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Full Length Research Paper

Month-of-the-year effects in Asian countries: A 20-year study (1990-2009)

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This paper investigates the presence of the month-of-the-year effect on stock returns and volatility in eleven Asian countries- Hong Kong, India, Indonesia, Japan, Malaysia, Korea, Philippines, Singapore, Taiwan, China and Thailand. GARCH (1,1) model was used to analyze the stock returns pattern for a period of twenty years (1990-2009). Results obtained exhibit positive December effect, except for Hong Kong, Japan, Korea, and China. Meanwhile, few countries do have positive January, April, and May effect and only Indonesia demonstrates negative August effect.

Key words: Month-of-the-year effect, Asian countries, GARCH (1,1) model.

INTRODUCTION

The Efficient Market Hypothesis (EMH) suggests that past prices of shares should have no predictive power on future prices. In effect, prices should be random. There are also few empirical researches which support the fact that using past stock prices to predict future price movements can be futile. During the early 1980s, finance researchers began to report an increasing (and increasingly bewildering) array of anomalies with respect to the joint hypothesis of the Capital Asset Pricing Model (CAPM) and the EMH. Fama French reported an anomalous behavior of share market returns around periods of non-trading at weekends, and Banz (1981) documented an anomaly in the performance of equity returns when classified by firm size.

These anomalies were in the form of capital market regularities that are not explained by theory or institutional practice (Dimson, 1988). Another widely examined seasonality effect is within the calendar year trading periods. Boudreaux (1995) performed a study on Denmark, France, Germany, Norway, Singapore/ Malaysia, Spain and Switzerland, but no study has been carried out thoroughly on the behavioral pattern of the stock market returns on countries in Asia. The purpose of this study therefore, is to investigate the existence of a monthly pattern or effect in investment returns for 11 Asian ment returns for eleven Asian markets. An examination using the GARCH model was carried out on the eleven countries' stock market indexes over a period of 20 years from 1990 to 2009. They are Hong Kong, India, Indonesia, Japan, Malaysia, Korea, Philippines, Singapore, Taiwan, China and Thailand. The results of this study should provide important insights on the investing environment and also serve as useful information for devising investment strategies for stock market participants.

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PRIOR RESEARCH

Seasonal anomalies or calendar effects have been much discussed by the academics and professionals in the stock market since decades. Other studies done on this field are as follows: the month of the year effects, day of the week effects, turn of the month effects, turn of the year effects, and holiday effects. This paper concentrates on the month of the year effects in the eleven mentioned Asian countries. As the name suggests, the month of the year effect provides seasonal pattern of stock returns during a particular month of the year.

One of the most prevalent findings over the decades is of course, the so-called 'January effect', showing higher returns in January than other months of the year. It was first founded by Watchel (1942). Then Rozeff and Kinney (1976) who further continued this work found that the New York Stock Exchange average returns were 3.5% in

January compared to 0.5% for other months for the period, 1904 to 1974. Other most recently done studies in similar field are by Fountas and Segredakis (2002), Mehdian and Perry (2002), Tonchev and Kim (2004), Rosenberg (2004), Al-Saad and Moosa (2005) and Marquering et al. (2006). Moreover, Keim (1983) demonstrated that nearly half the excess returns for small firms occurred in January and that half of this return came on the first five trading days of the same month (Agathee, 2008). Several studies such as Keim (1983), Ariel (1987) and Jaffe et al. (1989) have pinpointed the existence of a monthly effect on the US and other developed markets.

The main argument that January is the month with the highest return as compared with other months is that the in the tax-loss selling hypothesis investors sell in December and buy back in January such that returns are higher at the beginning of the year. Essentially, the tax-loss hypothesis is supported in most countries where the tax year ends in December (Agathee, 2008). Ignatius (1998) gave evidence for the December effect. He examined seasonality in a Bombay Stock Exchange index and in the Standard and Poor's 500 stock indexes for the period 1979-1990. Ignatius found that December generated the highest mean returns, and that April and June generated high returns in the Indian stock index. Pandey (2002) confirmed a tax-loss-selling hypothesis in the Indian market explaining the presence of abnormal returns in April only to be contradicted later by various other studies. Chakrabathi and Sen (2007) found evidence of the November effect at the market level. Yakob et al. (2005) examined seasonal effects in ten Asian Pacific stock markets for the period January 2000 to March 2005. They stated that this is a period of stability and is therefore ideal for examining seasonality as it was not influenced by the Asian financial crisis of the late nineties. Doran et al. (2008) found that using data from Chinese stock markets showed that Chinese stock market as a whole is highly volatile and Chinese stocks, in particular, outperform most stock during the seasons of Chinese New Year, but not in January.

Above and beyond the 'January effect', there are ample studies documented on other month of year effect. For example, Fountas and Segredakis (2002) and Balaban (1995) found evidence of low returns in October for the Athens and Turkish stock exchange, respectively. Besides, Bhabra et al. (1999) found evidence of excess trading activities in the month of December for the period 1980 to 1994 on the NYSE/AMEX monthly returns and associated this excess trading to tax related changes.

METHODOLOGY

The data set consists of daily observations from 11 Asian stock markets. A summary of countries, stock indices, periods, and number of observations are shown in Table 1. Daily stock returns are calculated using daily closing sector indices to calculate the differences in the natural logarithms of the indices (Mehdian and Perry, 2001).

$$R_{it} = \log (I_{it}/I_{it-1}) \times 100$$

Where
R_{it} = Daily percentage return of stock index i on day t
I_{it} = Closing value of stock index i on day t
I_{it-1} = Closing value of stock index i on day t-1

In the case of a trading day following a non-trading day, the return is calculated using the closing price index of the previous trading day. For example, the Monday daily return of price index is calculated by using the previous closing price index on Friday.

E-views program (version 5.0) is used to run all tests in this paper, including basic descriptive statistics, unit root test, and generalized autoregressive conditional heteroskedastic (GARCH) test.

Unit root test

Unit root test was applied to examine the random walk nature of stock and sector indices. The test is designed to discover whether the series is difference-stationary (the null hypothesis) or trend-stationary (the alternative hypothesis). A series with unit root is said to be non-stationary and this is an indication of random walk nature. Therefore, the stock indices need to be examined to verify if the data series is non-stationary and whether it contains a unit root. The method chosen to test the existence of a unit root was Augmented Dickey Fuller (ADF) test. If the series are stationary and have no unit root, the analysis is appropriate and further tests can be done. The unit root test is based on the following regression:

$$\Delta P = \mu + \gamma P_{t-1} + \sum_{j=1}^{q} (\rho_t \Delta P_{t-j}) + \varepsilon_t$$

Where Δ represents first differences and *Pt* is the log of the price index, μ is the constant, γ and ρ are coefficients to be estimated, q is the number of lagged terms, t is the trend and the error term ε*t* is assumed to be white noise. Then the null hypothesis to be tested is:

H_0: Returns have a unit root (Non-stationary)
H_1: Returns do not have unit root (Stationary)
The optimal lag length for the ADF is selected with Schwartz Info Criterion (SIC), maximum lag length is set to 12, and test for unit root in level and intercepts are only in the series (Chung, 2006).

Descriptive statistics

Descriptive statistics were used to describe the basic features of the data in a study which provide simple summaries about the sample and the measures. Measures like mean was used to describe the center of distribution, standard deviation to measure the variation of distribution, Kurtosis to measure "peakedness" of the distribution, skewness to measure the deviation of the distribution from symmetry and Jacque Bera test to determine the probability based on the sample that comes from a normally distributed population of observations (Gujarati, 2003)

Generalized autoregressive conditional heteroskedastic (GARCH) model

The Autoregressive Conditional Heteroskedastic (ARCH) model that allows the forecast variance of return to vary systematically over time was proposed by Engle (1982). The model assumes that

Table 1. Selected Asian countries, stock indices, periods, and number of observations.

Country	Stock index	Bloomberg code	Period	Observations (n)
Hong Kong	Hang Seng Index	HSI	1/1/1990 - 31/10/2009	4924
India	BSE Sensex 30 Index	SENSEX	1/1/1990 - 31/10/2009	4680
Indonesia	Jakarta Composite Index	JCI	1/1/1990 - 31/10/2009	4666
Japan	Nikkei 225	N225	1/1/1990 - 31/10/2009	4878
Malaysia	FTSE Bursa Malaysia KLCI	KLSE	1/1/1990 - 31/10/2009	4890
Korea	Korean Stock Exchange	KOPSI	1/1/1990 - 31/10/2009	4881
Philippines	Philippines Stock Exchange (PSEi)	PCOMP	1/1/1990 - 31/10/2009	4917
Singapore	Straits Times Index	STI	1/1/1990 - 31/10/2009	4958
Taiwan	Taiwan Taiex Index	TWSE	1/1/1990 - 31/10/2009	4839
China	Shanghai Stock Exchange Composite Index	SHCOMP	1/1/1995 - 31/10/2009	3755
Thailand	Stock Exchange of Thai Index	SET	1/1/1990 - 31/5/2008	4516

the conditional variance (h_t) depends on the lagged squared residuals of returns. The basic ARCH model for returns allows the data to determine the best weights for forecasting the changing conditional variance.

However, the ARCH specification was done by making the conditional variance, h_t, a function of lagged value of h_t in addition to the lagged values of squared residuals which was extended by Bollerslev (1986). This form of the model is known as generalized ARCH (GARCH). It has been extensively used to model financial time series and has been proven to be very successful in predicting conditional variances. The most common formulation of GARCH asserts that the best predictor of the variance in the next period is a weighted average of the long-run average variance; the variance predicted for this period and the most recent squared residuals capturing any new information, with declining weights assigned to past squared residuals (Seyyed et al., 2005).

In order to gain more insight into the month-of-the-year effects, the GARCH model was used to look at the variance of the return on each day more closely. Connolly (1989) stated that the GARCH model provides several advantages over OLS. It incorporates heteroscedasticity into the estimation procedure in a sensible way (for a time series). Besides, it also can be expanded to include other relevant variables in the conditional variance equation. Generally, the GARCH model offers more flexibility in robust modelling of stock returns. On the other hand, it also provides a more flexible framework in order to capture various dynamic structures of conditional variance and it allows simultaneous estimation of several parameters of interest and hypothesis (Gregoriou et al., 2004). Moreover, the GARCH models take into consideration not only mean return but also the risk or volatility of return (Chia et al., 2006).

The GARCH (1, 1) model is characterized by two equations which are conditional mean (mean return) and conditional variance (risk or volatility of returns) equations. The GARCH (1, 1) models that are applied to study the month-of-the-year stock index returns and volatility of returns are as follows (Choudhry, 2000):

$$y_t = \delta_1 D_{1t} + \delta_2 D_{2t} + \delta_3 D_{3t} + \ldots \ldots + \delta_{12} D_{12t} + \varepsilon_t$$

$$\varepsilon_t / \Psi_{t-1} \sim t.d.(0, h_t, v) \tag{5}$$

$$ht = \gamma 1D1t + \gamma 2D2t + \gamma 3D3t + \cdots + \gamma 12D12t + \sum_{j=1}^{p}(\beta_j h_{t-j}) + \sum_{j=1}^{\alpha}(\alpha_j \varepsilon^2{}_{t-j})$$

Where y_t = Daily yield of stock

D_{dt} = Dummy variables representing the twelve months of the year. D_{dt} is equal to one if the day t is in January (d = 1) otherwise it is zero. δ_j = Coefficients which represent the size and the direction of the effect of each month of the year on stock returns (coefficient δ_1, δ_2, δ_3, …, and δ_{12}) represent the January effect, February effect, March effect, … and December effect on stock returns respectively

ε_t = an error term

h_t = conditional variance

γ_1 = coefficients γ_1 to γ_{12} represent the size and direction of the month-of-the-effect on volatility

Statements of hypothesis

To get an empirical result on this research, hypotheses need to be set and tested. The hypotheses of this research study are constructed based on the research questions. Unit root test was applied to test whether the market was efficient. If the series of returns is non-stationary (has a unit root, do not reject H_0, when p-value > 0.1), it implies that the market is efficient as it follows random walk nature. However, if the series of returns is stationary (does not have a unit root, reject H_0, when p-value < 0.1), it implies that the market is inefficient as does not follow random walk nature. It also indicates the possibility of the occurrence of calendar effects (Chung, 2006).

Hypothesis 1

H_0: There is market efficiency in Asian stock markets

H_1: There is no market efficiency in Asian stock markets

The hypotheses of the existence of month-of-the-year effects in eleven Asian stock markets were tested using GARCH (1, 1) model. The hypothesis testing shows whether to accept or reject the null hypotheses in this research. Likewise, the significance of the variables depends on the P-value and confidence interval of 1, 5 and 10%. If the p-value is less than the confidence interval (0.1 or 10%), the null hypothesis is rejected, which means that there is existence of the month-of-the-year effects in eleven Asian stock markets. In contrast, if the p-value is greater than 0.1, therefore the null hypothesis will not be rejected and thus, implying there is absence of the month-of-the-year effects in eleven Asian stock markets.

Hypothesis 2

H_0: There is no month-of-the-year effect in Asian stock markets

H_1: There is month-of-the-year effect in Asian stock markets

EMPIRICAL RESULTS

Unit root test

The augmented Dickey-Fuller test strongly rejects the hypothesis of a unit root for all returns in all 11 countries' stock markets for all periods tested, implying that the series are stationary. This suggests that 11 Asian stock markets cannot be regarded as efficient as the various series of returns do not appear to follow random walk.

Descriptive statistics

Appendix 1 presents the basic descriptive statistics of the returns series from the 11 Asian countries. Based on the means of daily returns, the top three best-return stock markets are India, Hong Kong, and China. From the standard deviations of daily return, the top three most-risky stock markets are India, Korea, and Taiwan. The kurtosis of all countries investigated is consistently positive, suggesting that the series are leptokurtic, that is, all series have a thicker tail and a higher peak than a normal distribution. This is especially apparent in India's stock market as seen in the research done by Choudhry (2000). Most of the series present a positive skewness except Indonesia, Japan, Singapore and Thailand. This suggests high probability of daily returns to be positive in the most of the countries investigated. Hence, based on the results shown earlier, it is expected that all the series are found to be non normal using the Jarque-Bera test.

Appendix 2 shows the mean, standard deviation, skewness, kurtosis, and Jarque-Bera of stock index returns for each month of the year of the countries. Most countries exhibit traditional January effect (positive return) except Hong Kong, Japan, Singapore, and China, for India, based on the means of monthly returns, February, July and August offer best returns. Such result is consistent with the result of Pandey (2002). For Hong Kong, February and April offer best returns while for China, February, March, and April offer best returns. The result also shows that China has positive monthly returns from February to July, and negative monthly returns from August to January. On average, most of the countries show positive returns in January, February, April, July, and December while most of the countries show negative returns in August and September.

Generalized autoregressive conditional heteroskedastic (GARCH) model

The parameter estimates form the GARCH (1,1) conditional variance that investigates the month-of-the-year effect on stock index return and volatility and is shown in Appendix 3. The Bollerslev-Wooldridge robust standard error was computed for all the estimates (Gregoriou et al., 2004).This indicates that the series have positive and stationary variance. The Arch process is significant in all 11 Asian stock markets. The p-value was unable to reject the null hypothesis of no serial correlation in the residuals for up to 1 lag at the 5% level of significance for all series in the ARCH-LM test. Hence, the conditional mean and volatility estimates were not misspecified. This indicates that returns for all markets have taken into account the volatility of stock return.

In most of the countries, they do not exhibit traditional January effect (significantly positive return in January). It is described in the paper of Gu and Simon (2003) as declining January effect whereby January effect was gradually vanishing since 1988 (also in Moosa, 2007). For those countries which show positive January effect, only Taiwan shows consistent result with previous study. However, Indonesia, Philippines, Singapore, and Thailand do not show consistent results with previous study (Hsu, 2005; Yakob et al., 2005). This may be due to different periods of study.

In the study of Yakob et al. (2005), negative March effect existed in China and Hong Kong, and India during the period from year 2000 - 2005. However, in this study (from year 1995 to 2009), it shows positive March effect in China and no significant effect in Hong Kong and India. Such result implies that study of different periods or with different models will exhibit different month-of-the-year effect.

In this study, Japan shows no evidence of month-of-the-year effect as against previous study (Yakob et al., 2005).

In all, most of the Asian countries exhibit positive December effect. Meanwhile, few Asian countries exhibit positive January, April, and May effect. Only Indonesia shows negative August effect. Contrarily, most of the countries do not show evidence of month-of-the-year effect during the months of February, March, June, August and September.

Results shown for all countries investigated reject the null hypothesis. Thus, the presence of month-of-the-year effect in all countries is proven (Table 2).

CONCLUSIONS AND RECOMMENDATIONS

This paper examines the month-of-the-year effect in eleven Asian-country stock markets using GARCH (1,1) model for a period of twenty years (1990-2009). Two main objectives were pursued:

1. Whether the Asian stock markets hold the theory of market efficiency true.
2. Whether month-of-the-year effect persists in Asian stock markets.

All eleven Asian stock markets are said to be inefficient as

Table 2. Summary of month-of-the-year effects from GARCH (1,1) results.

	Hk	India	Indo	Japan	Msia	Korea	Phil	Spore	Taiwan	China	Thai
Jan (5+)			+				+	+	+		+
Feb (2+)	+								+		
Mar (1+)										+	
Apr (4+)			+		+	+				+	
May (4+)	+	+	+				+				
Jun (1+)		+									
Jul (3+)	+	+			+						
Aug (1+, 1-)		+	-								
Sep (2+)		+				+					
Oct (3+)	+		+		+						
Nov (3+)	+					+			+		
Dec (7+)		+	+		+		+	+	+		+

as they do not follow random walk pattern. The theory of random walk and EMH presents important challenges to both theorists and fund managers. If both beliefs are valid, then the work of fund managers is of no real value in stock market analysis. The only way fund managers can validate their existence is by showing that they can consistently use their techniques to make better-than-chance and meaningful predictions of future stock market prices (Fama, 1965). The results of this research help validate the existence of fund managers. It is possible for fund managers to devise a trading rule to exploit those detected anomalies to earn an abnormal rate of return for the clients (Lim et al., 2004). It also helps investors to make better predictions and earn abnormal profits.

The use of non-dividend-adjusted returns and exclusion of stock exchange account effects (non adjusted closing price) may distort the results, although previous evidence suggests that any such distortion will be extremely small (Coutts et al., 2000).

In this paper, we conclude that most of the Asian stock markets exhibit positive December effect, except Hong Kong, Japan, Korea, and China. Meanwhile, few countries do exhibit positive January, April, and May effect. Only Indonesia exhibits negative August effect.

Investors may use results of this study to increase their expected returns by altering the timing of trades which could include delaying purchases or sales planned for certain months (French et al., 1980). General strategies can be adopted by investors to gain abnormal profits by identifying the buy or sell signal provided from the results of GARCH (1,1) model shown in Table 2. Those months which show significantly positive returns do provide a sell signal to investors, that is investors should buy from any other months and sell on the significantly positive months to reap the profit with higher chance. On the other hand, significantly negative months do provide a buy signal to investors. However, several reasons may cause an investor not to successfully reap profits from exploiting the month-of-the-year effect. Firstly transaction costs might be more than the potential gain and thus making the transaction not profitable especially if it is small. Secondly, there may be reasons external to market such as the timing of public announcement of interest rate changes or publication of profit statements which result in the uncertainty as to whether the month-of-the-year effect will materialize as per the findings (Holden et al., 2005).

In conclusion, inconsistent results have been obtained by different researchers while using different periods of study and models. Such phenomenon may suggest that although month-of-the-year effect does hold true, it does not follow consistent patterns of having positive January effect and etc. That is why some researchers suggested that the reasons behind calendar effect might be certain happening events or conditions which may have or have no pattern to follow, such as tax-loss and tax-gain selling, macroeconomic factors, company announcements, investor psychological factors and etc. (Jeremy, 1994; Chen and Singal, 2004).

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Appendix 1. Descriptive statistics.

	HK	India	Indonesia	Japan	Malaysia	Korea	Philippines	Singapore	Taiwan	China	Thailand
Mean	0.0179628	0.027974	0.01658	-0.01202	0.006897	0.004927	0.008423	0.004992	-0.002432	0.017854	-0.000732
Std. Dev.	0.7487388	1.024394	0.719089	0.687531	0.708699	0.900916	0.724691	0.585052	0.850679	0.825297	0.794248
Skewness	0.0125471	0.164851	-0.181717	-0.017982	0.19534	0.076541	0.287907	-0.035715	0.271516	0.433682	-0.264762
Kurtosis	12.130653	303.44	15.53741	8.251972	39.49063	31.0437	23.6833	10.66717	10.00875	19.50885	22.18114
Jarque-Bera	17104.633	17601537	30585.4	5606.551	271337.7	159948.9	87713.24	12145.15	9963.805	42759.2	69282.29
Observations	4924	4680	4666	4878	4890	4881	4917	4958	4839	3755	4516

Appendix 2. Descriptive statistics – month's classification.

	HK	India	Indonesia	Japan	Malaysia	Korea	Philippines	Singapore	Taiwan	China	Thailand
January											
Mean	-0.036688	0.009948	0.068682	-0.012235	0.012133	0.052353	0.057968	-0.004951	0.061246	-0.003141	0.061524
Std. Dev.	0.888399	0.813452	0.835322	0.744085	0.702282	0.964621	0.859056	0.786557	0.984679	0.783259	0.875103
Skewness	-0.295894	0.023162	-0.380702	-0.011424	0.495179	0.309116	0.965272	-0.558697	1.090263	-0.655544	0.52965
Kurtosis	7.332674	4.799348	10.6962	5.004759	9.929944	4.737575	14.56183	9.133361	14.50428	5.686185	6.698219
Jarque-Bera	325.0787	53.1867	991.8702	63.64337	814.707	57.39829	2444.629	651.0171	2125.099	115.7767	247.2656
Observations	408	394	398	380	399	405	427	402	372	311	401
February											
Mean	0.074395	0.088075	0.017576	-0.012018	0.086273	-0.042661	0.016793	0.029361	0.087243	0.070408	-0.01363
Std. Dev.	0.724482	0.789761	0.665785	0.557795	0.743833	0.752053	0.675676	0.598552	0.817291	0.901605	0.881341
Skewness	1.09473	0.586417	0.912027	-0.085409	4.816891	-0.00589	0.610745	2.044546	0.501792	0.133501	0.272711
Kurtosis	13.93581	5.889481	21.57167	4.207957	62.91815	4.984266	10.3817	23.21735	5.508396	9.075287	9.496373
Jarque-Bera	1933.159	154.7838	5383.121	23.87546	53556.88	61.6867	919.031	6630.113	98.23546	405.2435	649.9011
Observations	373	382	371	385	349	376	394	374	323	263	367
March											
Mean	-0.029291	-0.005297	0.017819	-0.005099	-0.041507	0.005881	-0.011822	-0.01211	0.030853	0.07232	-0.0249
Std. Dev.	0.721965	1.013717	0.808659	0.726954	0.521073	0.685916	0.596186	0.536244	0.729897	0.713623	0.740388
Skewness	-0.347849	0.427705	0.260907	0.25161	-1.462721	0.176466	-0.274372	0.116783	-0.129263	0.285298	5.348839
Kurtosis	5.118425	7.390833	32.91085	4.405712	14.7408	5.448103	3.891228	5.794023	5.272705	6.224742	70.35651
Jarque-Bera	90.11244	330.1839	14617.21	39.47644	2592.582	108.5904	19.67169	141.1726	94.83046	147.0155	80429.42
Observations	435	396	392	425	425	426	431	431	435	329	415

Appendix 2. Cont'd

April											
Mean	0.052916	0.023001	0.059264	0.026416	0.018652	0.031998	0.002855	0.052227	0.002872	0.084216	0.015679
Std. Dev.	0.673103	0.908973	0.674946	0.679731	0.543086	0.816708	0.642538	0.591401	0.765295	0.772339	0.613899
Skewness	-0.035399	-0.748516	0.99193	-0.191293	-0.313796	-0.727988	-0.695829	-0.285847	-0.147099	0.125056	0.772873
Kurtosis	7.254478	8.864731	9.918434	6.017997	7.254837	8.638943	10.69874	12.56392	4.224163	7.674526	7.187528
Jarque-Bera	288.9351	557.1751	807.2234	158.8719	317.5405	586.4909	986.9667	1556.698	26.74902	291.2702	283.9272
Observations	383	365	374	412	412	415	387	407	405	319	342
May											
Mean	0.049048	-0.001379	0.065926	0.010942	0.015578	-0.007389	0.051237	-0.002205	-0.042721	0.043117	-0.027986
Std. Dev.	0.61211	0.973467	0.718019	0.562407	0.507727	0.775419	0.648736	0.510949	0.794113	1.161015	0.79788
Skewness	0.064166	0.275615	-0.620347	-0.110525	0.107477	-0.347705	0.046382	0.081789	-0.32949	2.087887	0.188433
Kurtosis	4.671294	13.56389	7.417242	4.001643	6.33758	5.020427	6.023502	5.897639	6.351089	41.09315	7.844053
Jarque-Bera	50.1062	1892.969	345.593	17.36052	187.3596	77.0465	158.9842	143.5431	208.0089	19702.72	361.9721
Observations	428	406	394	396	402	405	417	409	428	322	368
June											
Mean	0.000962	0.026521	0.033132	-0.016404	-0.02062	-0.020241	-0.016975	-0.012442	-0.037367	0.021601	0.008286
Std. Dev.	0.602737	0.723947	0.61845	0.553776	0.45194	0.77106	0.667166	0.458954	0.893954	0.906591	0.684423
Skewness	0.195611	0.076795	1.668007	-0.132373	-0.175427	0.064591	0.351383	0.276876	1.509915	0.014401	0.382201
Kurtosis	6.317125	4.749024	13.8347	3.499819	5.646247	7.593029	5.249413	6.053831	28.17461	6.474373	6.530118
Jarque-Bera	189.1935	52.79078	2163.416	5.691733	124.7001	359.7939	94.41356	169.3718	11009.33	159.9553	206.5624
Observations	407	411	404	427	420	409	408	422	411	318	380
July											
Mean	0.04363	0.064492	0.014179	-0.012704	0.014546	0.024754	-0.000581	0.01432	-0.025687	0.015859	-0.004818
Std. Dev.	0.551753	0.770474	0.499402	0.579856	0.465545	0.763239	0.626259	0.447399	0.818038	0.800623	0.740034
Skewness	0.06485	-0.124416	-0.384978	0.190235	-0.346098	0.263984	0.217469	0.092632	-0.129869	-0.292603	0.773977
Kurtosis	3.605389	4.572253	5.893446	4.020169	6.172586	6.97666	6.12217	4.491874	4.561555	5.101852	5.960034
Jarque-Bera	6.851813	44.34319	158.0057	21.33906	192.4359	288.3253	180.5243	41.62185	44.89772	65.65177	172.4835
Observations	429	420	423	432	438	430	436	442	430	331	371
August											
Mean	-0.026725	0.08469	-0.112263	-0.027514	-0.075494	-0.029431	-0.08993	-0.055293	-0.075714	-0.043065	-0.080379
Std. Dev.	0.736864	0.653605	0.699521	0.676322	0.721849	1.210004	0.714765	0.604511	0.864186	0.760433	1.05454

Appendix 2. Cont'd

Skewness	-0.289523	0.005903	-0.726151	-0.041039	-0.539098	1.282151	-0.58359	-0.502367	-0.199531	-0.580013	-3.855363
Kurtosis	7.405594	3.652975	6.246307	5.029302	10.02098	82.93881	9.636556	6.444589	5.577348	6.72784	40.22309
Jarque-Bera	356.2247	7.001965	212.3758	75.96517	889.2986	113543	809.7437	229.0621	121.8687	209.5838	22758.97
Observations	433	394	403	442	423	426	428	427	430	330	378
September											
Mean	-0.016323	0.032228	-0.058252	-0.06519	-0.033293	-0.024617	-0.025584	-0.040065	-0.102421	-0.002271	-0.038436
Std. Dev.	0.727961	0.725039	0.764781	0.700082	1.132632	0.819431	0.687054	0.567172	0.79742	0.765156	0.746162
Skewness	0.193722	-0.067312	0.164528	-0.237094	-0.056731	-1.050893	-0.127973	-0.098019	-0.475708	0.718158	-0.215818
Kurtosis	8.940449	5.287343	9.912465	4.439528	37.07187	10.05776	7.502967	9.832418	6.474708	7.501368	7.259779
Jarque-Bera	617.2301	87.93856	820.1238	37.51924	20267.47	897.0455	359.3792	829.2866	215.2315	294.8802	291.7848
Observations	418	402	411	392	419	397	424	426	398	317	382
October											
Mean	0.043016	-0.080061	-0.03569	-0.026557	0.0332	-0.000476	0.01295	0.009009	-0.018991	-0.023745	0.045238
Std. Dev.	1.122086	0.940217	0.887832	0.937839	0.528895	1.007076	1.070653	0.734001	0.941682	0.745834	0.765465
Skewness	0.193322	-0.410499	-0.578318	0.09548	0.157132	-0.236198	0.024453	-0.484104	-0.027745	0.187663	0.512241
Kurtosis	15.44391	7.574793	11.35952	14.45297	9.387674	6.827573	37.53223	9.808233	5.641146	7.025359	6.329629
Jarque-Bera	2693.134	338.4434	1270.079	2323.456	729.4038	260.9055	21563.96	855.151	120.3831	211.796	191.6476
Observations	417	376	428	425	428	421	434	434	414	311	379
November											
Mean	0.022954	0.019265	0.037944	-0.011014	-0.00106	0.062057	0.019501	0.038327	0.048206	-0.001123	-0.020071
Std. Dev.	0.727233	2.326421	0.66497	0.763485	0.611108	0.896096	0.727292	0.592518	0.901058	0.706986	0.752194
Skewness	-0.372581	0.209374	0.235082	0.047665	-1.278665	-0.494794	2.074726	0.442485	0.53924	-0.15617	-0.264949
Kurtosis	4.949559	145.4457	8.479952	5.654162	18.99908	7.168513	21.26598	6.451875	9.755865	7.181039	5.707218
Jarque-Bera	73.68976	308591.6	487.7962	109.9196	4232.984	311.2836	5423.773	208.4688	774.2299	218.2681	122.7083
Observations	406	365	387	374	387	407	371	394	397	298	387
December											
Mean	0.049559	0.073683	0.10891	0.008264	0.094228	0.002696	0.100924	0.054386	0.074293	-0.014731	0.076938
Std. Dev.	0.7308	0.678562	0.599412	0.673532	0.5901	0.956992	0.59933	0.499173	0.79936	0.789949	0.778018
Skewness	-0.267696	-0.439203	-0.516649	-0.236726	0.607039	0.517943	0.291042	0.258567	0.096388	-0.790098	-1.439029
Kurtosis	6.877192	4.919099	11.29095	4.847476	17.27662	6.507466	6.065015	5.021212	6.621206	12.26628	25.25977
Jarque-Bera	247.0231	66.44683	1035.479	58.80343	3344.61	202.8599	145.997	70.73177	216.9798	1126.603	7262.839
Observations	387	358	356	388	391	364	360	390	396	306	346

Appendix 3. Month-of-the-Year effect (GARCH Model)

	HK	India	Indonesia	Japan	Malaysia	Korea	Philippines	Singapore	Taiwan	China	Thailand
Mean equation											
Jan	0.039106	0.006447	0.049429**	0.011691	0.027401	-0.005265	0.074537**	0.082467***	0.062692*	0.028205	0.083766***
	(1.425428)	(0.205510)	(2.234363)	(0.374758)	(1.100805)	(-0.151414)	(2.333444)	(3.148504)	(1.871216)	(0.682199)	(2.725494)
Feb	0.068625**	0.069548	0.022610	-0.000990	0.032730	-0.002792	-0.023406	0.014918	0.082095**	0.038615	0.020438
	(2.236123)	(1.620172)	(1.016536)	(-0.039843)	(1.528848)	(-0.081740)	(-0.949393)	(0.676895)	(2.210528)	(0.669775)	(0.565746)
Mar	-0.038625	-0.023526	0.035584	0.011818	-0.011498	4.85E-05	-0.011831	-0.009155	0.010047	0.082722**	-0.035745
	(-1.416651)	(-0.537948)	(0.497802)	(0.369767)	(-0.658070)	(0.001753)	(-0.570528)	(-0.520544)	(0.340772)	(2.254817)	(-1.438671)
Apr	0.046122	0.003497	0.048056**	0.024898	0.044261**	0.076374***	0.017708	0.020881	0.015626	0.075204**	0.022862
	(1.519428)	(0.093473)	(2.150942)	(0.894514)	(2.045057)	(2.853191)	(0.686717)	(0.810198)	(0.463549)	(2.088018)	(0.833173)
May	0.067066***	0.061934**	0.064540***	0.034978	0.020246	0.036041	0.062033***	0.016573	-0.007002	0.053060	0.040339
	(2.915150)	(2.296631)	(2.668102)	(1.404773)	(1.152826)	(1.371071)	(2.644818)	(0.946183)	(-0.244786)	(1.120383)	(1.535849)
Jun	0.013800	0.060914**	-0.002612	0.007305	-0.004767	-0.026761	-0.009557	-0.019441	0.036617	0.002442	0.023822
	(0.661136)	(2.390344)	(-0.146669)	(0.306527)	(-0.315175)	(-0.964631)	(-0.410396)	(-1.282422)	(1.208944)	(0.069144)	(0.953792)
Jul	0.063133***	0.057899*	0.016835	-0.013884	0.039812**	0.035363	0.029707	0.014409	0.004916	0.001790	0.037608
	(2.713187)	(1.943495)	(0.828202)	(-0.600505)	(2.455315)	(1.350318)	(1.414741)	(0.784172)	(0.153142)	(0.050328)	(0.919535)
Aug	0.013408	0.069301**	-0.041724**	4.46E-05	0.004087	0.117830	-0.030883	0.020257	-0.024557	-0.011192	0.022631
	(0.447456)	(2.417217)	(-2.090489)	(0.001843)	(0.236782)	(1.000574)	(-1.345764)	(0.936402)	(-0.819856)	(-0.362770)	(0.784941)
Sep	0.023432	0.062938**	0.020444	-0.013123	-0.070073	0.073375**	-0.003731	0.008615	0.000347	-0.017689	0.020910
	(0.917972)	(2.296404)	(0.797278)	(-0.437070)	(-1.050893)	(2.311871)	(-0.159601)	(0.430177)	(0.010361)	(-0.514878)	(0.830752)
Oct	0.064593**	-0.022261	0.049508**	-0.003380	0.049330***	0.037688	-0.011988	0.025465	-0.007498	-0.005957	0.037551
	(2.331331)	(-0.676875)	(2.045064)	(-0.127636)	(3.193855)	(1.160294)	(-0.378680)	(1.213258)	(-0.238046)	(-0.170555)	(1.558243)
Nov	0.064891***	0.225349	0.013044	0.016398	0.012805	0.053182*	-0.008367	0.028918	0.053425*	-0.009366	-0.014914
	(2.619037)	(1.353382)	(0.664992)	(0.542040)	(0.775737)	(1.901593)	(-0.298822)	(1.343899)	(1.834599)	(-0.228428)	(-0.516348)
Dec	0.023210	0.073875**	0.095315***	0.031631	0.054988***	0.015092	0.079366***	0.065155***	0.063706*	-0.009062	0.088713**

Appendix 3. Contd

	(0.867443)	(2.106657)	(4.419319)	(1.148241)	(3.222939)	(0.449727)	(3.086147)	(3.199208)	(1.885961)	(-0.318254)	(2.527434)
Variance equation											
C	0.004687*	0.008857	0.020289***	0.008870**	0.005749**	0.014599***	0.025188***	0.005327**	0.008946***	0.005754	0.059897
	(1.745119)	(1.011730)	(2.805919)	(1.965570)	(2.059496)	(2.651457)	(3.773867)	(2.167027)	(3.297857)	(1.504817)	(1.083610)
β_1	0.085624***	0.187369***	0.231264***	0.097719***	0.167340***	0.160962***	0.155343***	0.142626***	0.083896***	0.078207***	0.128404***
	(7.865604)	(5.698254)	(6.454338)	(8.133960)	(8.893878)	(3.662604)	(8.457730)	(7.704843)	(17.39376)	(6.033369)	(7.192493)
α_1	0.904442***	0.767404***	0.758323***	0.883743***	0.822377***	0.835216***	0.809170***	0.844496***	0.906765***	0.910481***	0.860017***
	(89.06800)	(17.26213)	(24.48260)	(66.86594)	(56.36508)	(26.25526)	(48.21030)	(51.72436)	(164.3984)	(67.87001)	(38.86543)
Jan	0.000154	0.031128*	-0.008964	0.001705	0.006105	-0.002371	0.001621	0.005637	-0.001324	0.018881**	-0.057154
	(0.038227)	(1.853867)	(-1.158674)	(0.147355)	(1.364835)	(-0.276909)	(0.168950)	(1.256328)	(-0.291736)	(2.014855)	(-0.964425)
Feb	0.001140	0.067122**	-0.007913	0.002575	-0.001493	0.001682	-0.003254	0.000223	-0.000259	0.011053	-0.046302
	(0.256718)	(2.313068)	(-1.073775)	(0.396560)	(-0.429767)	(0.195391)	(-0.289645)	(0.061633)	(-0.059448)	(0.790847)	(-0.892317)
Mar	0.003754	0.055399*	0.053664	0.007723	-0.000757	-0.010675*	-0.014468**	8.86E-05	-0.005842*	-0.007214	-0.056685
	(0.839775)	(1.911444)	(1.267222)	(1.076217)	(-0.242873)	(-1.702223)	(-1.988263)	(0.026415)	(-1.706157)	(-1.146892)	(-1.056140)
Apr	-0.000767	0.025049	0.015804	0.000160	0.005582	0.001393	-0.000639	0.005860	0.002521	0.006168	-0.048791
	(-0.175843)	(1.352309)	(0.977571)	(0.022715)	(1.110091)	(0.191873)	(-0.081464)	(1.247062)	(0.671177)	(0.956701)	(-0.908967)
May	-0.000836	0.013836	-3.85E-05	-0.006633	0.001296	-0.007295	-0.008856	-0.002348	-0.007486**	0.050093	-0.047279
	(-0.232991)	(1.041340)	(-0.003880)	(-1.366504)	(0.315872)	(-1.033753)	(-1.201258)	(-0.726939)	(-2.184742)	(1.459907)	(-0.884767)
Jun	-0.002167	0.014299	-0.010427	-0.000636	-0.001904	-9.05E-05	-0.007429	-0.002057	0.002061	-0.013693	-0.052977
	(-0.650973)	(1.091631)	(-1.331222)	(-0.129382)	(-0.560576)	(-0.010792)	(-0.837950)	(-0.745708)	(0.493543)	(-1.424595)	(-0.997322)
Jul	0.001311	0.028154*	-0.007874	0.000513	0.003876	-0.001323	-0.007634	0.003925	-0.001158	0.001878	-0.017463
	(0.349002)	(1.764900)	(-0.988382)	(0.101561)	(0.944705)	(-0.162143)	(-1.010179)	(1.130454)	(-0.307627)	(0.257825)	(-0.311593)
Aug	0.014874	0.009490	-0.002211	2.51E-05	-0.001231	0.015932	-0.008734	0.003920	-0.001900	-0.000318	-0.057623
	(1.200170)	(0.737108)	(-0.276325)	(0.004819)	(-0.379432)	(0.824306)	(-1.144182)	(0.942337)	(-0.534730)	(-0.059111)	(-1.085768)
Sep	-0.003644	0.024266	0.009468	0.002827	0.023544	0.006707	-0.009293	-0.000152	0.003299	-0.003914	-0.048848

Appendix 3. Contd

	(-0.754766)	(1.621908)	(0.689638)	(0.499141)	(1.024746)	(0.621606)	(-1.106309)	(-0.041520)	(1.026804)	(-0.817748)	(-0.909926)
Oct	0.001149	0.026741*	-0.011934*	-0.002977	-0.003453	-0.001248	0.103261	0.005237	-0.000917	0.006023	-0.053226
	(0.312694)	(1.700048)	(-1.654822)	(-0.612388)	(-0.896377)	(-0.158033)	(1.411276)	(1.161629)	(-0.248291)	(1.182513)	(-0.995869)
Nov	0.000767	0.635704	-0.006442	0.001672	0.002732	-0.007996	-0.023189**	0.000251	-0.003979	-0.003404	-0.047191
	(0.144387)	(0.847555)	(-0.782862)	(0.257761)	(0.791984)	(-1.197080)	(-2.486204)	(0.065392)	(-1.120682)	(-0.393181)	(-0.865417)
L	-4605.997	-5503.280	-4232.299	-4503.752	-3300.776	-5405.611	-4739.362	-3475.309	-5252.500	-4068.469	-4669.052

Note: *, **, *** imply significance level at 10%, 5%, and 1% respectively, z-statistics in parentheses. L = Log-likelihood function value