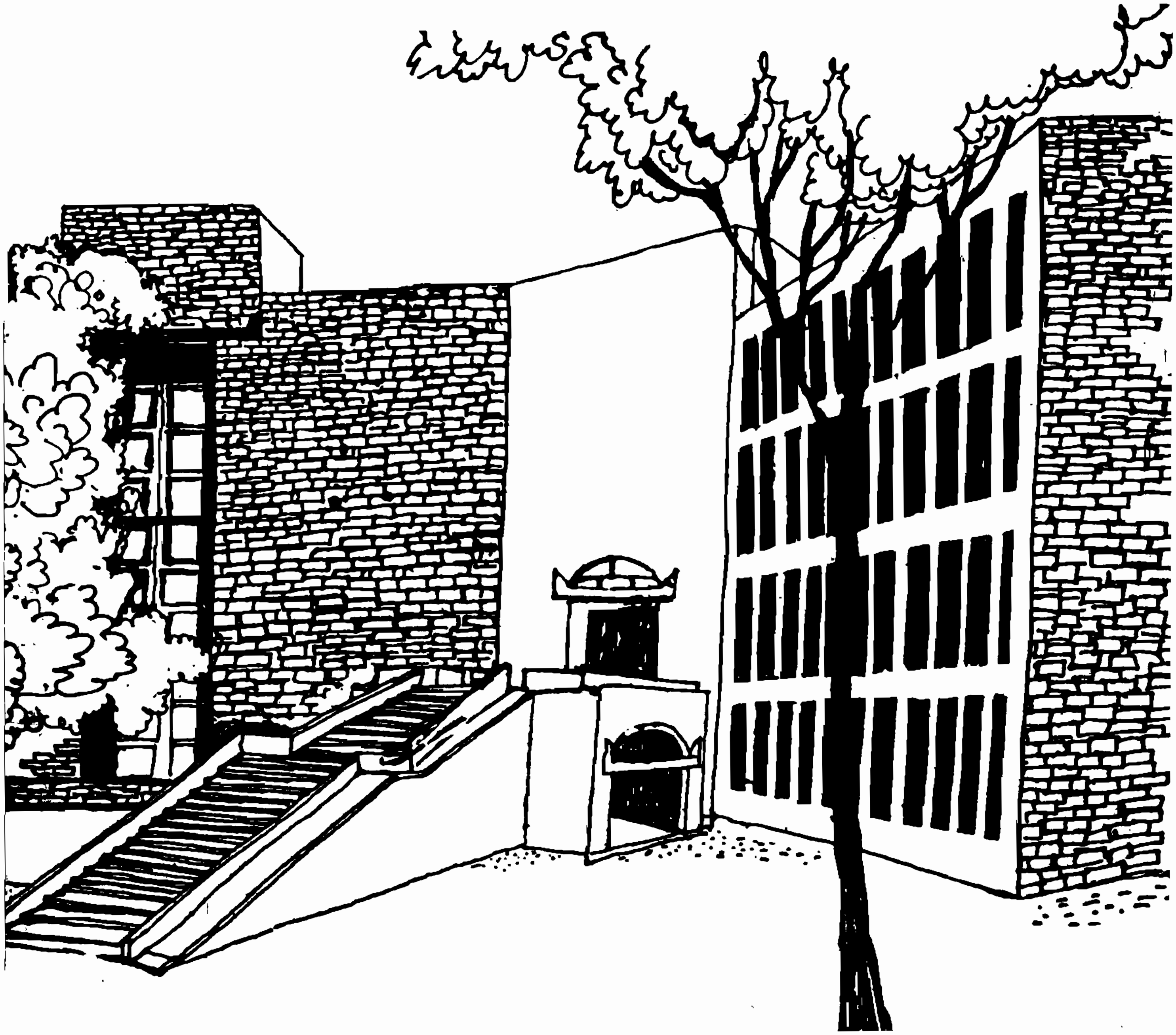
विद्याविनियोगाद्विकासः
IIM AHMEDABAD

Working Paper



Stock Return Seasonality in the Emerging Malaysian Market

I.M. Pandey

W.P.No. 2002-12-04
December 2002 1738

The main objective of the working paper series of the IIMA is to help faculty members to test out their research findings at the pre-publication stage.

INDIAN INSTITUTE OF MANAGEMENT
AHMEDABAD-380 015
INDIA

IIMA WP-2002-12-04

STOCK RETURN SEASONALITY IN THE EMERGING MALAYSIAN MARKET

ABSTRACT

This study investigates the existence of seasonality in Malaysia's stock market. The study uses the monthly return data of the Kula Lumpur Stock Exchange's two indices - Composite Index and EMAS Index. After examining the stationarity of the two returns series, we specify a combined time series and regression model to find the monthly effect in stock returns. The study reveals evidence of the existence of seasonality in stock returns in Malaysia. The coefficients for several months are statistically significant. The average return for December is positive, and it is statistically significant in case of the Composite Index. A positive December return rules out the tax-loss selling hypothesis. In Malaysia there are no capital gain taxes for both resident and non-resident investors. The evidence of seasonality implies that the Malaysian stock market is not informationally efficient. Hence, investors may be able to time their share investments to improve returns.

Key words: Market efficiency; efficient market hypothesis; tax-loss selling hypothesis; information hypothesis; stationarity; seasonality.

STOCK RETURN SEASONALITY

IN THE EMERGING MALAYSIAN MARKET

Introduction

Capital markets are generally considered efficient. The efficient market hypothesis (EMH) states that it is not possible to predict stock price and return movements using past price information. Researchers have recently collected evidence contrary to the EMH. One of the significant anomalies is the presence of the seasonal effect in stock returns. The existence of the seasonal effect negates the weak form of the EMH and implies market inefficiency. In an inefficient market, investors would be able to earn abnormal returns, that is, returns that are not commensurate with risk.

There are a few empirical studies that have examined the issue of seasonality of stock returns in the emerging capital markets (ECMs). The objective of this study is to investigate the existence of seasonality in stock returns in Malaysia. We use monthly closing price data of the Kuala Lumpur Stock Exchange's two indices, the Composite Index and the EMAS. The Malaysian tax system differs from the USA and many other developed and developing countries. The resident and non-resident shareholders in Malaysia are not required to pay any taxes on the capital gains. Hence, the 'tax-loss-selling' hypothesis should not provide an explanation for the seasonality in stock returns in Malaysia. Still if seasonality is found in the Malaysian stock market, then it should be due to the information hypothesis (Kiem, 1983).

This study specified a combined regression and an autoregressive moving average model with dummy variables for months to test the existence of seasonality in stock returns. The results of the study confirmed the monthly effect in stock returns in Malaysia. But it did not support the 'tax-loss selling' hypothesis. These findings have important implications for financial managers, financial analysts and investors. The understanding of seasonality should help them to develop appropriate investment strategies.

Overview of Prior Research

There would exit seasonality in stock returns if the average returns were not same in all periods. The month-of-the-year effect would be present when returns in some months are higher than other months. In the USA and some other countries, the year-end month (December) is the tax month. Based on this fact, a number of empirical studies have found the 'year-end' effect and the 'January effect' in stock returns consistent with the 'tax-loss selling' hypothesis. It is argued that investors, towards the end of the year, sell shares whose values have declined to book losses in order to reduce their taxes. This lowers stock returns by putting a downward pressure on the stock prices. As soon as the tax year ends, investors start buying shares and stock prices bounce back. This causes higher returns in the beginning of the year, that is, in the month of January.

In the US market, a number of studies have found the seasonal or the year-end effect in stock (Wachtel 1942; Rozeff and Kinney 1976; Keim 1983; Reinganum 1983). There is also evidence of the day-of-the-week effect in the US (Smirlock and Starks, 1986) and other markets (Jaffe and Westerfield, 1985; 1989) and intra-month effects in the US stock returns (Ariel, 1987). The existence of seasonal effect has also been found in Australia (Officer, 1975; Brown, Keim, Kleidon and Marsh, 1983), the UK (Lewis, 1989), Canada (Berges, McConnell, and Schlarbaum, 1984; Tinic, Barone-Adesi and West, 1990) and Japan (Aggarwal, Rao and Hiraki, 1990).

Boudreaux (1995) reported the presence of the month-end effect in markets in Denmark, Germany and Norway. In a study of 17 industrial countries with different tax laws, Gultekin and Gultekin (1983) confirmed the January effect. Jaffe and Westerfield (1989) found a weak monthly effect in stock returns of many countries.

The research on the seasonal effect in the ECMs has started surfacing recently. A few studies have revealed the presence of seasonal effect of stock returns for the ECMs (Aggarwal and Rivoli, 1989; Ho, 1990; Lee Pettit and Swankoski, 1990; Lee, 1992; Ho and Cheung, 1994; Kamath, Chakornpipat, and Chatrath, 1998; and Islam, Duangploy and Sitchawat, 2002). Ramcharran (1997), however, rejected the seasonal effect for the stock market in Jamaica. In a recent study, Pandey (2002) confirmed the tax loss-selling hypothesis and found the existence of the monthly effect in the returns of the Bombay Stock Exchange's Sensitivity Index. In this study, we extend the investigation of the monthly effect in stock returns for stock market in Malaysia.

Methodology and Data

The seasonal effect is easily detectable in the market indices or large portfolios of shares rather than in individual shares (Officer, 1975; Boudreaux, 1995). We measure stock return as the continuously compounded monthly percentage change in the share price index as shown below:

$$r_t = (\ln P_t - P_{t-1}) \times 100 \qquad (1)$$

where r_t is the return in the period t, P_t is the monthly closing share price of the share index for the period t and ln natural logarithm. We determine whether the Composite and EMAS return series are stationary. One simple way of determining whether a series is stationary is to examine the sample autocorrelation function (ACF) and the partial autocorrelation function (PACF). We also use formal tests of stationarity, that is, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests (see Pindyck and Rubinfeld, 1998, p.509).

We will next conduct a test for seasonality in stock returns. We use a month-of-the-year dummy variable for testing monthly seasonality. The dummy variable takes a value of unity for a given month and a value of zero for all other months. We specify an intercept term along with dummy variables for all months except one. The omitted month, that is January, is our benchmark month. Thus, the coefficient of each dummy variable measures the incremental effect of that month relative to the benchmark month of January. The existence of seasonal effect will be confirmed when the coefficient of at least one dummy variable is statistically significant. Thus, similar to earlier studies, our initial model to test the monthly seasonality is as follows:

$$\begin{aligned} y_t = {} & \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} \\ & + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varepsilon_t \end{aligned} \tag{2}$$

The intercept term α_1 indicates mean return for the month of January and coefficients $\alpha_2 \ldots \alpha_{12}$ represent the average differences in return between January and each month. These coefficients should be equal to zero if the return for each month is the same and if there is no seasonal effect. ε_t is the white noise error term. The problem with this approach is that the residuals may have serial correlation.

We improve upon Equation (2) by constructing an ARIMA model for the residual series, μ_t. We then substitute this ARIMA model for the implicit error term in Equation (2). The augmented model is as follows:

$$\begin{aligned} y_t = {} & \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} \\ & + \alpha_8 D_{Aug} + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \phi^{-1}(B)\theta(B)\eta_t \end{aligned} \tag{3}$$

where η_t is a normally distributed error term and it may have different variance from ε_t (Pindyck and Rubinfeld, 1998, p.590). The residuals may show extreme volatilities. Hence we check for the ARCH effects in the residuals. As we show later, since we not find any ARCH effect, we do not make any adjustment in the model.

Our data include the closing share price index of the KLSE's Composite Index and EMAS index. The KLSE launched the Composite Index in 1986 and the EMAS in the middle of 1991. The composite index includes 100 actively traded shares. The EMAS Index is a broad-based index and it includes all shares listed on the KLSE's main board. Currently there are more than 500 shares listed on the main board. Both indices are value (market capitalization) weighted share price indices. The equal-weighted index places greater weight on small firms and potentially would magnify anomalies related to small firms. Therefore, it is more appropriate to use a value-weighted index to detect the seasonal effect in stock returns. In our analysis, we use monthly returns, calculated by Equation (1), for the period from January 1987 to June 2002 for the composite Index and January 1992 to June 2002 for EMAS. This constitutes a sample size of 186 and 126 monthly observations, respectively for the Composite Index and EMAS.

Results

Descriptive Statistics

Composite Index: We first present descriptive statistics for both the Composite Index and the EMAS returns series. Table 1 presents results for the Composite Index series. The average monthly return for the entire period from January 1987 to March 2002 is positive, but small (0.246 percent). There are wide variations of returns across months. The average returns for the months of January, February and December are much higher than returns of other months. The maximum average return occurs in the month of February. The average returns in the months of March, June, August, September, October and November are negative. The month of August has the maximum negative average return. Stock returns show negative skewness for six months and positive for remaining six months. They also show leptokurtic (kurtosis >3) distribution for ten months. This means that the monthly return distributions have flatter tails than the normal distribution.

Table 1: Descriptive Statistics, KLSE-Composite Returns: January 1987-June 2002

	Mean	Median	Max.	Min.	Stdev	Skewness	Kurtosis	J-B Stat.	Prob.	Obs.
JAN	1.088	1.428	6.130	-6.820	3.242	-0.903	3.578	2.399	0.301	16
FEB	2.168	1.725	11.690	-3.770	3.691	0.927	4.038	3.009	0.222	16
MAR	-0.586	-0.655	2.799	-6.400	2.574	-0.584	2.749	0.952	0.621	16
APR	0.738	0.515	13.020	-5.910	5.042	0.672	3.189	1.227	0.542	16
MAY	0.638	0.665	4.990	-7.190	3.290	-0.548	3.116	0.809	0.667	16
JUN	-0.327	-0.240	5.010	-8.200	2.804	-0.933	5.582	6.769	0.034	16
JUL	0.287	0.360	4.610	-4.410	2.487	0.083	2.391	0.249	0.883	15
AUG	-2.133	-0.920	3.420	-11.990	4.528	-1.072	3.295	2.925	0.232	15
SEP	-0.498	-0.250	10.300	-7.120	4.187	0.823	4.151	2.523	0.283	15
OCT	-0.631	0.920	6.450	-18.630	5.935	-2.015	6.852	19.422	0.000	15
NOV	-0.377	0.130	8.950	-8.590	3.978	0.230	3.947	0.693	0.707	15
DEC	2.441	3.090	11.600	-3.100	3.424	0.924	4.703	3.946	0.139	15
Overall	0.246	0.410	13.020	-18.630	3.957	-0.529	6.474	102.19	0.000	186

EMAS: Table 2 shows the descriptive statistics for the EMAS returns. The average monthly return for the entire period from April 1992 to March 2002 is positive, but very small (0.08 percent). The average returns for the months of February and December are much higher than returns of other months. The maximum average return occurs in the month of February. The average returns in the months of January, March, May, June, July, August, and November are negative. The month of March has the maximum negative average return. Stock returns show negative skewness for seven months and positive for remaining five months. They also show leptokurtic (kurtosis >3) distribution for five months.

Table 2: Descriptive Statistics, KLSE-EMAS Returns: January 1992-June 2002

	Mean	Median	Max.	Min.	Stdev	Skewness	Kurtosis	J-B Test	Prob.	Obs.
JAN	-0.213	0.577	5.471	-8.152	3.968	-0.699	2.714	0.932	0.627	11
FEB	2.452	2.391	12.571	-4.181	4.304	0.895	4.121	2.044	0.360	11
MAR	-1.613	-1.117	3.111	-8.548	3.285	-0.578	2.973	0.613	0.736	11
APR	0.526	-0.735	12.436	-6.287	5.632	0.749	2.788	1.050	0.591	11
MAY	-0.167	-0.171	4.318	-6.225	3.138	-0.196	2.582	0.151	0.928	11
JUN	-1.112	-0.783	5.221	-7.311	3.185	-0.065	3.505	0.125	0.939	11
JUL	-0.158	-0.578	4.844	-4.935	2.936	0.155	2.222	0.292	0.864	10
AUG	-1.558	-0.329	5.091	-12.090	5.741	-0.980	2.696	1.640	0.440	10
SEP	0.559	1.345	9.648	-5.550	5.039	0.246	2.197	0.369	0.831	10
OCT	0.425	0.995	8.095	-12.391	5.348	-1.221	4.635	3.598	0.165	10
NOV	-0.102	0.126	10.312	-10.740	5.367	-0.097	3.729	0.237	0.888	10
DEC	1.963	1.608	11.597	-3.753	4.195	1.024	3.979	2.147	0.342	10
Overall	0.079	0.020	12.571	-12.391	4.405	-0.049	4.255	8.325	0.016	126

For both the Composite Index and EMAS Index, the average returns for the months of February and December are positive and high and for the month of August the average returns are negative and quite low. Further, the Jarque-Bera test indicates that returns are normally distributed in all months. It may possibly be due to small sample size for each month. Given positive skewness and excess kurtosis for many months, the monthly return distributions would have flatter tails than the normal distribution. The return series for the entire periods of both series shows high dispersion. The distributions are leptokurtic and skewness is negative. The Jarque-Bera ratios are very high with significant ρ-values. Thus the Composite Index and the EMAS returns are not normally distributed.

Tests for Stationarity of the Composite Index and EMAS Index Returns Series

Composite index: In this section, we examine the stationarity of the Composite Index and the EMAS returns. We use the autocorrelation function (ACF) and partial autocorrelation functions (PACF) for this purpose. ACF and PACF provide a preliminary indication about the possible nature of the time series. In Figures 1 and 2 we show the ACF and the PACF of the Composite Index series. Figure 1 shows that the autocorrelation function falls off quickly as the number of lags increase. This is a typical behaviour in the case of a stationary series. The PACF in Figure 2 also does not indicate any large spikes. In Table 3 we present result of the ADF and PP (Phillips-Peron) tests. Each of the ADF and PP test scores is well below the critical value at 5 percent level. The results show consistency with different lag structures and to the presence of the intercept or intercept and trend.

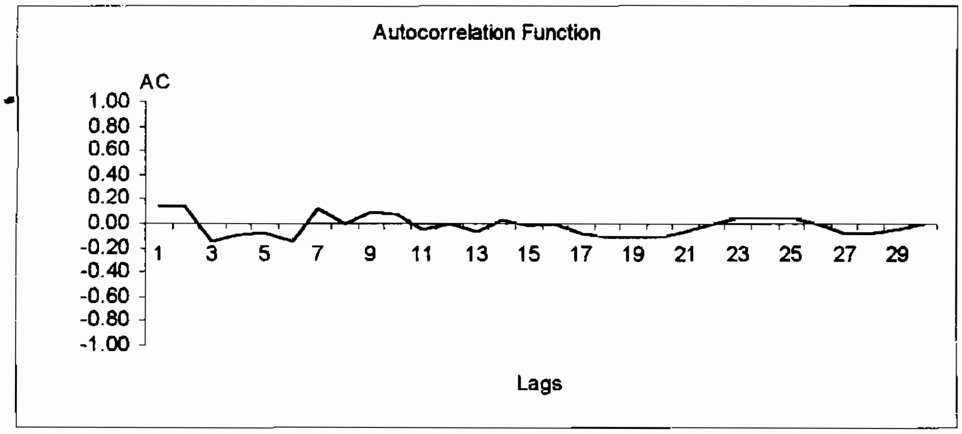


Figure 1: Autocorrelation Function of the Composite Index Returns

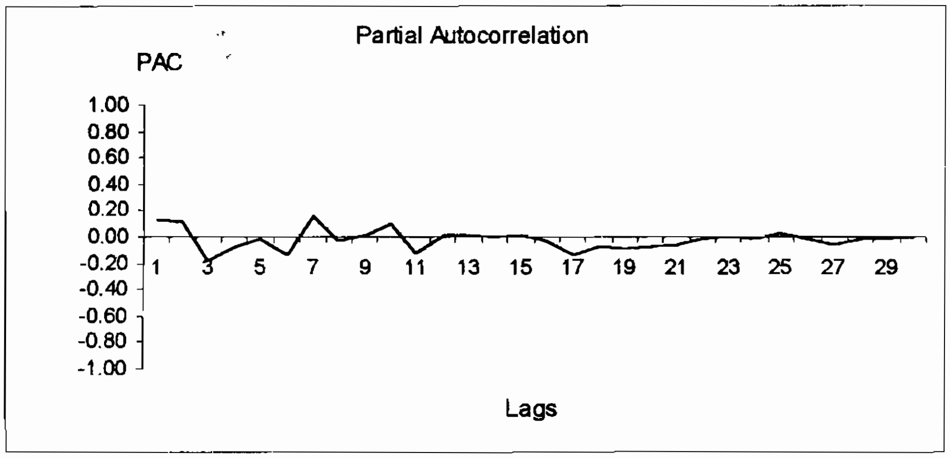


Figure 2: Partial Autocorrelation Function of the Composite Index Returns

Table 3: Augmented Dickey-Fuller Stationarity (ADF) Test

ADF: constant		**ADF: constant & trend**	
5 lags	-6.667 (-2.887)	5 lags	-6.828 (-3.435)
10 lags	-3.919 (-2.887)	10 lags	-4.071 (-3.435)
PP: with constant		**PP: with constant & trend**	
5 lags	-11.764 (-2.887)	5 lags	-11.802 (-3.435)
10 lags	-11.697 (-2.887)	10 lags	-11.735 (-3.435)

Parentheses have critical t-statistics for ADF stationarity testing at 5% level of significance. A value greater than the critical t-value indicates non-stationarity.

EMAS: For the EMAS series Figures 3 and 4 show the ACF and the PACF of the series. Figure 4 shows that the ACF falls off quickly as the number of lags increase. The falling ACF for the EMAS returns indicates that the series is stationary. Like in the case of the Composite Index returns series, the ADF and PP tests generally confirm that the EMAS return series is stationary (Table 4).

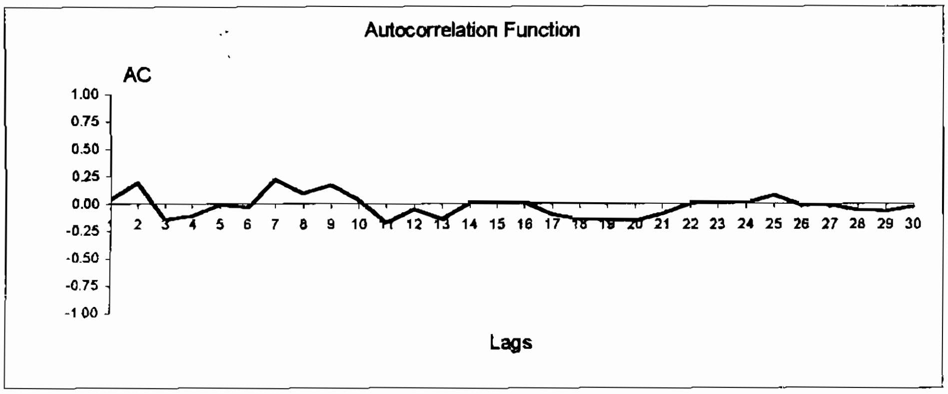


Figure 3: Autocorrelation Function of the KLSE-EMAS Returns

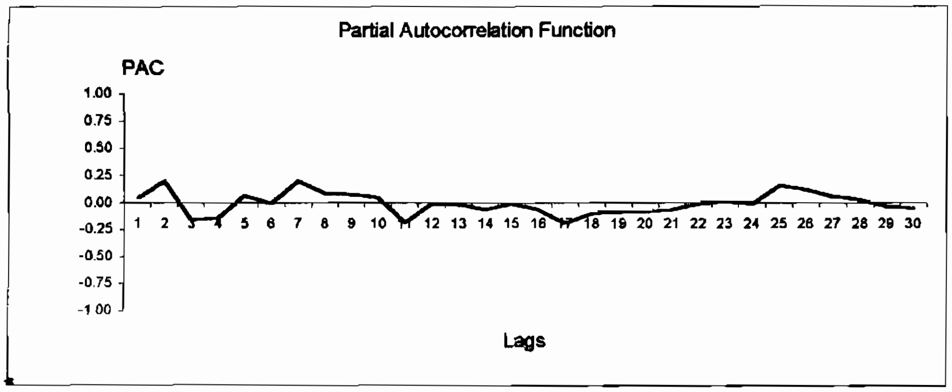


Figure 4: Partial Autocorrelation Function of the KLSE-EMAS Returns

Table 4: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Stationarity Tests

ADF: with constant		**ADF: with constant & trend**	
5 lags	-4.706	5 lags	-4.785
	(-2.887)		(-3.435)
10 lags	-2.906	10 lags	-2.992
	(-2.887)		(-3.446)
PP: with constant		**PP: with constant & trend**	
5 lags	-10.709	5 lags	-10.721
	(-2.887)		(-3.435)
10 lags	-10.789	10 lags	-10.778
	(-2.887)		(-3.435)

Parentheses have critical t-statistics for ADF stationarity testing at 5% level of significance.

Tests for Seasonality in the Composite Index and the EMAS Index Returns

Composite Index: We first use a regression model to test for seasonality in stock returns in Malaysia. We estimate Equation (2), which includes the month-of-the-year dummy variables on the right-hand side of the equation. The results for the Composite Index are presented as follows (t-statistics are given in the parentheses):

$$
\begin{aligned}
r_t = \underset{(1.21)}{1.088} + \underset{(0.79)}{2.080D_{Feb}} - \underset{(-1.22)}{1.674D_{Mar}} - \underset{(-0.26)}{0.350_{Apr}} - \underset{(-0.33)}{0.450D_{May}} - \underset{(-1.038)}{1.414D_{Jun}} - \underset{(-0.57)}{0.801D_{Jul}} - \underset{(-2.31)^{*}}{3.221D_{Aug}} \\
-\underset{(-1.14)}{1.586D_{Sep}} - \underset{(-1.23)}{1.719D_{Oct}} - \underset{(-1.05)}{1.4651D_{Nov}} + \underset{(0.97)}{1.353D_{Dec}}
\end{aligned}
$$

$R^2 = 0.10$ D-W stat. = 1.72 F-stat. = 1.665 (prob. = 0.08)

The coefficient for the month of August is significant. All other coefficients are not statistically different from zero. R^2 of 0.10 is low. F-statistic is significant at 10 percent level. Durbin-Watson statistic of less than 2 indicates serial correlation in the residuals. One simple test to check the adequacy of the model is to see if the residuals from the model are white noise. We can check the autocorrelation function and the partial autocorrelation function for the residuals of the model. The residuals from a correctly specified model should be white noise. This means that the autocorrelation and partial autocorrelations should all be zero. We can also examine the Ljung-Box Q-statistics, which is given by

$$Q = T(T+2)\sum_{k=1}^{p} \frac{\tilde{r}_k^2}{T-k}$$

If the ρ-value for the computed Q-statistic is insignificant, it means there is no serial correlation. The Ljung-Box Q-statistic for the hypothesis that there is no serial correlation up to order of 36 is 51.61 with a significant ρ-value at 5% level is rejected. Thus, the residuals of the model are not white noise.

We next examine stationarity of the residuals obtained from the estimation of Equation (2). The sample autocorrelation function (not shown here) for the residuals shows steady decline. The steadily declining autocorrelation function implies that the residuals series is stationary. We can fit an ARIMA model to the residuals. After experimenting, we fit the ARIMA (8,0,6) model to the residual series. The results of the model are given below:

$$(1 - 0.250B + 1.202B^2 - 0.213B^3 + 0.908B^4 - 0.040B^5 + 0.310B^6 + 0.186B^7 + 0.016B^8)\ \mu_t$$
$$= -0.257 + (1 - 0.126B + 1.414B^2 - 0.280B^3 + 1.223B^4 - 0.301B^5 + 0.439B^6)\ \varepsilon_t$$

$R^2 = 0.231$ D-W stat. 2.00 F-stat. = 3.501 (prob. = 0.000)
Q-stat. (36) = 28.59 (ρ-value = 0.157)

The Ljung-Box Q-statistic to order of 36 is 28.59 is insignificant with ρ-value of 0.157. Thus, we can conclude that the residuals of the ARIMA (8,0,6) model are white noise.

We combine the ARIMA (8,0,6) model with the regression model (Equation 2) and estimate all parameters simultaneously as given in Equation (3). The results of the estimation of Equation (3) are given below (t-statistics are given in the parentheses):

$$\underset{(4.05)^*}{r_t = 0.902} + \underset{(1.21)}{1.108D_{Feb}} \underset{(-1.73)^*}{-1.597D_{Mar}} \underset{(-0.45)}{-0.405D_{Apr}} \underset{(-0.50)}{- 0.460D_{May}} \underset{(-1.53)}{- 1.402D_{Jun}} \underset{(-0.94)}{- 0.850D_{Jul}} \underset{(-3.32)^*}{- 3.093D_{Aug}}$$

$$\underset{(-1.73)^*}{-1.573D_{Sep}} \underset{(-1.70)^*}{-1.552D_{Oct}} \underset{(-1.53)}{- 1.448D_{Nov}} + \underset{(1.43)}{1.361D_{Dec}} + [(1 + 0.270B + 0.560B^2 + 0.083B^3 - 0.561B^4$$

$$+ 0.055B^5 + 0.556B^6)/(1 - 0.399B - 0.634B^2 + 0.227B^3 + 0.534B^4 - 0.118B^5 - 0.484B^6 - 0.076B^7$$
$$+ 0.085B^8)]\eta_t$$

$R^2 = 0.230$ D-W stat. = 2.00 F-stat. = 1.880 (prob. 0.000)

Q (36) = 19.01 (ρ-value = 0.645)

The R^2 is 0.23 and the D-W statistic is 2. The sample autocorrelations (not shown here) for the residuals of the model are almost zero. Further, the Ljung-Box Q-statistic is mostly insignificant. Q-statistic of 19.01 to order of 36 is insignificant with a ρ-value of 0.645. Thus, the residuals of the model are white noise. Hence, our estimations do not suffer from the problem of serial correlation. The residuals do not exhibit conditional autoregressive heteroskedasticity. A Lagrange Multiplier (LM) test for the presence of the ARCH effects in the residuals (F-statistic of 0.911 with ρ-value of 0.341) reveals no such effects.

We note from the estimation of Equation (3) that the estimated coefficients of the monthly dummy variables change significantly once we account for the serial correlation in the residuals. We find the coefficient of intercept term that represents the benchmark month of January to be significant. The average return in the benchmark month of January is 0.902 percent. The coefficients of the dummy variables for the months of March, August, September and October are negative and statistically significant. The average returns for these months are lower than the benchmark month of January. The months of February and December have the higher returns as compared to other months.

EMAS: The results of the estimation of Equation (2) for the EMAS are given below (t-statistics are given in the parentheses):

$$
\begin{aligned}
r_t = & \underset{(-0.16)}{-0.213} + \underset{(1.41)}{2.665}D_{Feb} \underset{(-0.74)}{-1.400}D_{Mar} + \underset{(0.39)}{0.739}D_{Apr} + \underset{(0.02)}{0.046}D_{May} - \underset{(-0.48)}{0.899}D_{Jun} + \underset{(0.03)}{0.055}D_{Jul} - \underset{(-0.69)}{1.345}D_{Aug} \\
& + \underset{(0.40)}{0.772}D_{Sep} + \underset{(0.33)}{0.639}D_{Oct} + \underset{(0.06)}{0.111}D_{Nov} + \underset{(1.12)}{2.176}D_{Dec}
\end{aligned}
$$

$R^2 = 0.07$ D-W stat. = 1.85 F-stat. = 0.829 (prob. = 0.61)

None of the coefficients is significant. R^2 of 0.07 is low, and the insignificant F-statistic suggests poor model fit. Durbin-Watson statistic of less than 2 indicates serial correlation in the residuals. Further, the Ljung-Box Q-statistic for the hypothesis that there is no serial correlation up to order of 36 is 60.03 with a significant ρ-value at 1% level is rejected. Thus, the residuals of the model are not white noise.

The steadily declining autocorrelation function for the residuals (not shown here) implies that he residuals series is stationary. After experimenting, we fit the ARIMA (8,0,6) model to the residual series. The results of the model are as follows:

$$(1 - 0.142B^2 - 0.303B^2 - 0.653B^3 + 0.369B^4 + 0.451B^5 - 0.045B^6 - 0.262B^7 + 0.136B^8)\,\mu_t$$
$$= 0.551 + (1 - 0.122B - 0.133B^2 - 0.951B^3 + 0.288B^4 + 0.500B^5 + 0.308B^6)\,\varepsilon_t$$

$R^2 = 0.241$ D-W stat. 2.00 F-stat. = 2.331 (prob. = 0.008)
Q-stat. (36) = 19.50 (ρ-value = 0.614)

The residuals of the ARIMA (8,0,6) model are white noise since the Ljung-Box Q-statistic to order of 36 is 19.50, and it is insignificant with ρ-value of 0.614

The results of the estimation of Equation (3) are given below (t-statistics are given within parentheses):

$$\underset{(-0.65)}{r_t = -0.851} + \underset{(1.64)^*}{2.942D_{Feb}} - \underset{(-0.46)}{0.759D_{Mar}} + \underset{(0.56)}{1.094D_{Apr}} + \underset{(0.21)}{0.389D_{May}} - \underset{(-0.11)}{0.176D_{Jun}} + \underset{(0.26)}{0.487D_{Jul}} - \underset{(-0.45)}{0.745D_{Aug}}$$
$$+ \underset{(0.89)}{1.693D_{Sep}} + \underset{(0.67)}{1.358D_{Oct}} + \underset{(0.36)}{0.593D_{Nov}} + \underset{(1.65)^*}{3.022D_{Dec}} + [(1 - 0.567B - 0.329B^2 - 0.581B^3 + 0.533B^4$$
$$+ 0.584B^5 - 0.234B^6)/(1 - 0.630B - 0.495B^2 - 0.257B^3 + 0.553B^4 + 0.466B^5 - 0.525B^6 - 0.218B^7$$
$$+ 0.324B^8)]\eta_t$$

$R^2 = 0.293$ D-W stat. = 2.00 F-stat. = 1.661 (prob. = 0.041)

The model's F-statistic is significant at 5 percent level. The R^2 is 0.29. The D-W statistic of 2 is insignificant and implies absence of autocorrelation. The sample autocorrelations for the residuals (not shown here) are almost zero. Further, the Ljung-Box Q-statistic of 18.221 to order of 36 is insignificant with a ρ-value of 0.693. This indicates that the residuals of the model are white noise. A Lagrange Multiplier (LM) test for the presence of the ARCH effects in the residuals (F-statistic of 2.340 with ρ-value of 0.129) testifies the absence of such effects.

The estimated coefficients of the monthly dummy variables change once we account for the serial correlation in the residuals. We find the coefficients of dummy variables for the months of February and December to be statistically significant at 10 percent level. The average return in the benchmark month of January is negative (-0.851 percent), and it is the lowest. The months of February and December have the highest returns as compared to other months. The average return for the month of December is the highest.

There is evidence of seasonality in both the Composite Index and EMAS returns. The statistically significant coefficients for the months of March, August, September and October clearly indicate the monthly in the KLSE's Composite Index returns. The coefficient of the intercept term, which represents the benchmark month of January, is also statistically significant. Thus, there is evidence of the January effect for the Composite Index returns in Malaysia. Like in the case of the Composite Index returns, the statistically significant coefficients for the months of February and December indicate the presence of seasonality in the EMAS returns. The coefficient of the intercept term, which represents the benchmark month of January, is not statistically significant. Thus, we can rule out the January effect for the EMAS returns. This finding is contrary to the results for the Composite Index.

The Malaysian tax year, like in the USA, ends in December. There is no capital gain tax in Malaysia. The average return for December is positive for the Composite Index and EMAS. It appears that investors in Malaysia trade in shares towards the end of the year and make capital gains on which they are not required to pay any tax. Thus there is the year-end effect (the coefficient for December in case of the EMAS is significant) but unlike in the USA and some other countries, this cannot be attributed to the 'tax-loss-selling' hypothesis. Investors sell shares and book losses (rather than making capital gains) to save taxes under the 'tax-loss' selling hypothesis. The results of the study could be rather ascribed to the 'information' hypothesis.

Summary and Conclusions

The focus of this study was on investigating the existence of seasonality in stock returns in Malaysia. We used the monthly returns data of the KLSE's two indices, the Composite Index and EMAS. For EMAS, the maximum average return (positive) occurred in the month of February and lowest (negative) in the month of March. The positive average returns arose for five months and negative for the remaining months. For seven months the skewness of returns is negative and kurtosis is in excess of three for three months. For the Composite Index, the month of December has the maximum average return and August the lowest. Positive and negative average returns occur for six months each. The Jarque-Bera statistics indicate that the Composite Index and EMAS returns for all months are normally distributed. This may be an account of small sample size. The returns for the entire period are leptokurtic and they are not normally distributed.

The results of the study confirmed the seasonal effect in stock returns in Malaysia. We found that returns were statistically different in months of February and December in case of EMAS. December average returns are *positive* and the highest as compared to all months. The positive average returns cannot be explained by the tax-loss selling hypothesis; rather it may be attributed to the informational inefficiency. For the Composite Index, the coefficients for the months of March, August, September and October are significantly different from the benchmark month of January. The coefficient of January is also significant. The average return for

December is positive, but it is statistically insignificant. Thus, 'the tax-loss selling' hypothesis is rejected.

The results of the study indicate that stock returns in Malaysia are not entirely random. This implies that the Malaysian stock market is not informationally efficient. Hence investors can perhaps improve their returns by timing their investments.

References

1. Aggarwal, Raj, Ramesh P. Rao and Takto Hiraki, "Regularities in Tokyo Stock Exchange Security Returns: P/E, Size and Seasonal Influences," *Journal of Financial Research*, Vol. 13, (Fall 1990), 249-263.
2. Aggarwal. R. and P. Rivoli, "Seasonal and Day-of-the Week effects In Four Emerging Stock Markets. "*The Financial Review*, 24, (1989), 541-550.
3. Ariel, Robert A., "A Monthly Effect in Stock Returns, " *Journal of Financial Economics*, Vol. 18, (March 1987), 161-174.
4. Berges, A., J. McConnell, and G. Schlarbaum, "An Investigation of the Turn-of-the-Year Effect, the Small Firm Effect and the Tax-Loss Selling Pressure Hypothesis in Canadian Stock Returns," *Journal of Finance*, 39, (March1984), 185-192.
5. Boudreaux, Denis O., "The Monthly Effect in International Stock Markets: Evidence and Implications", *Journal of Financial and Strategic Decisions*, Vol. 8, No. 1, (1995), 15-20.
6. Brown, P., D.B. Keim, A.W. Keleidon, and T.A. Marsh "Stock Return Seasonalities and the Tax-Loss-Selling-Hypothesis: Analysis of the Arguments and Australian Evidence," *Journal of Financial Economics*, 12, (June1983), 105-127.
7. Gultekin, M.N., and N.B. Gultekin, "Stock Market Seasonality: International Evidence," *Journal of Financial Economics*, 12, (December 1983), 469-481.
8. Ho, R. and Y. Cheung, "Seasonal Patterns in Volatility in Asian Stock Markets," *Applied Financial Economics*, 4, (1994), 61-67.
9. Ho, Y., "Stock Return Seasonalities in Asia Pacific Markets," *Journal of International Financial Management and Accounting*, 2, (1990), 47-77.

10. Islam, Anisul M., Orpin Duangploy, and Saowanww Sitchwart, "Seasonality in Stock Returns: An Empirical Study of Thailand," *Global Business and Finance Review*, Vol. 6, No. 2, (2001), 65-75.

11. Jaffe, Jeffery, and Randolph Westerfield, "The Week-End Effect in common Stock Returns: The International Evidence," *Journal of Finance*, Vol. 40, (June 1985), 433-454.

12. Jaffe, Jeffrey F., and Randolph Westerfield and M. Christopher, "A Twist on The Monday Effect in Stock Prices: Evidence from the U.S. and Foreign Stock Markets," *Journal of Banking and Finance*, Vol. 13, (1989), 641-650.

13. Jaffe, Jeffrey F., and Randolph Westerfield, "Is There a Monthly Effect in Stock Market Returns? Evidence from Foreign Countries," *Journal of Banking and Finance*, Vol. 13, (1989), 237-244.

14. Kamath, R., R. Chakornpipat, and R. Chatrath, "Return Distribution and the Day-of-the-Week Effects in the Stock Exchange of Thailand," *Journal of Economics and Finance*, 22, 2-3, (1988), 97-107.

15. Kato, K. and J.S. Schallheim, "Seasonal and Size Anomalies in the Japanese Stock Market," *Journal of Financial and Quantitative Analysis*, 20, (1985), 243-272.

16. Keim, D.B., "Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence," *Journal of Financial Economics*, 12, (June 1983), 13-32.

17. Lee, I., "Stock Market Seasonality: Some Evidence From the Pacific-Basin Countries," *Journal of Business Finance and Accounting*, 19, (1992), 192-209.

18. Lee, I., R. Pettit, and M.V. Swankoski, "Daily Return Relationship Among Asian Stock Markets," *Journal of Business Finance and Accounting*, 17, (1990), 265-283.

19. Lewis, Mario, "Stock Market Anomalies: A Re-Assessment Based on The U.K. Evidence," *Journal of Banking and Finance*, Vol. 13, (1989), 675-696.

20. Officer, R.R., "Seasonality in Australian Capital Markets: Market Efficiency and Empirical Issues," *Journal of Financial Economics*, Vol. 2, (March 1975), 29-52.

21. Pandey, I. M., "The Monthly Effect in Stock Returns: The Indian Experience", unpublished paper, Indian Institute of Management, Ahmedabad, (September 2002).

22. Pindyck, Robert S. and Daniel L. Rubinfeld, Econometric Models and Economic Forecasts, New York: McGraw-Hill, (1997), p. 509.

23. Ramacharran, H., "Seasonality in the Jamaican Stock Market: An Examination of Stock Returns and the Volume Traded," *Journal of Emerging Markets*, 2, 1, (1997), 23-35,

24. Reinganum, M.R. "The Anomalous Stock Market Behavior of Small Firms in January Empirical Test for Year-End Tax Effect," *Journal of Financial Economics*, 12, (June 1983), 89-104.

25. Rozeff, Michael S., and William R. Kinney, "Capital Market Seasonality: The Case of Stock Market Returns, " *Journal of Financial Economics*, Vol. 3, (October 1976), 376-402.

26. Smirlock, Michael, and Laura Starks, "Day of the Week and Intraday Effects in Stock Returns," *Journal of Financial Economics*, Vol. 17, (1986), 197-210.

27. Tinic, Seha M., and Richard R. Wesst, "Risk and Return: January and the Rest of the Year," *Journal of Financial Economics*, Vol. 13, (December 1984), 561-574.

28. Tinic, Seha M., Giovanni Barone-Adesi and Richard R. West, "Seasonality in Canadian Stock Prices: A Test of the 'Tax-Loss Selling' Hypothesis," *Journal of Financial and Quantitative Analysis*, Vol. 22, (1987), 51-64.

29. Wachtel, S.B., "Certain Observation on Seasonal Movement in Stock Prices," *Journal of Business*, 15, (1942), 184-193.