Full Length Research paper

Stock market returns and the temperature effect: Thailand

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This research focus on investigation of the relationship between stock market returns and temperature. Research in behavioral finance shows that lower temperature can lead to aggression, while higher temperature can lead to both apathy and aggression. This research considers daily financial and temperature data of Thailand. Both a Autoregressive (AR(p))-Generalized Autoregressive Conditional Heteroscedasticity (GARCH (p,q). Based on AR(1)-GARCH(1,1) estimation found that a negative relationship between temperature and stock market returns for Thailand.

Keywords: stock market return, temperature, Thailand

INTRODUCTION

It is well established in the psychological literature that mood, feelings and emotions affect people's decision making (Schwartz, 1990; Loewenstein et al., 2001), and mood itself can be influenced by environmental factors such as weather conditions (Watson, 2000). In this article, we empirically investigate whether stock market returns are related to temperature. People tend to rate their life satisfactions much higher on sunny days than on cloudy or raining days (Schwartz and Clore, 1983). Evidence suggests that low temperature tends to cause aggression, and high temperature tends to cause aggression, hysteria and apathy (Cao and Wei, 2005). Firstly, Saunders (1993) uses data from the city of New York for the period 1927–1989. He shows that less cloud cover is associated with higher returns, and the return difference between the most cloudy days and the least cloudy days is statistically significant. The results show that investors' mood is upbeat or optimistic on sunny days, which uplifts the stock market returns. However, their pessimistic mood on cloudy days depresses the stock returns. Returns remain lower on cloudy days after adjusting for Monday and January effects. These findings are confirmed by Hirshleifer and Shumway (2003) for 26 international stock indices. They report that rainfall has no influence on stock returns. Furthermore, Cao and Wei (2002) investigate eight stock exchanges, and find that

(on average) low temperatures are associated with high returns and high temperatures are associated with low returns. Keef and Roush (2002) report a weak negative effect of temperature on stock returns of the New Zealand Stock Exchange. They also show that the weather in New Zealand is multifaceted. Kamstra et al. (2003) examine the impact of seasonal affective disorder (SAD) on stock market returns. They find that longer nights are associated with lower stock returns due to the SAD effect. Goetzmann and Zhu (2003) find that while cloud cover does not affect the propensity of investors to buy or sell, it does seem to be associated with wider bid-ask spreads. Loughran and Schultz (2004) find little evidence that cloudy weather in the New York City affects Nasdaq returns. Pardo and Valor (2003) also report no influence of temperature on Spanish stock returns of Madrid Stock Exchange, indicating a rational behavior of the market. They argue that these findings do not contest the notion of efficient markets. More recently, Keef and Roush (2005) examine the influence of New York's weather on the returns of the Dow Jones Industrial Average index and Standard and Poor's 500 index for the period 1 January 1984 to 31 August 2002. They find that the level of wind has a very weak influence on stock returns, consistently with Keef and Roush (2002). They also report that observed temperature exhibits no influence on stock returns, while de-seasonalised temperature has a positive influence on cool days but no influence on warm days. Furthermore, Cao and Wei (2005) examine many stock markets worldwide (United

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Table 1. Summary statistics of financial data (returns)

Statistics	SET index (Thailand)
Mean	-0.000165
Median	-0.000343
Maximum	0.113495
Minimum	-0.160633
Std. Dev.	0.01776
Skewness	0.102994
Kurtosis	9.374802
Jarque-Bera	5856.302
Probability	0
Observations	3455
ADF (Level)	-53.11909
ADF (1st diff.)	-31.59681
Test critical value at 5%	-2.862179

Table 2. Summary statistics of temperature data (in levels)

Statistics	(Thailand)
Mean	28.84436
Median	29
Maximum	33.88889
Minimum	17.22222
Std. Dev.	1.882766
Skewness	-0.727453
Kurtosis	4.631598
Jarque-Bera	687.9573
Probability	0
Observations	3455

States, Canada, Britain, Sweden, Australia, Japan and Taiwan). Using an AR(1) model, they find a statistically significant negative correlation between temperature and returns. This article re-examines the empirical link between temperature and stock market returns. Our investigation is based on Thailand stock markets and also we consider daily financial and weather data from Thailand. This research is the first article of Thailand that investigates the influence of temperature on stock market returns using both AR(p)-GARCH(p,q) and Generalize Extreme Value methodology.

DATA AND METHODOLOGY

The summary statistics of data

We investigate whether stock market returns are related to temperature using daily weather (average temperature) and financial data from Thailand. These indices are the leading representatives of aggregate changes on the local stock exchange.

The data cover the periods from 3 January 1996 to 24 February 2010 (Thailand) and the temperature data (Thailand) is collected from the U.S. Environmental Protection Agency. The average daily temperatures are the average of 24 hourly temperature readings.

Tables 1 and 2 gives the descriptive statistics for both daily returns of stock and temperature indices. Daily returns are computed as logarithmic price relatives: $R_t = \ln(P_t / P_{t-1})$, where P_t is the daily price at time t. The values for kurtosis are high for all indices. So, we find that prices show excess kurtosis (i.e. leptokurtic pdf), implying fatter tails than a normal distribution. The Jarque–Bera test rejects normality at the 5% level for all distributions. Also, all log-prices are nonstationary I(1), while all returns are stationary I(0). The financial data are plotted in returns (R) in Figure 1. Figure 1 shows the fluctuation of returns (volatility clustering) over time. Figure 2 show the change of temperature (in levels) over time. It is obvious that temperature data is characterized by seasonality.

Financial research shows much evidence that returns characterized by leptokurtosis, skewness and volatility clustering. A usual way to capture the above stylized facts is to model the conditional variance as a (G)ARCH process. The GARCH (p, q) model captures the tendency in financial data for volatility clustering, and also, it incorporates heteroskedasticity into the estimation procedure (see Engle, 1982; Bollerslev, 1986; Engle and Ng, 1993; Enders, 1995). We examine if the average daily temperature is negatively correlated with stock returns market using an AR(1)-GARCH(1,1) model with normal (Gaussian), Student's-t and general error distributions (GED). Given that the fat tails are observed in all indices, we use the Student's-t and GED assumptions for the standardized residuals. We make these assumptions to model more adequately the thickness of tails.

AR(p)-GARCH(p,q) Model

The notation AR(p) refers to the autoregressive model of order p (see equation1). The AR(p) model is defined as

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

------ (1)

where
$\varphi_1, \ldots, \varphi_p$ are is the parameters of the model,
c is a constant,
ε_t is white noise.
The processes in the AR(1) model with $|\varphi_1| \geq 1$ are not stationary. More generally, for an AR(p) model to be wide-sense stationary, the roots of the polynomial $z^p - \sum_{i=1}^{p} \varphi_i z^{p-i}$ must lie within the unit circle, i.e., each root z_i must satisfy $| z_i | < 1$.
A simple GARCH(1,1) specification is given by:

$Y_t = X_t^1 \theta + \varepsilon_t$ (Mean Equation)

$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$ (Variance Equation)

in which the mean equation is written as a function of exogenous variables with an error term. Since σ_t^2 is the one-period ahead forecast variance based on past information, it is called the conditional variance. The conditional variance is a function of three terms: a constant (ω), the ARCH term (the lag of the squared residual from the mean equation) and the GARCH term (last period's forecast variance). Given a distributional assumption, GARCH models are estimated by the method of maximum
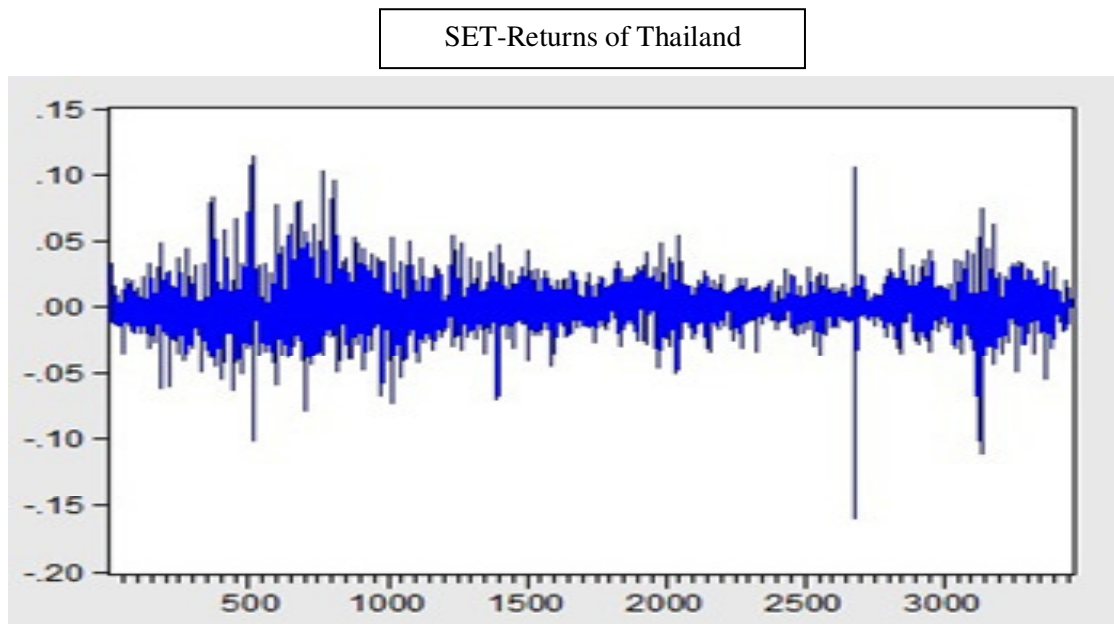
SET-Returns of Thailand

Figure 1. Plots of returns (R)
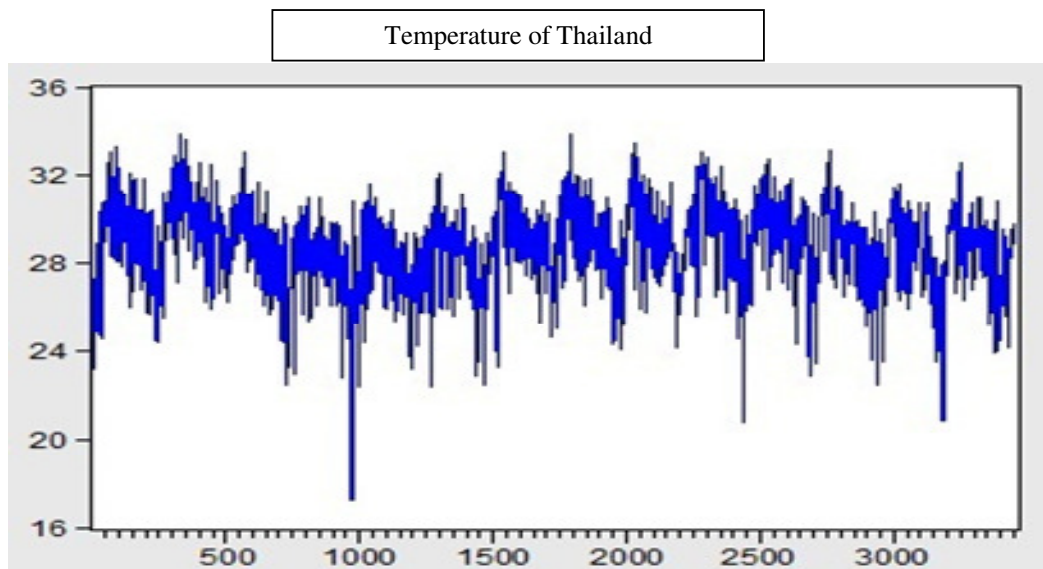
Temperature of Thailand

Figure 2. Plots of temperature (in levels.)

likelihood. For the GARCH(1,1) model with conditionally normal errors, the log-likelihood contributions are of the form:

$$l_t = -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log\sigma_t^2 - \frac{1}{2}\log\left(y_t - X_t^1\theta\right)^2 / \sigma_t^2$$

For the Student's t-distribution, the log-likelihood is given by:

$$l_t = -\frac{1}{2}\log\left(\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma((v+1)/2)^2}\right) - \frac{1}{2}\log\sigma_t^2 - \frac{(v+1)}{2}\log\left(1 + \frac{\left(y_t - X_t^1\theta\right)^2}{\sigma_t^2(v-2)}\right)$$

where the degree of freedom $v > 2$ controls the tail behavior. The t-distribution approaches the normal as $v \rightarrow \infty$. For the GARCH(1,1) model with GED, the contribution to the log-likelihood for observation t is given by:

$$l_t = -\frac{1}{2}\log\left(\frac{\Gamma(1/r)^3}{\Gamma(3/r)(r/2)^2}\right) - \frac{1}{2}\log\sigma_t^2 - \left(\frac{\Gamma(3/r)\left(y_t - X_t^1\theta\right)^2}{\sigma_t^2\Gamma(1/r)}\right)^{r/2}$$

where the tail parameter $r > 0$. The GED is a normal distribution if $r = 2$, and fat-tailed if $r > 2$.

The GARCH(1,1) model with several distributional assumptions. We employ an autoregressive of order one with a temperature proxy variable (TEMP) as a mean equation, while we also use a

Table 3. AR(1)-GARCH(1,1) results under different distributions.

Bangkok	Normal		Student's-t		GED	
AR(1)	0.109438	(4.82806)*	0.089786	(5.109327)*	0.078639	(4.650275)*
α	0.132863	(7.78777)*	0.123176	(8.877355)*	0.124975	(7.861466)*
β	0.817109	(23.42848)*	0.862369	(63.43028)*	0.851766	(51.58175)*
TEMP	-0.000362	(-2.184144)*	-0.000166	(-1.310305)	-0.000157	(-1.27903)
TDF			6.722797	(12.46836)*		
GED					1.292757	(51.37771)*
(α+β)	0.949972		0.985545		0.976741	
AIC	-5.451529		-5.549118		-5.530709	
SBC	-5.440851		-5.53666		-5.518251	

Note : The parameters TDF and GED describe the thickness of the distribution tails, t-Statistics in the parentheses, *Significant at 5% level.

conditional variance equation with GARCH(1,1) errors. We use the GARCH(1,1) model because it provides positive and significant parameters for all indices. Only GARCH(1,1) is reported here because it is an adequate representation. We select the parsimonious AR(1)-GARCH(1,1) model since many articles argue that it accounts for temporal dependence in variance and excess kurtosis. We also apply the AR(1) specification for the conditional mean, consistent with the non-synchronous trading effect. The AR(1)-GARCH (1,1) model, for returns R and prices P, can be expressed as follows:

$$R_t = c_0 + c_1 R_{t-1} + c_2 TEMP_t + \varepsilon_t,$$
$$where\ R_1 = \ln(P_t) - \ln(P_{t-1})$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + e$$

An iterative procedure is used based upon the method of Marquardt algorithm. Heteroskedasticity consistent covariance option is used to compute quasi-maximum likelihood (QML) covariances and standard errors using the methods described by Bollerslev and Wooldridge (1992). This is normally used if the residuals are not conditionally normally distributed.

EMPIRICAL RESULTS OF RESEARCH

The empirical results of AR(1)-GARCH(1,1) estimation

Table 3 presents the results of research for Thailand. The AR(1)-GARCH(1,1) model shows a good fit to the data (all variance parameters are significant). In all cases, the GARCH-t and GARCH with GED models show a good performance, since the tdf and GED coefficients are always positive and significant.

This implies that we have evidence of leptokurtic behavior in returns. Also, the relatively small degrees of freedom parameter for the t-distribution suggests that the distribution of the standardized errors departs significantly from normality. These models capture leptokurtosis in our data. The distribution of the Student's-t has significant thicker tails than the normal one. In addition, the sum of the ARCH and GARCH coefficients is very close to one, indicating that volatility

shocks are quite persistent. A large sum of these coefficients will imply that a large positive or a large negative return will lead future forecasts of the variance to be high for a protracted period. Also, the GARCH coefficient is larger than the ARCH coefficient, which means that the conditional variance will exhibit reasonably long persistence of volatility. Furthermore, the results of research found that the Set-Index of Thailand has been effected by temperature of itself. The result of this research is similarly with the results of research from Cao and Wei (2005). The coefficients of temperature (TEMP) are small with significant t-ratios at 5% level.

SUMMARY AND CONCLUSIONS

Empirical research reveals that stock market returns are associated with nature-related variables (temperature and sunshine). The study on temperature anomaly relies on a body of psychological literature concerning the impact of temperature on people's mood and behaviors. The existing psychological evidence suggests that lower temperature can lead to aggression, and higher temperature can lead to both apathy and aggression (Cao and Wei, 2005). The temperature anomaly is characterized by a negative relationship between stock market returns and temperature (the lower the temperature, the higher the returns, and vice versa). In this research, we identify the relationship between stock returns and temperature based on AR (p)-GARCH (p,q) models analysis under different distributional assumptions (Normal, Student's-t and GED) for the errors. We test the temperature anomaly using daily data of Thailand and also the set-index of Thailand based on AR (1)-GARCH (1, 1) approach. We found that the Set-Index of Thailand has been a negative affected by the temperature of Thailand. It can be implied that if the temperature of Thailand will be increased then the Set-Index of Thailand will be decreased. Otherwise, if the temperature of Thailand will be decreased then the Set-Index of Thailand

will be increased.

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