Int. Journal of Economics and Management 5(1): 216 – 225 (2011) ISSN 1823 - 836X

The Halloween Puzzle in Selected Asian Stock Markets

HOOI HOOI LEAN*

Universiti Sains Malaysia

ABTRACT

Limited studies have looked into the presence of Halloween effect in stock market. This paper examines the existence of Halloween effect in the stock market of six Asian countries namely Malaysia, China, India, Japan, Hong Kong and Singapore. Results show that the effect is only found in Malaysia and Singapore with the OLS model. However, with the conditional variance model; China, India and Japan also show evidence of the Halloween effect. Hence, the "Sell in May" strategy might be profitable to the investors in these markets.

Keywords: Halloween effect, Asian stock markets, volatility, GARCH

INTRODUCTION

According to Bouman and Jacobsen (2002), Halloween effect exists if the stock returns are lower during the May to October period compared to the remainder of the year. Thus, "Sell in May and go away" strategy has been introduced where investing in the stocks only if the trading period falls between November – April. This strategy has its economic significance and of its interest to the practitioners, as benefits can be obtained by just two trades a year and is therefore not worn out by transaction costs. Bouman and Jacobsen (2002) stated that the month of May signals the start of bear market and therefore it is better for an investor to sell their stocks and hold cash. They suggested that the investors should invest in the stock market starting October 31 through April 30 and withdraw from the market during the other half of the year.

This study attempts to examine the Halloween effect in Asian. In other words, we test whether the stock returns are significantly higher during the November-April period than the remainder of the year. We add to the literature by examining some selected major markets in Asian with the more recent data. Besides, the model

* Corresponding Author: E-mail: hooilean@usm.my

Any remaining errors or omissions rest solely with the author(s) of this paper.

specification is improved by taking into account the conditional variance effect of stock returns and asymmetric market reactions.

The rest of the paper is structured as follows. The next section briefly reviews previous studies on the existence and significance of the Halloween effect. Section 3 introduces the data and describes the methodology used for the analysis. Section 4 presents and discusses the empirical results. Finally, Section 5 concludes the paper.

REVIEW OF RELATED STUDIES

The issue of Halloween effect is one of calendar anomaly in equity markets. Although it has not been widely discussed as of the day-of-the-week effect and January effect; it has been studied by some researchers. Among them are Bouman and Jacobsen (2002), Maberly and Pierce (2003), Maberly and Pierce (2004) and Jacobsen and Visaltanachoti (2006). We note that the academic literature of Halloween effect started from year 2002 when Bouman and Jacobsen successfully published their findings in the American Economic Review in 2002. While the literature on calendar anomaly has been well documented[1], we focus our review on the literature of Halloween effect only.

Bouman and Jacobsen (2002) suggested that the Sell in May effect is present in 36 out of 37 countries from various regions of the world such as Europe, Asian and others. The effect is strong and highly significant in European countries. Only New Zealand has the higher average return in May through October compare to the remainder of the year. In general, the bad months for stock markets occurred during August and September in almost all countries. Bouman and Jacobsen (2002) also documented that the Halloween strategy does well when judged on its ability to time bear and bull markets. Better skills in forecasting bull markets compared to bear markets are noticed by using Halloween strategy. They found that the size of the effect is significantly related to the length and timing of vacations as well as the impact of vacations on trading activity in different countries. If summer vacations are indeed the cause of a Sell in May effect, one would expect the opposite effect in countries on the Southern Hemisphere. However, Bouman and Jacobsen (2002) do not find this.

However, Maberly and Pierce (2003) figured out that the Halloween effect in Japan disappeared after its internalization in 1986. The mean return is more negative over the November-April periods conditional on a bear market during 1970-1986. The authors suggested that the optimal strategy is to long stocks in the bull market year and out of stock during bear market year provided the investor is able to identify a bull market year from a bear market year ex ante. The increased buying pressure or money inflows during the bull markets might explain the anomalous pattern.

---

[1] Interested reader may refer to Chia, *et al*. (2008), Berument and Kiymaz (2001) and Basher and Sadorsky (2006) for example.

Maberly and Pierce (2004) re-examined the existence of Halloween effect in the S&P 500 index because they suspected the Halloween effect that presented by Bouman and Jacobsen (2002) was driven by the outliers and January effect. Maberly and Pierce (2004) added the January effect and two outliers; which are the October 1987 world equity prices crash and the August 1998 associated with the collapse of the hedge fund. They found the Halloween effect is no longer statistically significant. In addition, the coefficients of the two outliers are found to be negatively significant. Thus, they concluded that the Halloween effect documented by Bouman and Jacobsen (2002) is being driven by the large negative returns during October 1987 and August 1998. The significance of the Halloween effect as reported before has also been reduced after taking the January dummy into account. Maberly and Pierce (2004) also rejected the existence of Halloween effect in the S&P 500 futures market.

Recently, Jacobsen and Visaltanachoti (2006) discussed the significance of Halloween effect in the US stock market's sectors and industries from 1926 to 2005. Similar to Bouman and Jacobsen (2002), the US sectors returns are higher during the winter months compared to the summer months. Strong Halloween effect is found in the raw material and production sectors, while consumer oriented sectors exhibit weak form of Halloween effect.

Based on the existing limited four studies, the results are mixed and lack of consistent conclusion. In addition, the empirical studies are mainly for the US markets and are lacking of Asian markets except the Japan. Hence, this paper is trying to add some Asian evidence to the existing literature.

DATA AND METHODOLOGY

The data used for this study consists of daily index from 1st January 1991 to 30th June 2008 for Kuala Lumpur Composite Index (KLSE), Shanghai Composite Index (SSEC), India BSE SENSEX (BSESN), Japan Nikkei 225 Index (N225), Hang Seng Index (HSI) and Singapore Straits Times Index (STI). All data are downloaded from the *Datastream* database and are transformed into logarithm prior to the analysis.

Similar to the previous studies, several simple statistical methodologies such as descriptive statistics, time series plot as well as unit root test are used to provide initial view on how the variables behave. After the indices are found to be stationary, regression analysis with dummy variables as suggested by Bouman and Jacobsen (2002) is used:

$$r_t = \mu + \alpha_0 S_t + \varepsilon_t \qquad (1)$$

where S_t is a seasonal dummy variable, μ is a constant. Dummy variable, S_t equals to 1 if the month falls on the period of November through April and equals to 0 otherwise. If the coefficient, α_0 appears to be positively significant, the null hypothesis of no "Sell in May" effect is rejected and implies evidence of Halloween effect.

Maberly and Pierce (2004) suggested that the intercept term μ represents the monthly mean return over the May-October periods and $\mu + \alpha_1$ represents the monthly mean return over the November-April periods. As the period of November to April included January, Maberly and Pierce (2004) argued that the Sell in May effect might be due to the January effect where the high positive returns is recorded during the month. Hence, regression model by adding January dummy has been introduced:

$$r_t = \mu + \alpha_1 S_1^{adj} + \alpha_2 Jan_t + \varepsilon_t \tag{2}$$

where Jan_t denotes the January dummy that equal to 1 if the returns fall in January or 0 otherwise. All excess returns in January are entirely due to a January effect and not caused by the "Sell in May" effect after this regression is estimated.

Furthermore, the GARCH, EGARCH and TARCH models are employed in this study to capture the time-varying volatility of the series. Bollerslev (1986) suggested a way to deal with large lag value by extending the ARCH model to GARCH(p,q) by introducing the idea of the influence of previous conditional variance in the conditional variance equation. p and q represent the lagged term of squared error term and observation of past conditional variances respectively. In this study, the model which will be used is set to be the GARCH(1,1):

$$r_t = \mu + \alpha_0 S_t + \lambda\sigma_t + \varepsilon_t$$

$$\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + a_2\sigma_{t-1}^2 \tag{3}$$

The GARCH model generally imposes symmetry effect of shocks on the volatility. However, many empirical studies have documented asymmetric behavior in financial data whereby falls which can be interpreted as bad news usually contribute more to the increase in volatility than an increase (interpreted as good news) in the equity returns. This phenomenon that is better known as the leverage effect implies that the volatility tends to decline as the returns rise, and to increase when the returns fall. Therefore, to cope with this problem, Nelson (1991) has developed the exponential GARCH (EGARCH) to allow for asymmetric shock to volatility and the variance equation can be written as:

$$\log\sigma_t^2 = a_0 + a_1\log\sigma_{t-1}^2 + a_2\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + a_3\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4}$$

where the term $\log\sigma_t^2$ represents the conditional variance. Thus, this implies that the leverage effect is exponential rather than quadratic. Moreover, the forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be known by testing the hypothesis of $a_3 > 0$. If the result found to be $a_3 \neq 0$, the impact is asymmetric. If $a_3 < 0$ implies that a bad news in the market will increase the volatility more than a good news of an equal magnitude. Furthermore, this study also applies Threshold ARCH (TARCH) which was introduced independently by Zakoian (1994) and Glosten et al. (1993). The specification for the conditional variance can be written as:

$$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2\varepsilon_{t-1}^2 + a_3\varepsilon_{t-1}^2 d_{t-1} \quad (5)$$

where $d_t = 1$ if $\varepsilon_t > 0$, and 0 otherwise. In this model, good news which occurs if $\varepsilon_t > 0$ and bad news when $\varepsilon_t < 0$ have differential effects on the conditional variance. Good news has an impact of a_1, while bad news has an impact of $(a_2 + a_3)$. If $a_3 > 0$, it can be said that the leverage effect exists. In addition, if $a_3 \neq 0$, the news is asymmetric.

EMPIRICAL RESULTS AND DISCUSSION

The Augmented Dickey Fuller (ADF) and Phillip and Perron (PP) tests are employed to determine the integration order of each stock index. Consistent with other studies and shown from Table 1, the null hypothesis of unit root cannot be rejected in level. However, the index becomes stationary after first differencing. Hence, it is suggested that the stock indices are I(1).

Table 1 Unit root tests for Asian stock markets

Indices	Level		1st Differenced	
	ADF	PP	ADF	PP
STI	-1.873	-1.919	-13.265***	-46.7849***
KLSE	-1.861	-1.834	-18.518***	-59.7994***
SSEC	-2.104	-2.304	-16.785***	-68.1372***
BSESN	-1.389	-1.390	-17.580***	-59.6932***
N225	-2.394	-2.388	-18.478***	-70.0056***
HSI	-2.419	-1.923	-17.256***	-67.2776***

*** denotes significant at 1% level

The daily returns of the six stock indices have been computed and reported in Table 2. The mean daily returns for all the countries appear to be higher in the November-April period with the exception of Hong Kong. Three markets show negative return in the May-October period. As for the standard deviation, India, Japan, Hong Kong and Singapore recorded higher risk during the November-April period while Malaysia and China have a higher risk in the May-October period. Based on the mean-variance criterion, the November-April period is better performed than the May-October period in Malaysia and China while the reverse happened in Hong Kong. This finding rule out the possibility of risk related explanation as there is no consistent result on the relationship between risk and return among the examined markets.

Table 2 Mean and standard deviation for Asian stock markets

Index	Full sample		November-April		May-October	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
STI	0.021	1.241	0.060	1.316	-0.019	1.159
KLSE	0.019	1.458	0.059	1.406	-0.022	1.507
SSEC	0.067	2.557	0.102	2.124	0.032	2.928
BSESN	0.057	1.647	0.083	1.721	0.03	1.571
N225	-0.013	1.395	0.011	1.44	-0.037	1.348
HSI	0.044	1.587	0.042	1.621	0.045	1.553

The average daily returns by month for the six markets are displayed in Table 3. We note that for Malaysia, Singapore and Japan; the worst month is in the May-October period while the best month is in the November-April period. For Hong Kong and India, both the worst and the best months are in the November-April period; while this situation happens in the May-October period for China. Again, the returns by month do not show any significant and consistent Halloween effect in our sample markets.

Table 3 Average daily returns by month for Asian stock markets

Countries	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec
STI	0.01	0.08	-0.05	0.12	-0.07	-0.03	0.00	-0.07	-0.03	0.09	0.12	0.11
KLSE	0.03	0.17	-0.09	0.04	-0.01	-0.06	0.00	-0.14	-0.03	0.10	0.01	0.20
SSEC	0.10	0.17	-0.03	0.23	0.21	0.02	-0.16	0.24	-0.05	-0.10	0.19	-0.03
BSESN	0.06	0.24	-0.08	-0.03	-0.07	0.03	0.08	0.17	0.06	-0.07	0.12	0.21
N225	0.01	0.01	0.01	0.05	-0.02	-0.04	-0.03	-0.02	-0.05	-0.04	0.01	-0.01
HSI	-0.05	0.17	-0.09	0.09	0.07	-0.01	0.06	-0.01	0.02	0.15	0.06	0.09

The estimation results with the original and modified models are represented in Table 4. All coefficients of S are positive except the Hong Kong showing that the stock returns in the November-April period are higher than those in the May-October period. However, only Malaysia and Singapore have the significant results. Therefore, we conclude that there exists significant evidence of the Halloween effect in Malaysia and Singapore stock markets with the OLS model.

Table 4 Estimated Results

		Original model					Modified model			
		OLS	**GARCH**	**EGARCH**	**TARCH**		**OLS**	**GARCH**	**EGARCH**	**TARCH**
STI	S	0.079**	0.066**	0.1141***	0.0771***	S_{adj}	0.0942**	0.0481*	0.0724***	0.0573**
		(0.0367)	(0.0273)	(0.0189)	(0.0236)		(0.0386)	(0.0286)	(0.0210)	(0.0247
						Jan	0.0074	0.1766***	0.2799***	0.1866***
							(0.0674)	(0.0449)	(0.0246)	(0.0394)
	a_0		0.0217***	-0.1048***	0.0236***	a_0		0.0227***	-0.1248***	0.0248***
	a_1		0.0908***	0.1443***	0.0451***	a_1		0.0949***	0.1715***	0.0475***
	a_2		0.8989***	0.0599***	0.0869***	a_2		0.8946***	-0.0637***	0.0903***
	a_3			-0.9856***	0.8988***	a_3			0.9819***	0.8943***
KLSE	S	0.0802*	0.0323	0.0535***	0.0397	S_{adj}	0.0870*	0.0269	0.0417*	0.0335
		(0.0431)	(0.0250)	(0.0206)	(0.0241)		(0.0454)	(0.0265)	(0.0220)	(0.0259)
						Jan	0.0480	0.0582	0.1035***	0.0684*
							(0.0791)	(0.0381)	(0.0315)	(0.0351)
	a_0		0.0128***	-0.1265***	0.0138***	a_0		0.0127***	-0.1270***	0.0137***
	a_1		0.1104***	0.1755***	0.0720***	a_1		0.1102***	0.1761***	0.0718***
	a_2		0.8900***	0.9911***	0.8938***	a_2		0.8902***	0.9910***	0.8940***
	a_3			-0.0391***	0.0648***	a_3			-0.0396***	0.0649***
SSEC	S	0.0702	0.1304***	0.3158***	0.1283***	S_{adj}	0.0722	0.1284***	0.2956***	0.1277***
		(0.0757)	(0.0302)	(0.0294)	(0.0346)		(0.0796)	(0.0303)	(0.0313)	(0.0349)
						Jan	0.0606	0.1384**	-0.1166***	0.1310**
							(0.1389)	(0.0695)	(0.0408)	(0.0666)
	a_0		0.0872***	-0.1650***	0.0965***	a_0		0.0874***	-0.1566***	0.0966***
	a_1		0.2222***	0.3127***	0.2676***	a_1		0.2223***	0.2865***	0.2676***
	a_2		0.8189***	0.9692***	0.8091***	a_2		0.8188***	0.9757***	0.8090***
	a_3			0.0240***	-0.0684***	a_3			0.0248***	-0.0683***

Table 4 (*Cont'd*)

BSESN	S	0.0530	0.0032	0.0482*	0.0211	S_{adj}	0.0579	0.0108	0.0578**	0.0266
		(0.0488)	(0.0364)	(0.0264)	(0.0365)		(0.0513)	(0.0379)	(0.0289)	(0.0383)
						Jan	0.0298	-0.0342	0.0147	-0.0053
							0.0894	(0.0679)	(0.0567)	(0.0661)
	a_0		0.0574***	-0.1422***	0.0656***	a_0		0.0573***	-0.1424***	0.0656***
	a_1		0.1140***	0.2296***	0.0928***	a_1		0.1140***	0.2300***	0.0930***
	a_2		0.8714***	0.9685***	0.8652***	a_2		0.8714***	0.9684***	0.8651***
	a_3			-0.0366***	0.0469***	a_3			-0.0366***	0.0468***
N225	S	0.0479	0.0445	0.0838***	0.0517*	S_{adj}	0.0484	0.0437	0.0781***	0.0567*
		(0.0413)	(0.0356)	(0.0263)	(0.0309)		(0.0434)	(0.0376)	(0.0295)	(0.0327)
						Jan	0.0455	0.0481	0.1076	0.0290
							(0.0757)	(0.0596)	(0.0380)	(0.0522)
	a_0		0.0374***	-0.0885***	0.0360***	a_0		0.0374***	-0.0889***	0.0361***
	a_1		0.0748***	0.1344***	0.0221***	a_1		0.0748***	0.1349***	0.0219***
	a_2		0.9076***	0.9756***	0.9122***	a_2		0.9076***	0.9757***	0.9122***
	a_3			-0.0804***	0.0973***	a_3			-0.0801***	0.0977***
HSI	S	-0.0026	0.0037	-0.0013	-0.0115	S_{adj}	0.0189	-0.0024	-0.0045	-0.0165
		(0.0476)	(0.0381)	(0.0358)	(0.0294)		(0.0500)	(0.0408)	(0.0317)	(0.0384)
						Jan	-0.1046	0.0313	0.0142	0.0098
							(0.0872)	(0.0653)	(0.0574)	(0.0619)
	a_0		0.0287***	-0.0976***	0.0399***	a_0		0.0287***	-0.0976***	0.0398***
	a_1		0.0735***	0.1460***	0.0329***	a_1		0.0736***	0.1460***	0.0330***
	a_2		0.9154***	0.9831***	0.9079***	a_2		0.9153***	0.9831***	0.9079***
	a_3			-0.0572***	0.0832***	a_3			-0.0572***	0.0832***

Note: ***, ** and * denotes significant at 1%, 5% and 10% level. Value in parenthesis indicates the standard errors of the coefficient.

Controlling of January effect does not impact the coefficients of S as well except for Hong Kong. The coefficient of S changing from negative in the original model to positive in the modified model inferring that the lower returns in November-April period is mainly due to the negative January effect in Hong Kong. We note that with the model specification of time-varying volatility, more markets show the existence of Halloween effect. The Halloween effect appears in China with the three conditional variance models. There is evidence of Halloween effect in India with the EGARCH model and in Japan with the EGARCH and TARCH models. Hong Kong is the only market that does not show any evidence of Halloween effect. A number of diagnostic tests are conducted to the conditional variance models showing the validity of the estimation[2]. Specifically, the ARCH-LM test shows absence of heteroskedasticity and Ljung-Box Q Statistic shows no serial correlation in the residuals respectively.

The sum of the ARCH term, a_1 and the GARCH term, a_1 measures the level of volatility persistency. If the sum of a_1 and a_2 appears to be more than one, this indicates that the volatility in the market have explosive effect. Hence, the distant past conditional variances and information shocks contribute significantly to the future expected conditional variance. The GARCH and EGARCH models for Malaysia, the three conditional variance models for China, the EGARCH models for India, Japan and Hong Kong show this explosive effect. Hence, such models may be better specified by an integrated GARCH or GARCH (2, 2) process. We re-estimate the KLSE and SSEC series with the GARCH (2, 2) model and find that the sum of a_1 and a_2 is less than one without affecting the significant of coefficient of S[3].

If the sum is less than but close to one, this means shocks to the volatility have highly persistent effect and the high volatility decays at a slow pace. In addition, a negative leverage effect term (a_3) implies the existence of the leverage effect in stock returns. In other word, a bad news in the market increases volatility more than an equal magnitude of good news. Moreover, it is noticed that the coefficients for volatility are about the same for both original and modified models. This might implies that the volatility remains at the same pace even with the control of January effect.

CONCLUSION

This study examines the existence of Halloween effect in the stock markets of six selected Asian countries namely Malaysia, China, India, Japan, Hong Kong and Singapore. The OLS estimation reveals the existence of Halloween effect in Malaysia and Singapore only. However, the conditional variance models show evidence of Halloween effect in all the five Asian markets except Hong Kong.

[2] Results are available upon request.

[3] Results are available upon request.

Therefore, we conclude that this calendar anomaly is exist in these five Asian markets. Thus, the "Sell in May and go away" strategy might be applicable to the investors for earning an abnormal return.

Seems Halloween effect is still a puzzle in finance literature. Bouman and Jacobsen (2002) addressed a number of potential explanations for it, but none appear to explain the puzzle. Bouman and Jacobsen (2002, p. 1630) argued that "history and practice tells us that the old saying is right, while stock market logic tells us it is wrong. It seems that we have not yet solved this new puzzle." Our result supports that the puzzle still alive in the Asian markets.

REFERENCES

Basher, S.A. and Sadorsky, P. (2006) Day-of-the-week effects in emerging stock markets. *Applied Economic Letters* 13, pp. 621-628.

Berument, H. and Kiymaz, H. (2001) The day of the week effect on stock market volatility. *Journal of Economics and Finance*, 25(2), Summer, pp.181-193.

Bollerslev, T. (1986) Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31, pp.307-327

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

Chia, R.C.J., Liew, V.K.S. and Syed, A.W.S.K.W (2008) Day-of-the-week effects in selected East Asian stock markets. *Economics Bulletin*.

Jacobsen, B. and Visaltanachoti, N. (2006) The Halloween effect in US sectors. *Working Paper*, May.

Glosten, L.R., Jagannathan, R. and Runkle, D. (1993) " On the relation between the expected value and the volatility of the normal excess return on stocks. *Journal of Finance*, 49, pp 1779-1801

Maberly, E.D. and Pierce, R.M. (2003) The Halloween effect and Japanese equity prices: Myth or exploitable anomaly. *Asia-Pacific Financial Markets*, 10, pp.319-334.

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

Nelson, D.B, (1991) Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59, pp.347-370

Zakoian, J.M. (1990) Threshold heterosekdastic models. Manuscript, CREST. INSEE, Paris.