. K. (1991). The anomalous stock market behavior of large firms in January: the evidence from the S&P Composite and component indexes. *Quarterly Journal of Business and Economics*, 14-32.

Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies, 1*(4), 403-425.

Maberly, E. D., & Pierce, R. M. (2004). Stock market efficiency withstands another challenge: Solving the "sell in May/buy after Halloween" puzzle. *Econ Journal Watch, 1*(1), 29-46.

Malkiel, B. G. (2000). Are markets efficient? *The Wall Street Journal*, 28.

McQueen, G. R., & Thorley, S. (1999). Mining fool's gold. *Financial Analyst Journal, 55*(2), 61-72.

Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects. *Journal of Financial Economics*, *12*(1), 89-104.

Rozeff, M. S., & Kinney, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of financial economics, 3*(4), 379-402.

Sullivan, R., Timmermann, A., & White, H. (1999). Data-snooping, technical trading rule performance, and the bootstrap. *The journal of Finance*, *54*(5), 1647-1691.

Yakob, N. A., Beal, D., & Delpachitra, S. (2005). Seasonality in the Asia Pacific stock markets. *Journal of Asset Management*, *6*(4), 298-318.