ARE STOCK MARKET RETURNS RELATED TO THE WEATHER EFFECTS? EMPIRICAL EVIDENCE FROM THAILAND

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An Independent Study
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for the Degree of Master of Science (Finance)

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By

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(Assoc.Prof. Dr. Seksak Jumreornvong)

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ABSTRACT

This study employed model with GJR-GARCH process to investigate the relationship between weather factors and stock market returns in Thailand during May 4th 1992 to December 30th 2008. The weather factors include temperature, humidity, and rain. Based on these 3-weather factors, the results show negative relationship between temperature and stock market returns and no relationship for humidity and rain. This study has significant implications for both individual investors and financial institutions in Thai stock market. This study implies that Thai stock market may be inefficient due to the irrationality (temperature effect) in the market.

I. INTRODUCTION

Psychological research has long recognized that weather conditions can influence an individual's mood, which can create predisposition to engage in particular behaviors. The most essential finding is that good (bad) weather can induce positive (negative) mood state, which affects the process of rational or optimal decision-making. Based on these studies, behavioral finance theory has recently considered the possibility of the stock market maybe relate to weather factors.

This paper investigates the relationship between Thai stock return and weather factors which are temperature, humidity, and rain. By using model with the GJR-GARCH process on error terms using the daily data for the period of 4 May 1992 -30 December 2008.

The remainder of this paper is organized as follows. Section II reviews the relate literature. Section III describes the data used in this study. Section IV discusses the methodology used. Section V presents the empirical results. Section VI concludes this paper.

II. LITERATURE REVIEW

In behavioral finance, there are many studies research the relationship between stock prices and variables based on widespread proxies for mood. One of the proxies is the weather. This section reviews the fundamental ground of the psychology for this paper and shows the finding of previous research in the area.

2.1 Mood and Decisions making

A literature in psychology examines how moods affect human decision making. Good mood individual make more optimistic choices. Isen et al. (1978) and Forgas and Bower (1987) reported that people who are in bad moods (good moods) find negative (positive) material to be salient. Clore, Schwarz, and Conway (1994) and Forgas (1995) found that in the limited information situation, people abstract decisions are strongly affect by mood.

From Bless, Schwarz, and Kemmelmeier (1996) and Isen (2000) paper showed that individuals who are in good mood use more of simplifying heuristics to make decisions.

From Schwarz (1990), Petty, Gleicher, and Baker (1991), and Sinclair and Mark (1995) reported that bad mood individual engage in detailed analytical activity while good mood individual engage in less information processing, resulting in good mood individual more open to weaker argument compare to bad mood individual who receptive to strong argument in Mackie and Worth (1991) paper. In the side of bad decision Bless et al. (1996) showed evidence indicating good mood individual rely on information category and make more mistake of stereotyping. However relying more to "pre-existing knowledge" does not mean a lack of motivation and capacity to think.

In the positive side, good mood individual tend to use more unusual associations resulting in more creative problem-solving and greater mental flexibility. Moreover good mood individual perform well in tasks involving neutral or positive material in Isen (2000) paper.

Johnson and Tversky (1983) and Arkes, Herren, and Isen (1988) reported that influence of good emotion affect more favorable assessment of prospect future. And also in assessment of risk was reported by Loewensttein et al. (2001) and Slovic et al. (2002). However Isen (2000) pointed out that emotion affect risk assessment is complex and depends on task and situation.

From Frijda (1998) and Schwarz (1990) stated that an important concept of the theory of affective states (emotion or moods) must hold that such states provide information to individuals about environment.

2.2 Weather and Mood

Weather is one source of the environment that affect mood. According to Howarth and Hoffman (1984) summaries research on the weather and mood as, "weather variables affect an individual's emotion state or mood, which creates a predisposition to engage in particular behaviors". The essential finding is that good weather induces positive mood states and bad weather induces negative mood states.

The variables of weather that affect mood which have been researched were sunshine in Cunningham (1979) paper, humidity in Allen, and Fischer (1978) paper, and temperature in Bell, and Baron (1976) paper.

2.3 Weather and Stock price

Saunders (1993) and Hirshleifer and Shumway (2003) argued that weather can affect the behavior of investors and that effect is reflected in stock returns. Saunders (1993) reported that NYSE index returns tended to be negative on cloudy days. However there have been many researchers argued about weather factors. Trombley (1997) replicated Saunders data with different methodology and conclude that relationship between weather and return was weaker than what Saunders (1993) suggested. Krämer and Runde (1997) applied Saunders (1993) work with German stock market and find no relationship between weather and stock market. Similar results were found in Madrid Stock Exchange by Pardo and Valor (2003) and in Istanbul Stock Exchange by Tufan and Hamarat (2004)

The studies which support weather factors are Kamstra et al. (2003) found that number of hours of daylight is related to the returns on international equity indices. Hirshleifer and Shumway (2003) find a strong positive correlation between morning sunshine and stock market index return of 26 countries. Keef and Roush (2004) examined New Zealand Stock Exchange and find that cloud cover have no effect, temperature have small affect, and wind have large affect on returns.

Dowling and Lucey (2005) had taken different approach by linking eight proxy of investor’s mood base on weather, biorhythms, and belief with Irish Stock returns. Their result were consistent with the psychological research showing that people who are in good mood re more likely to allow the mood-related factors, such as weather, to influence their decision-making process.

III. DATA

The daily weather data for temperature in Celsius degrees, humidity in percentage and rain in millimeter in Bangkok from 4 May 1992 to30 December 2008 are used. All weather data are from The Thai Meteorological Department. I adapt stock data from the SETSMART database and include the daily closing index of Stock Exchange of Thailand with the same time length as the weather data. Following the conventional approach, daily stock returns are calculated as the logarithmic difference in the daily stock index, i.e., $R_t = \ln P_t - \ln P_{t-1}$, where P_t and P_{t-1} are the daily closing prices of Stock Exchange of Thailand index on day t and $t-1$, respectively.

[Table I is here]

The descriptive statistics for the variables in this study are reported in Table I. The sample mean and medium of stock return are -0.000128 and -0.000367, respectively. The statistics of skewness and kurtosis show that the distribution of stock returns is non-normal. The Jauque-Bera tests results provide further support that the stock returns do not have a normal distribution. As for the weather factors, the sample mean of temperature is 29.1626, while the maximum and minimum values are 34.2 and 18.4, respectively. The sample mean of humidity is 72.181, and the maximum and minimum values of humidity are 94 and 41, respectively. The sample of rain is 4.5521, with the maximum and minimum values of rain being 132.9 and 0, respectively. The statistics of skewness, kurtosis and Jarque-Bera tests also show that the distribution of temperature, humidity, and rain, respectively is non-normal. The null hypothesis of no serial correlation is rejected by the Ljung-Box Q statistic, with lad of 5 and 10 for series; they are denoted by Q. Thus, there is significant evidence of autocorrelation in the series.

IV. METHODOLOGY

4.1 Traditional linear model

This study use the traditional linear model to test the general relationship between stock returns and weather factors, and then test for autoregressive conditional heteroskedasticity (ARCH) to see if the error variance is related to the squared error term in the previous term.

The traditional linear model is set as follow:

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 W_t + \varepsilon_t \tag{1}$$

Where R_t represents the stock market returns time series data, and W_t represent the weather factors variables, namely temperature, humidity, and rain. In this model, autoregressive processes are utilized to correct the autocorrelation of returns. The criteria of determining optimal lags are the minimal optimal lags that will correct the autocorrelation of the returns.

4.2 Model with the GJR-GARCH

In order to correct autoregressive conditional heteroskedasticity (ARCH), this study employ model with the GJR-GARCH(1,1) process, as follow:

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 W_t + \varepsilon_t \tag{2}$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t), \tag{3}$$

$$h_t = \alpha + \theta h_{t-1} + \gamma \varepsilon_{t-1}^2 + \delta \varepsilon_{t-1}^2 I_{t-1}, \tag{4}$$

Where R_t represents the stock market returns time series data, and W_t represent the weather factors variables, namely temperature, humidity, and rain. ε_t is an error term. In this model, autoregressive processes are utilized to correct the autocorrelation of returns. The criteria of determining optimal lags are the minimal optimal lags that will correct the autocorrelation of the returns.

In Eq. (4), Ω_{t-1} is the information set at time *t-1*. I_{t-1} is a dummy variable, where I_{t-1} equal one if ε_{t-1} is less than zero, and I_{t-1} equals zero otherwise. This allows good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) to have difference impacts on the conditional variance. For example good news has only a γ impact on volatility, whereas bad news has a $\gamma + \delta$ impact on volatility. Thus, if δ is significant, an asymmetric effect would be detected. The reason for adopting the GJR-GARCH in this study is that GJR-GARCH model is best parametric model for measuring news on volatility on market returns base on Eagle and Ng (1993) paper.

V. EMPIRICAL RESULT

[Table II is here]

Table II implies that there is a relationship between the stock market returns and temperature.

[Table III is here]

Table III shows that there are significant autoregressive conditional heteroskedasticity (ARCH) effects in the model. This require GARCH model to correct the problem.

[Table IV is here]

Table IV shows the estimated results for SET, SET50, SET100, and MAI index, respectively. Based on the coefficients of ψ_i in the table, it is evident that the stock market returns have first-order effect as well as second-order effect, which may be partly explained by the price limits in the Thailand stock market.

Overall, temperature has effects on stock market returns, and the effect is negative. It is indicated that stock market returns tend to be lower when the weather is hot.

As for humidity and rain, unlike the temperature, the coefficients of neither one are significantly different from zero. Thus the results indicate that humidity and rain does not have effect on stock market returns.

[Table V is here]

Table V presents GJR-GARCH models for Eq. (4). According to Eagle and Bollerslev (1986), γ can be viewed as the "new" coefficient, with higher values implying that more recent news has greater impact on stock market returns, and θ reflects the impact of the past variance on stock market returns, while $\theta + \gamma$ measures the persistence of volatility. The result in Table IV indicates that both γ and θ are statistically significantly difference from zero in the model. In addition, the significantly positive test statistics for the δ coefficients further indicate that the asymmetric effect exist in conditional variance models. The conditional volatility in the Thailand stock market tends to be higher when the news is unfavorable ($\varepsilon_{t-1} < 0$). A possible explanation for this phenomenon is that risk-taking investors would be more speculative, and feedback traders follow market price trends upon unexpected news in the Thailand market.

[Table VI is here]

Table VI reports the diagnostic checks on the residuals of the models and results shows that models are well-specified.

The results are consistent with previous paper in behavioral finance. They indicated that the weather factors have effects on Thailand stock market returns. Other finding from this study is that the asymmetric effects are found in conditional variance models, indicating that the conditional volatility in the Thailand stock market tends to be higher when the news is bad.

VI. CONCLUSIONS

In this study, I have employed a model with the GJR-GARCH process to explore the relationship between three weather factors and stock market returns in Thailand using daily data covering the period of 4 May 1992 to 30 December 2008. This study use temperature, humidity and rain as the weather factors. Empirical evidence shows that temperature has effect on stock market returns in Thailand.

Weather is an important factor that may affect human moods, and thus may affect investors' behavior in the stock market. Overall, this study found that temperature has effect on Thai stock market returns, and Thai stock returns tend to be lower when the weather is hot. The psychologists have suggested that an increase in temperature would make people impatient or upset, and thus affects the stock return. Considering that the weather can affects human moods, it would also affect investor's decisions making. This study has significant implications for both individual investors and financial institutions in Thai stock market. This study implies that Thai stock market may be inefficient due to the irrationality (temperature effect) in the market.

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Table I
Descriptive statistics of sample data

The table presents summary statistics for the variables: stock returns, temperature in Celsius degrees, humidity in percentage and rain in millimeter in Bangkok from 4 May 1992-30 December 2008. The Jarque-Bera residual normality testis a test statistic for the null hypothesis of normal distribution. The Ljung-Box Q-statistics at lag (q) is a test statistic for the null hypothesis that there is no autocorrelation up to order q.

	Stock returns		Temperature		Humidity		Rain	
Mean	-0.000128		29.1626		72.1810		4.5521	
Medium	-0.000367		29.3000		73.0000		0.0000	
Maximum	0.113495		34.2000		94.0000		132.9000	
Minimum	-0.160633		18.4000		41.0000		0.0000	
Std. Dev.	0.017360		1.7517		8.2947		12.0681	
Skewness	0.076560		-0.8121		-0.3643		4.3984	
Kurtosis	9.521724		4.9707		3.0194		28.9760	
Jarque-Bera statistics	7250.5347	***	1111.1099	***	90.5308	***	128145.2785	***
Ljung-Box Q(5)	55.3405	***	7229.5312	***	5773.7128	***	302.5452	***
Ljung-Box Q(10)	73.1060	***	10395.6773	***	7844.1711	***	448.1058	***

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively

2. The numbers in parentheses denote the lag periods.

Table II

Traditional linear model

The table presents the result from the traditional linear model set as follow:

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 W_t + \varepsilon_t$$

Where R_t represents the stock market returns time series data, and W_t represent the weather factors variables, namely temperature, humidity, and rain. In this model, autoregressive processes are utilized to correct the autocorrelation of returns. The criteria of determining optimal lags are the minimal optimal lags that will correct the autocorrelation of the returns.

Index	SET						SET50					
Weather	Temperature		Humidity		Rain		Temperature		Humidity		Rain	
β_0	0.009989		0.000640		-0.000108		0.012885		0.000905		-0.000313	
	(2.213708)	**	(0.271165)		(-0.374470)		(2.056568)	**	(0.292955)		(-0.813141)	
ψ_1	0.099931		0.101725		0.101674		0.095070		0.096823		0.096831	
	(6.393846)	***	(6.513264)	***	(6.507678)	***	(5.444344)	***	(5.5475445)	***	(5.547353)	***
ψ_2	0.033539		0.035557		0.035575		0.034432		0.036441		0.036470	
	(2.145222)	**	(2.276631)	**	(2.277503)	**	(1.971183)	**	(2.087897)	**	(2.088586)	**
ψ_3												
ψ_4												
β_1	-0.000346		-0.000010		0.000003		-0.000451		-0.000017		0.000002	
	(-2.238878)	**	(-0.313672)		(0.121735)		(-2.108600)	**	(-0.394097)		(0.065865)	

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively
2. The numbers in parentheses are the *t*-statistics.
3. The numbers in the table are the estimates of the coefficients.

Table II continued

Traditional linear model

The table presents the result from the traditional linear model set as follow:

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 W_t + \varepsilon_t$$

Where R_t represents the stock market returns time series data, and W_t represent the weather factors variables, namely temperature, humidity, and rain. In this model, autoregressive processes are utilized to correct the autocorrelation of returns. The criteria of determining optimal lags are the minimal optimal lags that will correct the autocorrelation of the returns.

Index	SET100			MAI					
Weather	Temperature	Humidity	Rain	Temperature		Humidity		Rain	
β_0	-0.001777	-0.000592	-0.000368	0.000804		-0.003777		0.000312	
	(-0.176501)	(-0.119765)	(-0.576539)	(0.122234)		(-1.186680)		(0.769840)	
ψ_1	0.000509	0.000398	0.000602	0.064623		0.063982		0.064692	
	(0.015247)	(0.011905)	(0.018029)	(2.539204)	**	(2.514881)	**	(2.541632)	**
ψ_2				0.028025		0.027254		0.028065	
				(1.101391)		(1.071395)		(1.102928)	
ψ_3				0.067932		0.067217		0.067779	
				(2.672373)	***	(2.645623)	***	(2.665950)	***
ψ_4				0.014970		0.014121		0.014931	
				(0.588931)		(0.555697)		(0.587474)	
β_1	0.000046	0.000002	-0.000012	-0.000018		0.000057		-0.000005	
	(0.133490)	(0.031973)	(-0.269581)	(-0.078725)		(1.285917)		(-0.168806)	

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively
2. The numbers in parentheses are the t-statistics.
3. The numbers in the table are the estimates of the coefficients.

Table III
ARCH-LM Test

The table presents the Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals. The ARCH LM test statistic is used to test the null hypothesis that there is no ARCH up to order (q) in the residuals.

	SET		SET50		SET100		MAI	
Temperature (5)	113.042785	***	103.8273085	***	27.50716731	***	30.66199648	***
Humidity (5)	113.583797	***	104.3044713	***	27.41846515	***	31.0521154	***
Rain (5)	113.9351534	***	104.8333831	***	27.38465288	***	30.61154941	***

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively

2. The numbers in parentheses denote the lag periods.

Table IV
Model with the GJR-GARCH

The table presents the result from the Model with the GJR-GARCH set as follow:

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 W_t + \varepsilon_t$$

Where R_t represents the stock market returns time series data, and W_t represent the weather factors variables, namely temperature, humidity, and rain. ε_t is an error term. In this model, autoregressive processes are utilized to correct the autocorrelation of returns. The criteria of determining optimal lags are the minimal optimal lags that will correct the autocorrelation of the returns.

Index	SET						SET50					
Weather	Temperature		Humidity		Rain		Temperature		Humidity		Rain	
β_0	0.010694		0.002567		0.000250		0.014822		0.003382		0.000030	
	(2.947425)	***	(1.333677)		(0.999277)		(3.092009)	***	(1.357717)		(0.091360)	
ψ_1	0.119855		0.121039		0.121959		0.100110		0.101054		0.101751	
	(6.924941)	***	(6.984712)	***	7.071136	***	5.221281	***	(5.264339)	***	5.322354	***
ψ_2	0.056658		0.058702		(0.059319)		(0.049950)		0.051358		(0.051814)	
	(3.483351)	***	(3.613609)	***	3.652176	***	2.654998	***	(2.740394)	***	2.764797	***
ψ_3												
ψ_4												
β_1	-0.000361		-0.000033		-0.000020		-0.000507		-0.000048		-0.000019	
	(-2.905220)	***	(-1.250604)		(-1.089658)		(-3.102377)	***	(-1.378579)		(-0.845158)	

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively
2. The numbers in parentheses are the z-statistics.
3. The numbers in the table are the estimates of the coefficients.

Table IV continued

Model with the GJR-GARCH

The table presents the result from the Model with the GJR-GARCH set as follow:

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 W_t + \varepsilon_t$$

Where R_t represents the stock market returns time series data, and W_t represent the weather factors variables, namely temperature, humidity, and rain. ε_t is an error term. In this model, autoregressive processes are utilized to correct the autocorrelation of returns. The criteria of determining optimal lags are the minimal optimal lags that will correct the autocorrelation of the returns.

Index	SET100						MAI					
Weather	Temperature		Humidity		Rain		Temperature		Humidity		Rain	
β_0	0.038381		0.009984		0.000209		0.004192		0.001215		0.000250	
	(6.752821)	***	(3.539177)	***	(0.383774)		(0.860463)		(0.538434)		(0.903299)	
ψ_1	0.134776		0.158110		0.160599		0.069548		0.069497		0.069985	
	(3.266406)	***	(4.041334)	***	(4.081774)	***	(2.385107)	**	(2.387670)	**	(2.403499)	**
ψ_2							0.072574		0.073737		0.073915	
							(2.440560)	**	(2.473791)	**	(2.486175)	**
ψ_3							0.056146		0.055217		0.055443	
							(1.972432)	**	(1.934947)	*	(1.952525)	*
ψ_4							0.024257		0.023882		0.023714	
							(0.896051)		(0.882284)		(0.875422)	
β_1	-0.001308		-0.000138		-0.000027		-0.000134		-0.000014		-0.000001	
	(-6.781392)	***	(-3.54319)	***	(-0.873986)		(-0.811141)		(-0.425435)		(-0.031295)	

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively
2. The numbers in parentheses are the *z*-statistics.
3. The numbers in the table are the estimates of the coefficients.

Table V

The estimated results from the GJR-GARCH model

The table presents the result from the GJR-GARCH model set as follow:

$$h_t = \alpha + \theta h_{t-1} + \gamma \varepsilon_{t-1}^2 + \delta \varepsilon_{t-1}^2 I_{t-1},$$

Ω_{t-1} is the information set at time *t-1*. I_{t-1} is a dummy variable, where I_{t-1} equal one if ε_{t-1} is less than zero, and I_{t-1} equals zero otherwise. This allows good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) to have difference impacts on the conditional variance. Good news has only a γ impact on volatility, whereas bad news has a $\gamma + \delta$ impact on volatility. Thus, if δ is significant, an asymmetric effect would be detected.

Index	SET						SET50					
Coefficients	Temperature		Humidity		Rain		Temperature		Humidity		Rain	
α	0.000015		0.000015		0.000015		0.000018		0.000017		0.000017	
	(16.967939)	***	(15.353633)	***	(15.871238)	***	(14.172561)	***	(12.729229)	***	(12.619704)	***
θ	0.099386		0.095398		0.095161		0.099483		0.092909		0.092717	
	(10.452319)	***	(10.4758567)	***	(10.53400)	***	(9.129567)	***	(9.109955)	***	(9.132369)	***
γ	0.104745		0.099321		0.097873		0.101542		0.092541		0.090434	
	(6.290663)	***	(6.191753)	***	(6.140877)	***	(5.478222)	***	(5.3466978)	***	(5.248713)	***
δ	0.800802		0.807849		0.808468		0.812205		0.823597		0.824182	
	(65.720154)	***	(65.8755)	***	(65.973614)	***	(58.893726)	***	(59.999255)	***	(59.743265)	***

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively
2. The numbers in parentheses are the *z*-statistics.
3. The numbers in the table are the estimates of the coefficients.

Table V continued

The estimated results from the GJR-GARCH model

The table presents the result from the GJR-GARCH model set as follow:

$$h_t = \alpha + \theta h_{t-1} + \gamma \varepsilon_{t-1}^2 + \delta \varepsilon_{t-1}^2 I_{t-1},$$

Ω_{t-1} is the information set at time *t-1*. I_{t-1} is a dummy variable, where I_{t-1} equal one if ε_{t-1} is less than zero, and I_{t-1} equals zero otherwise. This allows good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) to have difference impacts on the conditional variance. Good news has only a γ impact on volatility, whereas bad news has a $\gamma + \delta$ impact on volatility. Thus, if δ is significant, an asymmetric effect would be detected.

Index	SET100						MAI					
Coefficients	Temperature		Humidity		Rain		Temperature		Humidity		Rain	
α	0.000042		0.000045		0.000050		0.000002		0.000002		0.000002	
	(6.789487)	***	(7.437445)	***	(9.037545)	***	(4.340677)	***	(4.475873)	***	(4.464986)	***
θ	0.111400		0.060314		0.058231		0.167100		0.165205		0.165329	
	(2.480845)	***	(1.569884)	***	(1.550986)	***	(9.955830)	***	(9.9358956)	***	(9.930355)	***
γ	0.845634		0.730735		0.700502		0.007881		0.009211		0.009443	
	(7.856179)	**	(8.138949)		(7.760103)		(0.463821)	***	(0.551791)	***	(0.563274)	***
δ	0.455622		0.513236		0.501256		0.842429		0.843194		0.843026	
	(14.335042)	***	(13.839001)	***	(14.161575)	***	(80.374899)		(80.420187)		(80.488235)	

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively
2. The numbers in parentheses are the *z*-statistics.
3. The numbers in the table are the estimates of the coefficients.

Table VI
Diagnostic checks on the model residuals

The Ljung-Box Q-statistics at lag (q) is a test statistic for the null hypothesis that there is no autocorrelation up to order q. The Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals. The ARCH LM test statistic is used to test the null hypothesis that there is no ARCH up to order (q) in the residuals.

Index	SET			SET50		
Test statistics	Temperature	Humidity	Rain	Temperature	Humidity	Rain
Ljung-Box Q (2)	2.826001	2.840869	2.592273	2.718027	2.692422	2.524305
Ljung-Box Q (4)	3.125450	3.238446	2.981065	4.060326	3.893171	3.644118
Ljung-Box Q (6)	5.322132	5.379942	5.146064	5.072224	4.839329	4.533360
Ljung-Box Q (8)	5.496695	5.517382	5.320247	5.217444	4.954209	4.704477
Ljung-Box Q (10)	15.104956	15.348624	14.963751	13.814663	13.454180	13.243711
ARCH-LM (5)	0.199060	0.184339	0.185304	0.213588	0.191790	0.196355

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively
2. The numbers in parentheses denote the lag periods.

Table VI continued
Diagnostic checks on the model residuals

The Ljung-Box Q-statistics at lag (q) is a test statistic for the null hypothesis that there is no autocorrelation up to order q. The Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals. The ARCH LM test statistic is used to test the null hypothesis that there is no ARCH up to order (q) in the residuals.

Index	SET100			MAI		
Test statistics	Temperature	Humidity	Rain	Temperature	Humidity	Rain
Ljung-Box Q (2)	2.071777	0.950453	0.448437	4.001578	3.817193	3.804133
Ljung-Box Q (4)	3.004779	1.251576	0.682804	4.079542	3.891812	3.878125
Ljung-Box Q (6)	3.696774	2.177524	1.687564	9.187378	9.261414	9.136539
Ljung-Box Q (8)	3.858253	2.342374	1.749215	11.629771	11.810013	11.714233
Ljung-Box Q (10)	7.154637	6.205768	5.607382	14.492546	14.899060	14.792160
ARCH-LM (5)	0.240139	0.075581	0.056859	0.473990	0.477057	0.472653

Note:

1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively
2. The numbers in parentheses denote the lag periods.