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Physica A 364 (2006) 343–354

PHYSICA A

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Are stock market returns related to the weather effects? Empirical evidence from Taiwan

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Received 21 May 2005; received in revised form 29 August 2005
Available online 11 October 2005

Abstract

In this study, we employ a recently developed econometric technique of the threshold model with the GJR-GARCH process on error terms to investigate the relationships between weather factors and stock market returns in Taiwan using daily data for the period of 1 July 1997–22 October 2003. The major weather factors studied include temperature, humidity, and cloud cover. Our empirical evidence shows that temperature and cloud cover are two important weather factors that affect the stock returns in Taiwan. Our empirical findings further support the previous arguments that advocate the inclusion of economically neutral behavioral variables in asset pricing models. These results also have significant implications for individual investors and financial institutions planning to invest in the Taiwan stock market.

Keywords: Stock market returns; Weather factors; Threshold model with the GJR-GARCH on error

1. Introduction

Over the past few decades, an increasing number of researchers in behavioral finance have dedicated their efforts toward investigating whether mood fluctuations, namely those induced by weather, actually influence investors' evaluations of equities. Prior studies in this area have, in fact, found a relationship between a wide variety of variables known to cause mood fluctuations and equity returns. More precisely, they have determined that one of the most important sets of variables, termed the *mood proxy* variables, is the one consisting of the major weather factors (see Refs. [1–9, 24]).

Saunders [1] as well as Hirshleifer and Shumway [5] argued that weather can indeed affect the behavior of market traders and that this effect is likely reflected in stock returns. Some researches have attempted to delve into this under the assumption that people in a good mood typically tend to make more optimistic decisions. Saunders [1], for example, showed that the weather in New York City had a long history of being significantly correlated with major US stock indices. He reported that the NYSE index returns tended to be negative on

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0378-4371/$ - see front matter
doi:10.1016/j.physa.2005.09.040

cloudy days. Trombley [2], however, replicated Saunders' [1] study, using essentially identical data but with different statistical methodology, and came to the conclusion that the relationship between Wall Street weather and security returns was neither as clear as nor as strong as what Saunders [1] suggested. Along the same lines, Krämer and Runde [3] applied Saunders' [1] study to German stock market. They took aim at Sanuders' [1] claim but instead asserted that short-term stock returns were not affected by local weather whatsoever. Similar empirical results were also found by Pardo and Valor [6] for the Madrid Stock Exchange and Tufan and Hamarat [8] for the Istanbul Stock Exchange.

Nevertheless, Kamstra et al. [25] studied the number of hours of potential daylight, which is generally less in winter, and observed that it is significantly related to the returns on international equity indices. Hirshleifer and Shumway [5] documented a strong positive correlation between morning sunshine at the leading stock exchanges of 26 countries and the corresponding stock market index returns. Probing further into the weather effects, Goetzman and Zhu [4] considered another potentially interesting behavioral mechanism, i.e. the weather-induced changes in the degree of risk aversion among NYSE specialists. Interestingly enough, they drew a link between liquidity, as measured by bid-ask spread, and cloud cover in New York City. When this cloud cover is included as an explanatory variable in a regression of stock returns on weather factors, the previously documented weather effects are greatly reduced, however. Complicating the issue even further, Keef and Roush [7] examined how the daily returns of the New Zealand Stock Exchange are influenced by different facets of the weather in Wellington and contended that cloud cover has no influence at all on returns, temperature has only a small influence but wind indeed has a significant influence on returns.

Recent researches have claimed that investors' decisions tend to be influenced by their feelings, especially when such decision-making involves risk and uncertainty. Dowling and Lucey [9], for instance, investigated whether a relationship exists between eight proxy variables of investors' mood (based on the weather, biorhythms, and beliefs) and daily Irish stock returns during the period of 1988–2001. Their preliminary evidence lends credence to the view that the relationships between the mood proxy variables and equity returns are considerably more pronounced when the recent market performance is promising, a finding which is consistent with the psychological research results showing that people in a good mood are more likely to allow the mood-related factors, such as the weather, to influence their decision-making process.

Turning specifically to Taiwan, one is compelled to wonder if any of these weather factors would influence the Taiwan stock market in a similar situation. This study, therefore, addresses this issue to determine the extent, if any, to which the weather in Taiwan affects the daily equity returns listed on the Taiwan Stock Exchange. This paper explores whether there is a relationship between Taiwan equity returns and three specific mood proxy variables: temperature, humidity and cloud cover. Worth noticing here is that it has been substantially argued that although these variables are economically neutral, they are psychologically important (see Ref. [9]). While the previous studies have mostly focused on linear relationships, this study employs a recently developed econometric technique of the threshold model with the GJR-GARCH process on error terms to investigate the relationships between the three weather factors and stock market returns in Taiwan using daily data for the period of 1 July 1997–22 October 2003.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature pertaining to the ways in which mood is believed to influence investors' decision marking. Section 3 describes the data used in this study. Section 4 discusses the methodology used and presents the empirical results. Section 5 concludes this paper.

2. Environmental psychology, weather factors and stock returns

As a subject that focuses on the study of the relationships between the environment and human behavior, environmental psychology of course seeks to explain most of the related phenomena. The environment includes numerous elements, such as the weather, noise, color, buildings, crowds, and so on, but crucial to this study is the weather and how it affects human moods, and particularly how moods affect investors' behavior in the stock market. Numerous studies have assuredly found that weather is an important factor that affects human moods.

Bell et al. [10] pointed out that people demonstrate different behaviors when it is either extremely cold or hot. In their book, they illustrate that there is considerably more violence in society when it is very hot, a phenomenon which psychologists refer to as the "long and hot summer effect". Besides, the Uniform Crime Reports of the Federal Bureau of Investigation of the USA even list intense heat as a chief catalyst that leads people to commit crimes. Even in Major League of Baseball, there are reportedly more wild throws with higher temperatures. Bell et al. [10] demonstrated that people feel impatient or perhaps even angry when the temperature is over 84.2°F. As for the intense cold, some psychologists asserted that a chill commonly makes people impatient or upset, but they also showed that unlike the heat, the cold does not have a very significant influence on human behavior.

Temperature aside, humidity is yet another important factor since psychologists suggest that even when the temperature remains the same, people feel less comfortable if the humidity is high. Sunlight is the third important weather factor that affects human behavior. In his textbook on environmental psychology, McAndrew [11] pointed out that a lack of sunlight makes people melancholic and upset, and that phototherapy therefore is a kind of cure for seasonal affective disorder (SAD). He went on to explain that SAD, whereby people symptomatically feel extremely melancholic, is somewhat common both in the fall and winter seasons on account of the paucity of sunlight. McAndrew [11] further indicated that many psychologists have confirmed that sunlight is curative for melancholy. Given that weather evidently affects human moods, we expect that it may play an important role when investors make decisions in view of the bounded rationality [12].

In traditional economics, economists define people as rational economic person. Rational economic person makes rational choices by measuring opportunity cost and revenue. The most rational choice would be the one that yields the maximum economic profit, as represented by revenue minus opportunity cost. However, Simon [12] asserted that it is almost impossible for people always to make rational choices on the ground that people never know where stock prices will go since there are too many factors affecting the market; in other words, people involved in the stock market definitely only have limited rationality. Nevertheless, investors do have their expectations. A rational expectation is the one that is based on all the information a person has, and will then be followed by a learning process that leads the individual to make an optimal choice. Though rational expectations cannot predict outcomes precisely, people do not continually make systematic mistakes because of the learning process they have undergone. In general, when people have rational expectations, they tend to have more and more correct expectations due to the very learning process, and this means that they eventually are able to make optimal choices. From this perspective, if people make mistakes, the mistakes must be randomly occurring, unsystematic ones. The inherent problem with rational expectations is that people cannot make rational expectations based on different systems. Since it is a product of forming rational expectations, the learning process can no longer be useful when people obtain information from other systems. The background of the stock market in the real world is continuously changing, which strongly suggests that today's information may very well not be viable, let alone useful tomorrow. It follows that people often make unsystematic mistakes on the stock market because unexpected factors frequently arise. People typically chase the most useful information with respect to the stock market in the real world, but it is virtually changing too fast for them to always be able to catch up. In fact, for fear of making the wrong decisions, traders in the market have been trying to define trading rules for many years, but the market never ceases to astonish anyone. Traders in the stock market may only learn one thing, i.e. it is always bound to have a new surprise! The dilemma to invest or not is the most bothersome decision as people have no chance to correct what they have done when new information about a changing situation is announced. In short, using currently available information arms them with only one shot. When the future is uncertain and information is scarce, people come up with rational expectations by obtaining as much information as possible; nevertheless, investors in the stock market are very well aware that the information they have cannot completely explain the future and that it is impossible for them to never make a mistake again. This forces people to ask themselves what exactly the information they have means—for example, are stock prices rising or falling? The most important thing in this regard is that this question is answered in their own mind that evaluates all the information currently available to them and tries to justify their decisions. However, it is necessary to note that a person's mind is at all times affected by his/her mood. If he or she is in a good mood, his/her mind may interpret information in an optimistic way, and owing to his/her belief that something good will happen, he/she is likely to purchase a particular stock.

As mentioned earlier, it is widely accepted that weather factors affect people's moods, thus making them feel good or bad. Hence, we anticipate that being in a good mood makes people optimistic, whereas being in a bad mood makes them pessimistic. In light of this, we assume that if people in the market are optimistic (or pessimistic), they are likely to believe that the information they receive is indicative that the market is going to rise (or fall). For these reasons, we feel it is reasonable to conclude that weather must have a significant impact on investors' behavior with regard to the stock market.

Under no circumstances does this assumption deny that people do have rational expectations vis-à-vis the stock market, but what we question here is the learning process. The point of our assumption is that when people have no idea about the future, the way they interpret the new information is crucial. We not only assume but also believe that although mood affects people's minds which are responsible for any decisions they make, people are nonetheless rational because they still perform in a way which they consider to be the most appropriate to achieve their goals.

3. Data

We use the daily weather data for temperature in Celsius degrees, humidity and cloud cover in Taipei city from 1 July 1997–22 October 2003. All our weather data are from the Central Weather Bureau of Taiwan. We adopt our stock index data from the AREMOS database and include the daily closing index of the Taiwan stock market 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 Taiwan stock index on day t and t–1, respectively.

The descriptive statistics for the variables in our study are reported in Table 1. The sample mean and medium of stock returns are −0.000284 and −0.001171, respectively. The statistics of skewness and kurtosis show that the distribution of stock returns is non-normal. The Jarque-Bera test 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 23.6503, while the maximum and minimum values are 33.0 and 8.1, respectively. The sample mean of humidity is 76.8764, and the maximum and minimum values of humidity are 98 and 47, respectively. The sample mean of cloud cover is 7.5299, with the maximum and minimum values of cloud cover being 10.0 and 0.1, respectively. The statistics of skewness, kurtosis and the Jarque-Bera tests also show that the distribution of temperature, humidity, and cloud cover, respectively, is non-normal. The Ljung-Box Q statistics with time lags of 5 and 10 periods for each of the variables show that significant linear and non-linear dependencies exist in the weather factors and the stock market returns in Taiwan.

Table 1
Descriptive statistics of sample data

	Stock returns	Temperature	Humidity	Cloud cover
Mean	−0.000284	23.6503	76.8764	7.5299
Medium	−0.001171	24.3000	77.0000	8.3000
Maximum	0.061721	33.0000	98.0000	10.0000
Minimum	−0.067745	8.1000	47.0000	0.1000
Std. Dev.	0.017751	5.0910	8.9885	2.3818
Skewness	0.064248	−0.4158	−0.0584	−0.8444
Kurtosis	3.913310	2.2814	2.4359	2.6872
Jarque-Bera statistics	56.46172***	80.2378***	22.0397***	159.9066***
Ljung–Box Q(5)	15.960***	5463.3909***	752.7967***	5463.3909***
Ljung–Box Q (10)	18.576**	14536.3992***	796.7760***	14536.3992***
Ljung–Box Q^2(5)	123.75***	5720.4776***	744.9180***	5720.4776***
Ljung–Box Q^2 (10)	188.54***	12637.8093***	794.5302***	15406.3758***

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

4. Methodology and empirical results

4.1. Unit root tests

Previous studies have found that many macroeconomic and financial time series, including stock price series, contain unit roots dominated by stochastic trends (see Refs. [13,14]). Recently, conventional wisdom has been moving toward the possibility that stock price data exhibit non-linearities and that conventional tests for stationarity, such as the ADF, PP unit root tests, etc. may have low power to be able to detect the mean-reverting tendency of a series. Thus, stationarity tests in non-linear frameworks must be applied. We use both the traditional unit root tests and the non-linear unit root tests advanced by Kapetanios et al. [15] (henceforth, the KSS test) to examine the stationarity of our sample data.

We first incorporate the Augmented Dickey-Fuller (ADF) test of Said and Dickey [16], the KPSS test of Kwiatkowski et al. [17], the PP test of Phillips and Perron [18], and the NP test of Ng and Perron [19] into our study. Table 2 reports the results of the traditional unit root tests for all the variables studied using the ADF, KPSS, PP, and NP tests. The results of these tests indicate that all the variables, including the weather factors and the stock market returns, are stationary.

Furthermore, according to Kapetanios et al. [15], the more powerful KSS test can detect the presence of non-stationarity against a nonlinear but globally stationary exponential smooth transition autoregressive (ESTAR) process. The model is written as follows:

$$\Delta Y_t = \gamma\, Y_{t-1}\{1 - \exp(-\theta Y_{t-1}^2)\} + v_t\,, \tag{1}$$

where Y_t is the time series data of interest, v_t is an independently identically distributed error term with a zero mean and constant variance, and $\theta \geqslant 0$ is the transition parameter of the ESTAR model and governs the speed of transition. Our objective is to test the null hypothesis of $\theta = 0$ against the alternative hypothesis of $\theta > 0$. Under the null hypothesis Y_t follows a linear unit root process, but Y_t follows a non-linear stationary ESTAR process under the alternative hypothesis. One problem with this framework is that the parameter, γ, is not identified under the null hypothesis. Thus, Kapetanios et al. [15] used a first-order Taylor series approximation for $\{1 - \exp(-\theta Y_{t-1}^2)\}$ under the null hypothesis of $\theta = 0$ and then approximated Eq. (1) by using the following auxiliary regression:

$$\Delta Y_t = \xi + \delta Y_{t-1}^3 + \sum_{i=1}^{k} b_i\, \Delta Y_{t-i} + v_t, \quad t = 1, 2, \ldots, T\,. \tag{2}$$

In this framework, the null hypothesis and alternative hypothesis are expressed as $\delta = 0$ (non-stationarity) against $\delta < 0$ (non-linear ESTAR stationarity). The simulated critical values for this test are shown in Kapetanios et al. [15]. Table 3 presents the nonlinear KSS stationarity test results of this study, and they further confirm that all the sample data series are stationary.

Table 2
The traditional unit root tests

	Stock returns	Temperature	Humidity	Cloud cover
ADF	−20.9413(2)***	−3.6910(7)***	−7.1554(20)***	−16.7796(2)***
PP	−37.4818(10)***	−7.0784(6)***	−20.6025(6)***	−23.1114(6)***
KPSS	0.1060(8)	0.0448(31)	0.0451(20)	0.1087(21)
NP	−20.6560(10)**	−67.0669(7)***	−476.8220(9)***	−652.3880(14)***

Note:
1. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.
2. Numbers in parentheses represent the lag periods of the tests.
3. The lag periods of the ADF tests are determined to ensure the residuals of the test equations have no autocorrelations; the lag periods of the PP and KPSS tests are determined by the Newey–West method; the lag periods of the NP tests are determined by the modified AIC.

Table 3
The nonlinear KSS unit root tests

Variables	t statistics of $\hat{\delta}$
Stock returns	-3.719^{***} $(k = 14)$
Temperature	-3.432^{***} $(k = 9)$
Humidity	-16.786^{***} $(k = 2)$
Cloud cover	-3.545^{***} $(k = 12)$

Note:

1. Critical values for the t statistics of $\hat{\delta}$ are tabulated and presented in Kapetanios et al. [15]. The critical values for 10%, 5% and 1% are –1.92, −2.22 and –2.82, respectively.
2. k indicates the lag periods of the testing model.

$$\Delta Y_t = \xi + \delta Y_{t-1}^3 + \sum_{i=1}^{k} b_i \Delta Y_{t-i} + v_t, \quad t = 1, 2, \ldots, T.$$

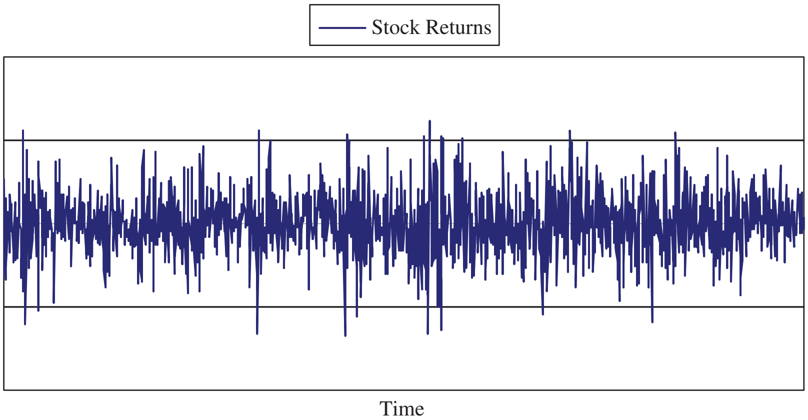

Fig. 1. Time series of stock returns.

4.2. Threshold model with the GJR-GARCH process

The results from the unit root tests presented in the previous section indicate that the stock market returns are stationary time series and may follow a non-linear process, as shown in Figs. 1 and 2. Furthermore, we adopt a non-linear threshold model with the GJR- GARCH (1,1) process to investigate the relationships between the stock market returns and the three weather factors. While the previous studies have focused on the linear models, we firmly believe that the non-linear models will be better specified for the relationships at the heart of this study, as clearly illustrated in Figs. 3–5. Thus, we first use the traditional linear models to test the general relationship between the stock returns and weather factors, and then use the non-linear threshold model to further examine the issue more closely. The results of the traditional linear model presented in Table 4 imply that there seems to be a close relationship between the stock market returns and temperature and cloud cover.

Furthermore, our non-linear threshold model is set as follows:

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 I^+ W_t + \beta_2 I^- W_t + \varepsilon_t, \tag{3}$$

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

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

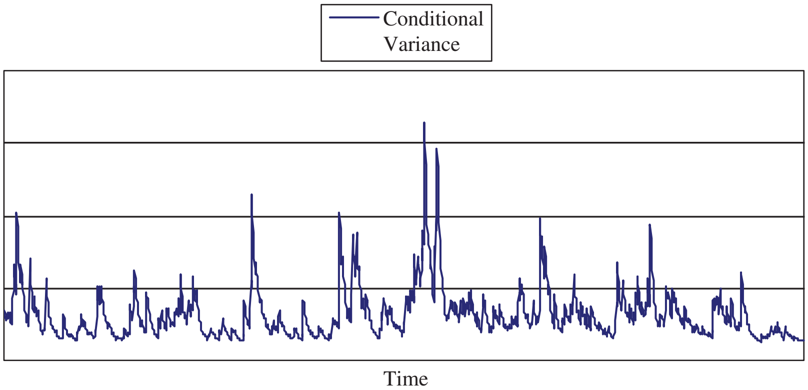

Fig. 2. Conditional variance of stock returns.

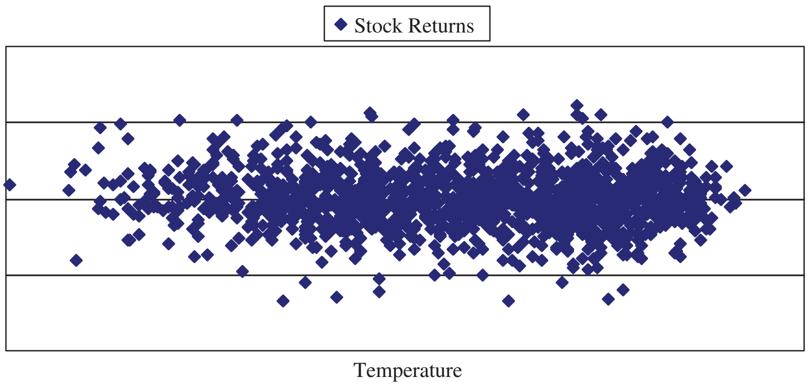

Fig. 3. Relationship between the stock returns and temperature.

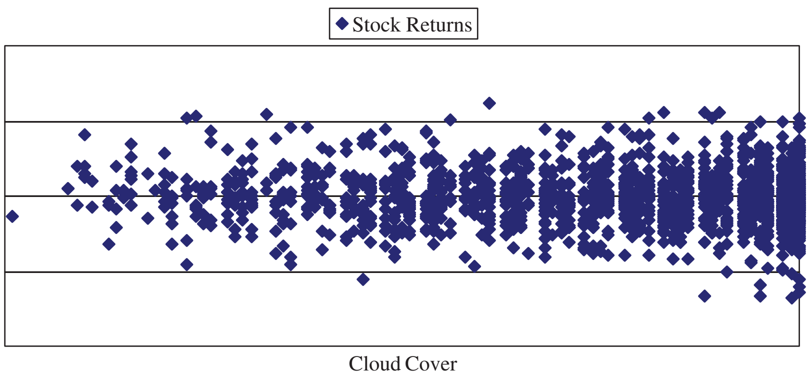

Fig. 4. Relationship between the stock returns and humidity.

where R_t represents the stock market returns time series data, and W represents the weather factor variables, namely temperature, humidity and cloud cover. Both I^+ and I^- are dummy variables. $I^+ = 1$ if $W_t > \tau$ (threshold value), while $I^- = 1$ if $W_t < \tau$ (threshold value). Ω_{t-1} is the information set at time $t-1$. I_{t-1} is a dummy variable, where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, and $I_{t-1} = 0$ if $\varepsilon_{t-1} \geqslant 0$. Several restrictions on the above equations should be noted: $\alpha > 0$, $\theta \geqslant 0$, $\gamma \geqslant 0$, and $\gamma + \delta \geqslant 0$. If δ is significant, there would be an asymmetric effect. The

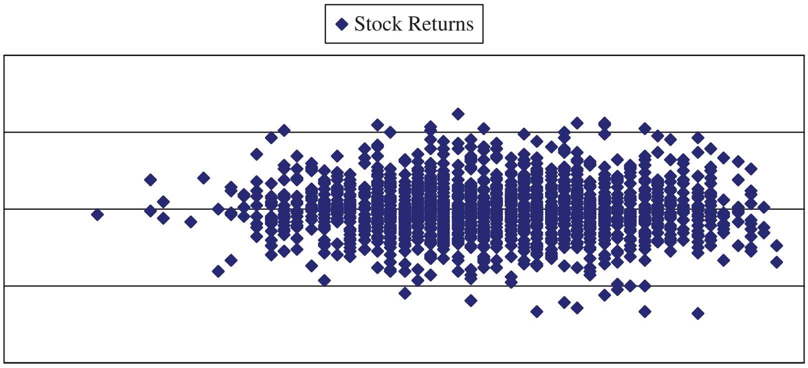

Fig. 5. Relationship between the stock returns and cloud cover.

Table 4
Traditional linear models to test the general relationship between the stock returns and weather factors

Coefficients	Temperature	Cloud cover	Humidity
β_0	0.004167	0.0021216	0.002271
	(1.971443**)	(1.443217)	(0.594018)
ψ_1	0.059796	0.06346907	0.063863
	(2.383815**)	(2.534257**)	(2.553507**)
ψ_2	0.030403	0.03409843	
	(1.2133)	(1.362798)	
β_1	−0.00019	−0.00031563	−3.28E-05
	(−2.13996**)	(−1.69609*)	(−0.66311)

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.

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

where R_t represents the stock market returns time series data, and W represents the weather factor variables, namely temperature, humidity and cloud cover.

reason for adopting the GJR-GARCH [26] as opposed to EGARCH [27] in our study is that the parameterization of the GJR-GARCH model makes it the more promising approach (see Ref. [20]).

Since we have no a priori knowledge about the true value of the threshold, we use Chan's [21] method to consistently estimate this parameter. This involves sorting the weather factors, such as temperature, in ascending order, excluding n% of the largest and smallest values, and selecting the optimal one from the remaining (100–2n)% of the threshold parameters, which yields the minimum residual sum of squares. Since such intense weather conditions as extreme cold or heat would affect human behavior, we only exclude 5% of the largest and smallest values and use the remaining 90% of the threshold parameters for our estimations. To ensure our model in this study is well specified, we also conduct several diagnostic checks on the residuals.

Tables 5–7 show the estimated results from our threshold models for temperature, cloud cover, and humidity, respectively. Based on the coefficients of ψ_i in the tables, it is evident that the stock market returns have strong first-order effects, which may be partly explained by the price limits in the Taiwan stock market. These results are highly consistent with those reported in the previous studies, thus signifying that strong autocorrelations exist in the stock market returns.

Table 5
Threshold model for temperature

Coefficients	Estimates	t-statistics
β_0	0.0069	2.8597***
ψ_1	0.0582	2.3243**
ψ_2	0.0292	1.1686
β_1	−0.0002	−2.4357**
β_2	−0.0003	−3.0804***
F-test		*F*-statistics
F_c		4.9766***
F_a		4.1007**
Threshold value	29.1	

Note:
1. F_c stands for the statistics of the joint tests of β_1 and β_2. The null hypothesis is H_0:$\beta_1 = \beta_1 = 0$.
2. F_a stands for the statistics of the asymmetric tests of the model. The null hypothesis is H_0:$\beta_1 = \beta_2$.

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 I^+ W_t + \beta_2 I^- W_t + \varepsilon_t.$$

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

Table 6
Threshold model for cloud cover

Coefficients	Estimates	t-statistics
β_0	0.004534176	2.16029**
ψ_1	0.064535621	2.57723***
ψ_2	0.034121864	1.36442
β_1	−0.000546564	−2.32679**
β_2	−0.000883095	−2.21555**
F-test		*F*-statistics
F_c		2.73534*
F_a		5.72501**
Threshold value	7.5	

Note:
1. F_c stands for the statistics of the joint tests of β_1 and β_2. The null hypothesis is H_0:$\beta_1 = \beta_2 = 0$.
2. F_a stands for the statistics of the asymmetric tests of the model. The null hypothesis is H_0:$\beta_1 = \beta_2$.

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 I^+ W_t + \beta_2 I^- W_t + \varepsilon_t\,.$$

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

Based on Chan's [21] method, the results reveal a threshold value of 29.1°C in our threshold model for temperature, as shown in Table 5. The coefficients of both β_1 and β_2 are individually and jointly statistically significantly different from zero, demonstrating that temperature has strong threshold effects. Moreover, from the results of F_a statistics, these threshold effects are asymmetric. Overall, temperature has strong asymmetric threshold effects on stock market returns, and these effects are negative for both above and below the threshold value. It indicates that stock market returns tend to be lower when the weather is extremely hot (above the threshold value) or extremely cold (below the threshold value), and the negative impact on stock returns seems stronger under the colder weather.

Table 7
Threshold model for humidity

Coefficients	Estimates	t-statistics
β_0	0.009323687	1.60072
ψ_1	0.064983409	2.59856***
β_1	−0.000116578	−1.62173
β_2	−0.000152675	−1.67426
F-test		F-statistics
F_c		1.50683
F_a		4.76332**
Threshold value	71	

Note:
1. F_c stands for the statistics of the joint tests of β_1 and β_2. The null hypothesis is $H_0{:}\beta_1 = \beta_2 = 0$.
2. F_a stands for the statistics of the asymmetric tests of the model. The null hypothesis is $H_0{:}\beta_1 = \beta_2$.

$$R_t = \beta_0 + \sum_{i=1}^{k} \psi_i R_{t-i} + \beta_1 I^{+} W_t + \beta_2 I^{-} W_t + \varepsilon_t .$$

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

In addition to temperature, cloud cover is also an important factor that may affect the stock market returns in Taiwan. A threshold value of 7.5 is found in our threshold model for cloud cover, as seen in Table 6. The coefficients of β_1 and β_2 are significantly negative, indicating that stock returns tend to be lower when cloud cover is too heavy or too little, a phenomenon similar to that for temperature. The results of F_a statistics clearly show that these threshold effects are asymmetric. In other words, cloud cover also has asymmetric impacts on stock market returns. As for humidity, the results identify a threshold value of 71, as shown in Table 7. Unlike the other two weather factors, the coefficients of neither β_1 nor β_2 are significantly different from zero. Thus, the results indicate that humidity does not have strong threshold effects on stock market returns.

Table 8 presents our GJR-GARCH models for Eq. (4). According to Engle and Bollerslev [22], γ can be viewed as the "news" coefficient, with higher values implying that more recent news has a greater impact on stock market returns, and θ reflects the impact of past variance on stock market returns, while $\theta + \gamma$ measures the persistence of volatility. The results in Table 8 indicate that both γ and θ are statistically significantly different from zero in our three threshold models. In addition, the significantly negative test statistics for the δ coefficients further indicate that the asymmetric effects exist in our three conditional variance models. The conditional volatility in the Taiwan stock market tends to be lower when the news is unfavorable ($\varepsilon_{t-1} < 0$). A possible explanation for this phenomenon is that investors would tend to be more pessimistic and are unwilling to make the major investment decisions when the unexpected negative information arrives in the market for fear of a further loss. Thus, the trading volume and stock return volatility would tend to be lower. Table 9 reports the diagnostic checks on the residuals of our three threshold models and the results clearly show that our models are unambiguously well-specified.

It is evident that our results are consistent with those reported in the previous studies of behavioral science, and most importantly, they indicate that the weather factors have strong effects on Taiwan stock market returns. Apart from this, this study makes both numerous and noteworthy contributions to the literature. For one, it is now apparent that there are threshold effects of the weather factors on the stock market returns, and these effects are strongly asymmetric. Secondly, asymmetric effects are also found in our conditional variance models, indicating that the conditional volatility in the Taiwan stock market tends to be lower when the news is unfavorable. Thirdly, our study fully supports the view that investor psychology tends to influence asset prices. The empirical findings fully comply with the arguments in favor of the inclusion of economically neutral behavioral variables in the asset pricing models.

Table 8
The estimated results from the GJR-GARCH model

Coefficients	Temperature	Humidity	Cloud cover
α	1.4644e-05	1.5219e-05	1.4843e-05
	(4.05388)***	(4.03375)***	(4.04923)***
θ	0.8648	0.8606	0.8625
	(39.48812)***	(37.69260)***	(38.39352)***
γ	0.1749	0.1697	0.1768
	(6.14934)***	(6.05242)***	(6.12083)***
δ	−0.1590	−0.1484	−0.1597
	(−5.75793)***	(−5.62770)***	(−5.73535)***

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.

$$h_t = \alpha + \theta h_{t-1} + \gamma\varepsilon_{t-1}^2 + \delta\varepsilon_{t-1}^2 \mathrm{I}_{t-1} \,.$$

Table 9
Diagnostic checks on the model residuals

Test statistics	Temperature	Humidity	Cloud cover
Ljung–Box Q (2)	1.1231	4.5020	0.9189
Ljung–Box Q (4)	3.3039	7.2832	2.9626
Ljung–Box Q (6)	3.3210	7.4652	3.2106
Ljung–Box Q (8)	4.6738	8.5182	3.9777
Ljung–Box Q (10)	5.4884	8.9360	4.5278
Ljung–Box Q (12)	5.6769	9.1989	4.7463
ARCH-LM (5)	5.325287	5.231313	5.470339

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

5. Conclusions

In this study, we employed a recently developed econometric technique of the threshold model with the GJR-GARCH process on error term to explore the relationships between three weather factors and stock market returns in Taiwan using daily data covering the period of July 1, 1997 to October 22, 2003. We use temperature, humidity and cloud cover as the major weather factors. Empirical evidence shows that temperature and cloud cover have the greatest effect on stock market returns in Taiwan.

Weather is an important factor that may affect human moods, and thus may affect investors' behavior in the stock market. Overall, we found that temperature has strong threshold effects on stock market returns, and stock returns tend to be lower when the weather is extremely hot (above the threshold value) or extremely cold (below the threshold value). The "long and hot summer" or the intense cold weather, suggested by the psychologists, would make people impatient or upset, and thus affect the stock returns. In addition to temperature, cloud cover is also an important factor that may affect the stock market returns in Taiwan. We found that stock returns tend to be lower when cloud cover is too heavy. As also suggested by the psychologists, a lack of sunlight would make people melancholic and upset. The seasonal affective disorder (SAD) is somewhat common in the fall and winter seasons on account of the paucity of sunlight. Given that weather evidently affects human moods, it would play an important role when investors make decisions in view of the bounded rationality. The empirical findings of our study fully advocate the inclusion of the economically neutral behavioral variables in the asset pricing models. Above all, this study has important implications for individual investors and financial institutions planning to invest in the Taiwan stock market.

Acknowledgements

The authors gratefully acknowledge the helpful comments and suggestions of the anonymous referees from *Physica A*.

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