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Day-Seasonal Efficiency of the Stock Exchange of Thailand

Anya Khanthavit *

Thammasat Business School, Thammasat University, Thailand

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Abstract

Market efficiency evolves with changing market conditions. Moreover, if the conditions are weekday dependent, the efficiency can be day-seasonal. In this study, I test for the day-seasonal efficiency of the Thai stock market and examine how it behaves over time. Using the daily returns on the Stock Exchange of Thailand index portfolio from April 30, 1975, to December 29, 2017, I find that the day-seasonal efficiency exists. However, it disappears as the efficiency of the market improves. The day-seasonal efficiency is empirically explained by the positive feedback strategies. The market has a delayed response to the information from foreign investors' trading volume.

Keywords

Adaptive markets hypothesis, Evolving market efficiency, Day-seasonal efficiency, Day seasonality, Weekday autocorrelation

*** Corresponding author**: akhantha@tu.ac.th **DOI**: 10.14456/tureview.2018.10

Introduction

Under the adaptive markets hypothesis (AMH), the degree of market efficiency varies with micro and macro environmental factors (Lo, 2004; 2005). The micro factors include the market microstructure, limits to arbitrage, psychological biases, noise trading, and market imperfections, while the macro factors are macro institutions, market regulations, and information technologies (Lim & Brooks, 2011). Zalewska-Mitura and Hall (1999) argued that the efficiency of the market should improve over time. It takes time for market participants to learn about the price discovery process. Therefore, it is likely that a young market is less efficient. As time passes, the market participants gain more experience and the market system develops further, thus resulting in the rising efficiency.

The AMH is supported by previous studies that used national and international market data. For example, Zalewska-Mitura and Hall (1999) Kalman-filtered the first-order autocorrelation (AR(1)) coefficients of the returns on U.K. and Hungarian stocks. The coefficients were time-varying in a decreasing manner. Because the sizes of the coefficients suggested the speed of information dissemination, the researchers concluded that the markets evolved toward efficiency. A similar finding was reported for the Thai market by Khanthavit (2016). For the U.S. market, however, Lo (2004, 2005) found that the sizes of the AR (1) coefficients from rolling regressions varied in a cyclical way. Their sizes for the 1950s subsample were smaller than those for the 1990s subsample.

Market anomalies, such as calendar and mood anomalies, also suggest market inefficiency (Nawaz & Mirza, 2012; Subrahmanyam, 2008). The significance levels of the anomalies indicate its degrees (Doyle & Chen, 2009). Researchers found the behaviors of the anomalies that supported the AMH. For the calendar anomalies, Doyle and Chen (2009) reported a wandering weekday effect for major stock markets, such as the Chinese, German, Indian, Japanese, and U.S. markets. Recently, Al-Khazali and Mirzaei (2017) found for eight Islamic stock indices that the weekday, week, and January effects were disappearing over time. For the mood anomalies, Khanthavit (2017a) reported wandering weather-driven mood effects for the Thai market. When Khanthavit (2017b) considered the recent sample of Thai stock returns, the effect disappeared.

In addition to evolving efficiency, there are at least six reasons to suggest day-seasonal efficiency. First, Gibbons and Hess (1981) found for the U.S. stock market that Friday returns were higher and Monday returns were lower than other weekdays' returns. The finding could be explained by the measurement errors being specific to Friday and Monday. This explanation implied significant, negative AR (1) coefficients for Monday and Tuesday.

Second, investors were pessimistic on Monday and optimistic on Friday (e.g., Pettengill, 1993), thus leading to high Friday and low Monday prices. Because the high and low prices are not driven by the fundamentals of stocks, the prices reverse and the results have negative return autocorrelations on Monday and Tuesday.

Third, in Admati and Pfleiderer's (1989) model, in order to mitigate the losses for informed traders, market makers designed a divide-and-conquer pricing rule to encourage liquidity traders to trade in separate periods. In equilibrium, the prices tend to reverse the price moves in the preceding, concentrated trading period. According to Foster and Viswanathan (1990), the information disadvantages are most severe after a non-trading period such that significant, negative autocorrelation is expected for Monday returns.

Fourth, Chen and Singal (2003) proposed that speculative short sellers did not want to hold the positions and take risks over weekends. Therefore, they bought stocks to close their short positions and drove the prices up, which led to positive Friday returns. Driven by short selling, the prices reversed and generated negative autocorrelated returns on Monday.

Fifth, it is relatively less costly and more convenient to individual investors to analyze stocks and make investment decisions during weekends. These investors tend to be more active on Monday. Because buy recommendations from stock brokers spread over weekdays, the information they receive during weekends tends to be bad news. On Monday, the investors sell stocks and pressure the prices downward (Lakonishok & Maberly, 1990; Miller, 1988). The Monday pressure is severe. It is not counter-balanced by institutional investors' trades. Low activities of the institutional investors are observed on Monday - their strategic planning day (Wang & Walker, 2000). The Monday price pressure suggests price reversals and negative autocorrelated returns on Tuesday.

Sixth, Abraham and Ikenberry (1994) found for the U.S. market that the negative Friday returns were associated with the stock selling of individual investors and the negative returns on Monday. This finding is consistent with the positive feedback strategies of individual investors and Monday's positive autocorrelated returns.

Day-seasonal efficiency is supported by previous empirical studies. For the U.S. market, Cross (1973) and Abraham and Ikenberry (1994) found that positive (negative) Friday returns tended to be followed by positive (negative) Monday returns, thus suggesting positive autocorrelated returns for Monday. In an autoregression analysis, Campbell, Grossman, and Wang (1993) reported that the explanatory power improved significantly when the AR(1) coefficient was a linear function of weekday dummy variables. In similar regressions, Keim and Stambaugh (1984), Bessembinder and Hertzel (1993), and Higgins and Peterson (1999) found that the returns' AR(1) coefficients were significant, positive, and largest for Monday or the days after non-trading days. Recently, Narayan, Mishra, and Narayan (2014) analyzed stocks' bid-ask spreads using an error-correction regression model. The researchers concluded that the speed of information dissemination in the U.S. market was the highest on Friday. Using the intraday data, Dong, Feng, Ling, and Song (2017) reported that the autocorrelation coefficient for Monday was less negative than the coefficients for other weekdays.

For other national markets, Herwartz (2000) and Blandon (2001) found in their autoregression analyses of stock returns in the German and Spanish markets, respectively, that the AR(1) coefficients were positive, significant, and largest for Monday. Khanthavit and Chaowalerd (2016) found the same result for the Thai Market.

Day-seasonal efficiency has been documented in studies of international stock markets. Jaffe and Westerfield (1985) found that the AR(1) coefficients for Monday were positive and largest for the Australian, Canadian, Japanese, U.K., and U.S. markets. Louhelainen (2005) tested for predictability of weekday returns in the Canadian, Dutch, Finish, Italian, Japanese, Singaporean, and U.S. markets. The researcher reported that Monday and Tuesday returns could be predicted.

In this study, I examine day-seasonal efficiency of the Thai stock market using the autoregression analysis of daily stock returns. I consider the Thai market because it is one of the world's most important emerging markets in terms of market capitalization and trading volume (Khanthavit, 2017a). As the market evolves, so should the degree of day-seasonal efficiency. Previous studies never raised this important and interesting question regarding whether and how day-seasonal efficiency evolves over time. To answer this question, I follow Khanthavit (2017a) to construct the autoregression model that allows the weekdays' autocorrelation coefficients to be different for each year in the sample period. Finally, I discuss and test alternative explanations of the day-seasonal efficiency. I successfully find one possible explanation for the Thai market.

Methodology

The Model

The size of the return's AR(1) coefficient suggests the speed of information dissemination and the degree of market efficiency (Lo, 2004; 2005). If the speed and degree are different for weekdays, the weekday coefficients must differ. Let R_t be the stock return on day t. The model for the evolving day-seasonal efficiency is the weekday-and-year specific AR(1) equation (1).

$$R_t = \sum_{y=1}^{Y}\sum_{d=1}^{5}\delta_{d,y}D_t + \sum_{y=1}^{Y}\sum_{d=1}^{5}\rho_{d,y}D_tR_{t-1} + \varepsilon_t. \quad (1)$$

The dummy variable D_t is 1.00 if day t falls on weekday d and in year y. Otherwise, D_t is 0.00. Weekday d=1 is Monday,..., and weekday d=5 is Friday. Year y=1 is the first year in the sample period, and year y= Y is the last. The term ε_t is the regression error. The parameters $\delta_{d,y}$ and $\rho_{d,y}$ are, respectively, the intercept and AR(1) coefficients for weekday d in year y.

If $\delta_{d,y}$ and $\rho_{d,y}$ are the same for years y= 1 to y= Y, equation (1) becomes the traditional regression model $R_t = \sum_{d=1}^{1} \delta_d D_t + \sum_{d=1}^{5} \rho_d D_t R_{t-1} + \varepsilon_t$ for the day-seasonal efficiency study (e.g., Bessembinder & Hertzel, 1993).

When the market evolves, $\delta_{d,y}$ and $\rho_{d,y}$ necessarily vary. Fixing the parameters induces misspecification problems (Khanthavit, 2017a). The specification of equation (1) mitigates the problems. Moreover, it enables the study to measure the degree of day-seasonal efficiency in each year.

Model Estimation

It is possible that the daily return R_t is not distributed normally and the regression error ε_t is heteroskedastic and serially correlated. In order to obtain the consistent estimates for $\delta_{d,y}$ and $\rho_{d,y}$, I use Hansen's (1982) generalized method of moments (GMM). GMM is an instrumental-variable approach whose estimators are consistent, asymptotically normal, and efficient among the class of estimators that do not use any information beyond moment conditions. GMM does not require normally distributed returns or regression errors.

It is important to note that when the error term ε_t is serially correlated, equation (1) is misspecified. More lagged returns must be added to the regression equation (1). I check for the serial correlation of ε_t with the Durbin-Watson (D.W.) and Wald statistics. The D.W. and (4-D.W.) statistics are compared with the available critical value of 1.9162 for the most extensive model with 2,000 observations and 21 regressors. ε_t is neither positively nor negatively serially correlated if the statistics D.W. and (4-D.W.) are greater than 1.9162. The Wald statistic is computed from the autoregression of ε_t with its five lags. Under the null hypothesis of no serial correlation, the statistic is a chi-square variable of five degrees of freedom.

Hypothesis Tests

Existence of Day-Seasonal Efficiency

In previous studies, Khanthavit and Chaowalerd (2016) tested the day-seasonal efficiency hypothesis using Bessembinder and Hertzel's (1993) regression. The researchers found that it existed in the Thai market for the sample period from 2002 to 2015. In this study, I re-examine the hypothesis using a different regression model in equation (1) and with a different sample period. Because $\rho_{d,y}$ is specific to year y, the weighted-average $\bar{\rho}_d$ over years 1 to Y represents the degree of efficiency on weekday d for the full sample. The weight is the number of observations in year y. If the day-seasonal efficiency does not exist,

$\bar{\rho}_{d=1} = \cdots = \bar{\rho}_{d=5}$. Under the null hypothesis, the Wald statistic is a chi-square variable with four degrees of freedom. Moreover, if the market is fully efficient on every weekday, $\bar{\rho}_{d=1} = \cdots = \bar{\rho}_{d=5} = 0.00$. The Wald statistic for the full efficiency is a chi-square variable with five degrees of freedom.

Evolving Day-Seasonal Efficiency

If day-seasonal efficiency does not exist in year y, $\rho_{d=1,y} = \cdots = \rho_{d=5,y}$. Under the null hypothesis, the Wald statistic is a chi-square variable with four degrees of freedom. The degree of the day-seasonal efficiency in year y can be measured by the size of the corresponding Wald statistic (Doyle & Chen, 2009). An interesting question is how the day-seasonal efficiency evolves over time. To answer this question, I regress the Wald statistics on the time trend. If the day-seasonal efficiency is wandering over time, the slope coefficient is not significant. However, if it is disappearing, the coefficient must be negative and significant.

Evolving Efficiency on Weekdays

If the degree of efficiency on weekday d does not exist over time, $\rho_{d,y=1} = \cdots = \rho_{d,y=Y}$. I use this fact to test for the evolving market efficiency hypothesis for weekday y. The Wald statistic is a chi-square variable with Y degrees of freedom.

Evolving Market Efficiency

The Wald statistic for the hypothesis $\rho_{d=1,y} = \cdots = \rho_{d=5,y} = 0.00$ measures the degree of market efficiency in year y. In full efficiency, the market is necessarily efficient on each and every day. It follows that $\rho_{d,y} = 0.00$ for all weekdays and years. In this study, I use the information on year y's day-seasonal efficiency to test for the evolving market efficiency. This approach is new. I regress the Wald statistic for the hypothesis $\rho_{d=1,y} = \cdots = \rho_{d=5,y} = 0.00$ on the time trend. If the degree of market efficiency is wandering, the slope coefficient is not significant. However, if the efficiency improves, the coefficient is negative and significant.

The day-of-the-week or weekday effect describes the market in which the average stock returns are different on weekdays. The effect suggests the inefficiency of the market (Nawaz & Mirza, 2012). From equation (1), if the weekday effect does not exist in year y, $\delta_{d=1,y} = \cdots = \delta_{d=5,y}$. The Wald statistic for the hypothesis $\delta_{d=1,y} = \cdots = \delta_{d=5,y}$ can be used as an alternative test for the evolving market efficiency (Doyle & Chen, 2009). After regressing the Wald statistic for year y on the time trend y, I will conclude wandering efficiency if the slope coefficient is not significant. I conclude improving efficiency if the coefficient is negative and significant.

The Data

The data are the daily returns from the Stock Exchange of Thailand (SET) index portfolio. It is computed from the log differences in the closing indexes. The data began on April 30, 1975, and ended on December 29, 2017 (10,481 observations). I retrieved the SET indexes from the SET database.

Table 1, column 2 reports the descriptive statistics of the SET index return. Its skewness and excess kurtosis are -0.1093 and 9.2385, respectively. The return distribution is negatively skewed and fat-tailed. The Jarque-Bera test rejects the normality assumption at the 99% confidence level. The AR(1) coefficient is positive and significant. The Jarque-Bera test result supports the use of GMM in estimation. The significant AR(1) coefficient is consistent with the model specification in equation (1).

Table 1 Descriptive Statistics

Statistics	SET Index Portfolio
Average	0.0003
Standard Deviation	0.0142
Skewness	-0.1093
Excess Kurtosis	9.2385
Maximum	0.1135
Minimum	-0.1606
AR(1) Coefficient	0.1373***
Observations	10,481
Jarque-Bera Statistic (χ^2_2)	37,294.0140***

Note: *** = significance at the 99% confidence level.

Empirical Results

Existence of Day-Seasonal Efficiency

I estimate the model in equation (1) using the daily returns on the SET index portfolio. The serial correlation property of the error ε_t is assessed by the D.W. and Wald tests. The D.W. and Wald statistics are 1.9928 and 7.6884, respectively. With respect to the test results for no serial correlation, I conclude that the model is well specified.

Table 2, columns 2 to 6 report the AR(1) coefficients $\rho_{d,y}$ for weekdays d=Monday to d=Friday and years y=1975 to y=2017. Most $\rho_{d,y}$s are positive, which is consistent with the positive and significant AR(1) coefficient in Table 1. All the weighted-average coefficients in the second row from the bottom are positive and significant. The Monday coefficient is the largest, and the Tuesday coefficient is the smallest. The largest Monday coefficient is similar to what was found for the Thai Market by Khanthavit and Chaowalerd (2016) and other national markets by other researchers (e.g., Jaffe & Westerfield, 1985). The Wald statistic for the hypothesis $\bar{\delta}_{d=1} = \cdots = \bar{\delta}_{d=5}$ is 109.58. It is significant at the 99% confidence level. Day-seasonal efficiency exists in the Thai market. The hypothesis $\bar{\delta}_{d=1} = \cdots = \bar{\delta}_{d=5} = 0.00$ is rejected. From the day-seasonal efficiency perspective, the Thai stock market is not efficient.

Evolving Day-Seasonal Efficiency

Table 2, column 7 reports the Wald statistics for the hypothesis $\rho_{d=1,y} = \cdots = \rho_{d=5,y}$. If the day-seasonal efficiency does not exist in year y, the statistic is not significant. I regress the statistics on the time trend. The slope coefficient equals -0.2555, which is not significant. Despite the insignificance, I do not conclude that the day-seasonal efficiency is wandering. The slope is estimated imprecisely. In the following subsection, from the day-seasonal efficiency perspective, the market efficiency improves. All the weekdays' AR(1) coefficients converge toward zero. The day-seasonal efficiency is disappearing.

Evolving Efficiency on Weekdays

The last row of Table 2 reports the Wald statistics for the hypothesis $\delta_{d,y=1975} = \cdots = \delta_{d,y=2017}$. The sample period is 42 years. Hence, the statistics are the chi-square variables with 42 degrees of freedom. The statistics are large and significant at the 99% level. The weekday efficiency of the market evolves over time.

Evolving Market Efficiency

I conduct two tests to examine how the market efficiency evolves. The first test is based on the regression of the Wald statistic for year y's A(1) coefficients $\rho_{d=1,y} = \cdots = \rho_{d=5,y} = 0.00$ on the time trend y. The second test considers the Wald statistic for year y's intercepts $\delta_{d=1,y} = \cdots = \delta_{d=5,y}$. The two sets of the Wald statistics are in Table 2, columns 8 and 9. From the regressions, the slope coefficients are -1.0805 and -0.1123, respectively. The former is significant at the 99% confidence level, while the latter is not significant. The market efficiency improves over time. Only the result from the day-seasonal efficiency regression points to the fact that the improvement is significant.

Table 2 Tests for Day-Seasonal Efficiency based on the Stock Exchange of Thailand Index Portfolio

Year	AR(1) Coefficients					Joint Hypothesis Tests		
						AR(1) Coefficients		
	Monday	Tuesday	Wednesday	Thursday	Friday	Equal (χ^2_4)	Zero (χ^2_5)	Equal Intercepts (χ^2_4)
1975	0.4972**	0.6322***	-0.1759	0.0404	0.2923***	22.73***	38.75***	8.97*
1976	0.0235	0.2709	0.0433	-0.1496	0.1337	3.70	4.70	6.50
1977	0.8102***	0.1414	1.1477***	0.2227**	0.2814	51.30***	158.65**	8.26*
1978	0.6522**	0.6802**	0.1362	-0.1430	0.0322	8.10*	24.84***	2.42
1979	1.3443***	-0.0814	0.1610	0.4001***	0.3175	50.34***	70.90***	4.94
1980	0.4808**	0.2712*	0.1346	0.4550***	0.4087**	2.60	36.72***	10.26**
1981	0.4990*	0.2139**	0.2828*	0.2691**	0.1314	1.95	44.79***	0.65
1982	0.8936***	0.0266	0.3392	-0.0677	0.3627**	17.56***	35.54***	6.53
1983	0.3508	0.3418**	-0.1598	0.2010	0.1656	12.55**	16.59***	3.44
1984	-0.1776	-0.1282***	0.7380***	0.0955	0.3078	51.71***	51.79***	8.68*
1985	0.3213*	0.3435	0.1795	0.2036	0.1816	0.85	14.88	25.78***
1986	0.3504**	-0.0227	0.2486*	0.3880**	0.4732**	15.28***	36.32***	3.97
1987	-0.1026	0.7937***	0.5652***	0.0661	0.3170***	11.16**	128.97***	7.64
1988	0.5744*	-0.1721	0.2514	0.1083	0.0468	7.78*	8.24	11.30**
1989	0.6223*	0.0191	-0.2080	0.3808***	0.2137*	13.35***	16.30***	16.07***
1990	0.2024	0.4046***	0.0899	0.1013	0.4095***	6.67	37.32***	18.11***
1991	0.0584	0.0022	-0.2214	0.4581***	0.0771	14.50***	21.20***	17.35***
1992	0.2617	-0.1885	-0.0222	0.4392***	-0.1442	15.42***	21.98***	14.08***
1993	0.8202***	0.2175*	-0.0795	0.2567**	0.2324***	9.30*	22.73***	32.20***
1994	0.4477*	-0.1710**	-0.1044	0.2002	0.1431	13.17**	13.34	10.74**
1995	0.4563***	0.1458	0.3585*	-0.0543	-0.0072	8.96*	29.78***	14.46***
1996	0.4160	-0.2025***	0.5247***	0.1624	0.3843***	69.01***	73.36***	5.42
1997	0.4191**	0.0636	0.1786**	0.3727*	0.1167	4.73	24.39***	3.16

Year	AR(1) Coefficients					Joint Hypothesis Tests: AR(1) Coefficients		
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Equal (χ^2_4)**	**Zero (χ^2_5)**	**Equal Intercepts (χ^2_4)**
1998	0.5672**	-0.0259	-0.0722	0.1960	0.1345	12.76**	13.07	14.36***
1999	0.1295	0.2848	0.2940	0.0059	0.1429	3.09	6.86	2.69
2000	-0.0404	0.0360	-0.1444	0.1998	-0.0965	2.84	2.96	16.62***
2001	0.3787***	-0.2990***	-0.0393	-0.1595**	0.4735*	29.13***	48.59***	11.88**
2002	0.2883***	-0.2877***	0.1008	0.0286	0.3455**	24.71	26.78***	5.15
2003	0.3392	0.0969	0.0664	0.1786	0.1092	2.29	7.45	4.92
2004	0.3468	-0.3458***	0.1832	0.0206	0.1131	12.05**	12.72	6.51
2005	0.1911	0.0886	0.1629	0.1277	0.1101	0.25	11.06	12.86**
2006	0.0727	0.2441	-0.5546***	-0.1150	0.0981	53.04***	59.78***	6.44
2007	0.4240**	-0.0471	-0.0389	0.2245	0.1584	4.18	24.74***	4.54
2008	0.0341	0.1923	0.2187	-0.0094	-0.0617	2.50	7.48	7.57
2009	0.4407***	0.0010	0.0062	-0.0857	-0.2521***	26.93***	26.94***	4.73
2010	0.0084	-0.1545	0.0123	-0.1064	0.3803***	11.43**	16.81***	1.43
2011	0.8347	-0.1025	-0.1938*	0.2284*	0.0778	12.21**	12.22	7.02
2012	0.4212***	0.0157	-0.1852	-0.0416	-0.0708	8.30*	8.35	4.09
2013	0.1576	-0.0441	0.1814*	0.0580	-0.0864	4.56	6.96	1.60
2014	0.3614	0.2032*	-0.2637***	0.3034	0.0503	10.38**	10.39	2.30
2015	0.2678	-0.1654	-0.1425	0.2262**	0.1148	11.11**	14.04	10.95**
2016	0.1850	-0.0511	0.0716	-0.0129	-0.0708	3.52	3.88	2.97
2017	0.1979	0.0804	-0.0214	0.3533*	0.0108	7.34	8.18	2.85
Average	0.3672***	0.0734***	0.0969***	0.1413***	0.1516***	109.58***	213.26***	N.A.
Hypothesis: Equal Coefficients (χ^2_{42})	81.71***	145.53***	217.83***	75.02***	91.91***	N.A.	N.A.	N.A.

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. N.A. = not applicable.

Discussion

Evolving Market Efficiency

The different values for years 1992 to 2017 of the Wald statistics for the hypotheses $\rho_{d=1,y} = \cdots = \rho_{d=5,y} = 0.00$ and $\delta_{d=1,y} = \cdots = \delta_{d=5,y}$ suggest that the degree of market efficiency varies as the Thai stock market evolves (Lo, 2004; 2005). The statistics are decreasing with time. The relationship is significant when the regression of the hypotheses $\rho_{d=1,y} = \cdots = \rho_{d=5,y} = 0.00$ is considered. This result is consistent with the weather-driven mood studies by Khanthavit (2017a, 2017b) when they are considered jointly. Thus, the Thai market is moving toward full efficiency. The rising efficiency can be explained by the market participants gaining more experience over time and the market system developing further (Zalewska-Mitura & Hall, 1999)

Explanations for Day-Seasonal Efficiency

In this study, I conclude that day-seasonal efficiency exists in the Thai stock market. It is important and interesting to assess the possible explanations.

Data Mining

It is possible that the day-seasonal efficiency is an artifact of data mining (Sullivan, Timmermann, & White, 2001). Although the day-seasonal efficiency was studied by Khanthavit and Chaowalerd (2016) with similar results, I argue that data mining cannot be the explanation. I consider a sample from 1975 to 2017, while Khanthavit and Chaowalerd (2016) studied a sample from 2002 to 2015. Moreover, I measure its degree for each and every year in the sample period and find significant results for most years. If data mining was the explanation, the significant results should disappear from the full sample average or from all the years in the sample.

Nonsynchronous Trading

Scholes and Williams (1977) showed that nonsynchronous trading could create spurious positive autocorrelations for returns. Lo and MacKinlay (1980) showed further that the positive autocorrelation coefficient represents the probability that the stock was not traded during the closing hours. From Table 2, some AR(1) coefficients, such as the ones for Tuesday in the years 1984, 1996, 2001, 2002, and 2004, are negative and significant at the 99% confidence level. Because the probability cannot be negative, the nonsynchronous trading cannot explain the weekdays' positive AR(1) coefficients that constitute the day-seasonal efficiency.

Nontrading Interval

In the study of the Spanish market, Blandon (2001) noticed that the AR(1) coefficient was positive and largest on Monday. The researcher associated the large size with the longer nontrading interval prior to Monday than that for other weekdays. When the researcher substituted the open-to-close returns for the close-to-close returns in the regression, the day-seasonal efficiency disappeared. In order to check whether the nontrading interval is the explanation, I follow Blandon (2001) to consider the open-to-close returns. The sample period, however, is from February 17, 1992, to December 29, 2017 (6,367 observations). February 17, 1992, is the first day the SET reported the opening SET index. The weighted-average AR(1) coefficients for weekdays are reported in Table 3. The coefficient for Monday is positive, largest, and significant at the 99% confidence level. The Wald statistic equals 26.8420, which shows that the day-seasonal efficiency is still present even when the open-to-close returns are considered. The nontrading interval cannot explain the day-seasonal efficiency.

Table 3 Test for the Open-to-Close-Return Explanation

Weekdays	AR(1) Coefficients
Monday	0.1857***
Tuesday	-0.0623**
Wednesday	-0.0588*
Thursday	-0.0005
Friday	-0.0344
Joint Hypothesis: Equal Coefficients (χ^2_4)	26.8420***

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively.

Measurement Errors, Moods, Strategic Market Making, Short Selling, and Individual Investors' Information Processing Explanations

In my review, measurement errors (Gibbons & Hess, 1981), moods (Pettengill, 1993), strategic market making (Admati & Pfleiderer, 1989; Foster & Viswanathan, 1990), short selling (Chen & Singal, 2003), and individual investors' information processing (Miller, 1988; Lakonishok & Maberly, 1990) could explain day-seasonal efficiency. For these explanations to be true, the AR(1) coefficients for weekdays must be negative. From Table 2, most of the AR(1) coefficients are positive and their weighted averages are positive for all the weekdays. Therefore, these explanations cannot be the correct explanations.

Positive Feedback Strategies

The positive feedback strategies can explain weekdays' positive AR(1) coefficients. In Abraham and Ikenberry (1994), individual investors observed bad news on Friday, had a delayed response, and sold stocks on Monday, therefore generating a positive AR(1) coefficient and negative returns on Monday. I examine whether the positive feedback strategies can explain the weekdays' significant AR(1) coefficients. I estimate the regression equation (2).

$$R_t = \sum_{y=1}^{Y}\sum_{d=1}^{5}\delta_{d,y}D_t + \sum_{y=1}^{Y}\sum_{d=1}^{5}\rho_{d,y}D_tR_{t-1} + \sum_{d=1}^{5}\gamma_d I_{t-1} + \varepsilon_t, \quad (2)$$

where I_{t-1} is the information on day t-1 to which the investors have delayed responses. The coefficient γ_d is fixed for all years y. Allowing γ_d to vary substantially raises the numbers of parameters to be estimated, and the resulting estimates could be imprecise.

For the information variable I_{t-1}, I consider the lagged return volatility, the lagged market trading volume, and the lagged investor groups' trading volumes. Return volatility and trading volumes can proxy the information considered by the market (e.g., Campbell et al., 1993).

I compute the return volatility using the squared realized return. The estimation is simple and offers an unbiased estimate (Lopez, 2001). Following Campbell et al. (1993), I compute the market's trading volume using the logged volume turnover ratio. Finally, I compute the trading volume of an investor group using the ratio of its trading volume over the market's trading volume (e.g., Nofsinger & Sias, 1999).

If the positive feedback strategies with respect to the information I_{t-1} are the explanation, $\bar{\rho}_{d=1} = \cdots = \bar{\rho}_{d=5}$ or $\bar{\rho}_{d=1} = \cdots = \bar{\rho}_{d=5} = 0.00$. The estimate γ_d necessarily differs from zero for some weekday d.

Table 4, columns 2 and 3 report the results when the lagged return volatility is the information. The joint test for zero information coefficients rejects the hypothesis at the 99% confidence level. The return volatility is useful information. However, hypotheses $\bar{\rho}_{d=1} = \cdots = \bar{\rho}_{d=5}$ and $\bar{\rho}_{d=1} = \cdots = \bar{\rho}_{d=5} = 0.00$ are rejected at the 99% confidence level. Moreover, all the AR(1) coefficients, except that for Tuesday, are positive and significant. Monday's coefficient is still the largest. The positive feedback strategies with respect to volatility information cannot explain the day-seasonal efficiency.

The results for the information from the market's trading volume are in columns 4 and 5. They lead to a similar conclusion as that for the volatility information. The trading volume is useful information, but it is not the explanation.

Table 4 Tests for the Positive Feedback Explanation based on Information from Return Volatility and the Market's Trading Volume

Weekdays	**Lagged Return Volatility**[a]		**Lagged Market's Trading Volume**[b]		**Average AR(1) Coefficient $\bar{\rho}_d$ when Estimation does not Include Variable I_{t-1}.**[b]
	Average AR(1) Coefficient $\bar{\rho}_d$	**Information Coefficient γ_d**	**Average AR(1) Coefficient $\bar{\rho}_d$**	**Information Coefficient γ_d**	
Monday	0.3368***	-1.89E-06	0.6061***	-0.0303**	0.3241***
Tuesday	0.0079	-2.99E-06	-0.1670	0.0178	-0.0158
Wednesday	0.0983***	-7.36E-06***	0.4700***	-0.0498***	0.0194
Thursday	0.1471***	-4.08E-06	0.1824*	-0.0071	0.1160***
Friday	4.5289**	-9.24E-07	0.2273**	-0.0145	0.0923***
Joint Hypothesis: Equal Coefficients (χ^2_4)	33.1629***	5.4335	20.9532***	14.7170***	41.7310***
Joint Hypothesis: Zero Coefficients (χ^2_5)	79.1504***	19.4615***	39.6500***	23.7877***	79.6107***

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. [a] = sample from April 30, 1975 to December 29, 2017 and [b] = sample from January 2, 1992 to December 29, 2017.

The test based on the trading volume information employs the sample from January 2, 1992, to December 29, 2017. In order to ensure that results for the trading volume information are meaningful, I re-estimate equation (1) using the same sample. The estimates and test results are in column 6. Day-seasonal efficiency also exists in this sample period.

Finally, I consider the information in the trading volumes of investor groups. The sample period is from January 2, 1992, to December 29, 2017. The results are in Table 5. Columns 2 and 3 report the results based on the information from institutional investors' trading volume. The information coefficients are not different from zero, thus suggesting that this information is irrelevant. Monday's AR(1) coefficient is positive, largest, and significant. The information from institutional investors' trading volume cannot explain the day-seasonal efficiency. In columns 4 and 5 and columns 8 and 9, the results for the information based on securities companies and individual investors' trading volumes, respectively, are similar. The information from these two sources is irrelevant, and it is not the explanation.

Table 5 Tests for the Positive Feedback Explanation based on Information from Trading Volumes of Investor Groups

Weekdays	Institutional Investors		Securities Companies		Foreign Investors		Individual Investors	
	Average AR(1) Coefficient $\bar{\rho}_d$	**Information Coefficient** γ_d	**Average AR(1) Coefficient** $\bar{\rho}_d$	**Information Coefficient** γ_d	**Average AR(1) Coefficient** $\bar{\rho}_d$	**Information Coefficient** γ_d	**Average AR(1) Coefficient** $\bar{\rho}_d$	**Information Coefficient** γ_d
Monday	0.4299**	-0.0033	0.4390***	-0.0076	-0.1515	0.0492**	1.1163***	-0.0836*
Tuesday	-0.1369	0.0038	0.0275	-0.0028	-0.0506	0.0037	0.0870	-0.0107
Wednesday	-0.2127	0.0074*	0.2415	-0.0142	-0.3093*	0.0343*	0.5729	-0.0582
Thursday	0.1011	0.0005	0.0233	0.0061	-0.0845	0.0208	0.6022*	-0.0513
Friday	0.0931	-2.38E-05	0.2390**	-0.0095	-0.0755	0.0173	0.3419	-0.0266
Joint Hypothesis: Equal Coefficients (χ^2_4)	8.2245*	2.4742	6.4246	3.0805	1.4137	3.7224	5.0097	2.4797
Joint Hypothesis: Zero Coefficients (χ^2_5)	8.8035	5.4178	11.8473**	3.6399	4.5232	11.8209**	16.4453***	10.2005*

Table 6 Tests for Day-Seasonal Efficiency in the ASEAN Stock Markets

Weekdays	**ASEAN Stock Markets (Sample Period)**				
	Indonesia (01/01/88-12/29/17)	**Malaysia (01/01/88-12/29/17)**	**Philippines (01/01/88-12/29/17)**	**Singapore (01/01/75-12/29/17)**	**Vietnam (01/01/07-12/29/17)**
Monday	0.2817***	0.3761***	0.2966***	0.3446***	0.2093***
Tuesday	0.0076	-0.0327	0.0838***	-0.0026	0.1646***
Wednesday	0.1816***	0.1201***	0.0833***	0.0649***	0.0999**
Thursday	0.2430***	0.1573***	0.1511***	0.1307***	0.1127**
Friday	0.1768***	0.1192***	0.1226***	0.0939***	0.1189**
Joint Hypothesis: Equal Coefficients (χ^2_4)	46.8968***	70.9018***	26.4948***	78.7596***	3.3126
Joint Hypothesis: Zero Coefficients (χ^2_5)	141.0567***	167.9558***	161.8956***	179.8299***	50.6820***

Note: **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively.

The results in columns 6 and 7 for the information from foreign investors' trading volumes are most interesting. The joint test of zero information coefficients rejects the hypothesis at the 95% confidence level. The market considers this information and has a delayed response to it. The AR(1) coefficients are negative and small for all the weekdays. Only Wednesday is significant at the 90% confidence level. Consistently, the joint tests of equal coefficients and zero coefficients cannot reject the hypotheses. These findings lead me to conclude that the positive feedback strategies, based on the information from the trading volume of foreign investors, explain the day-seasonal efficiency of the Thai market.

Richards (2005) explained the role of the information from the foreign investors' trading volumes in the positive feedback strategies as follows. Positive news in a foreign market, such as the U.S. market, causes foreign investors to revise the performance of the Thai market upward, buy Thai stocks, and raise their trading volume. The foreign capital inflows had the impact on the returns on and beyond the day of the inflows.

Day-Seasonal Efficiency in the ASEAN Stock Markets

The Association of Southeast Asian Nations (ASEAN) is a regional intergovernmental organization that promotes intergovernmental cooperation and facilitates integration among its members, other Asian countries, and globally. The combined economy of the ASEAN countries is the sixth largest in the world.

Some ASEAN countries have established stock markets with different degrees of development. For these markets whose countries share location proximity and promote economic integration, it is interesting to ask whether the markets share a similar characteristic of day-seasonal efficiency. This question has never been addressed elsewhere.

I estimate the model in equation (1) for the Indonesian, Malaysian, Filipino, Singaporean, and Vietnamese markets using the Morgan Stanley local-return country indexes. They were retrieved from the Bloomberg database. Table 6 reports the weekdays' weighted average AR(1) coefficients and the hypothesis test statistics. The results are similar for all five markets and with the results for the Thai market. Monday's coefficients are positive, largest, and significant. The coefficients for the remaining weekdays are positive and significant for most markets. Day-seasonal efficiency also exists in the five markets.

Conclusion

Day-seasonal efficiency exists when the market's macro and micro factors behave differently on weekdays. Because it suggests market inefficiency, it is important and interesting to test whether it exists in a market. I tested for the day-seasonal efficiency of the Thai stock market and found that it existed but that it disappeared over time. I empirically checked for the proposed explanations in the literature. The positive feedback strategies of the investors, based on the information from foreign investors' trading volumes, were the only possible explanation.

The study was extended to include the five ASEAN stock markets — Indonesia, Malaysia, the Philippines, Singapore, and Vietnam. Although these markets are in different states of development, they shared the same characteristic. Day-seasonal efficiency existed in all the markets. Due to the lack of data, I was unable to examine whether the explanation was similar to or different from the Thai market. I leave this question for future research.

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