Causality of Weather Effects on Stock Returns and Volatility

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Date Received: 23 December 2018 Revised: 5 March 2019 Accepted: 18 March 2019

Abstract

Causality tests for weather effects on stock market returns and volatility were conducted to ensure that the weather was in fact the cause. Based on the data for Thailand from 1992 to 2016 (6,091 daily observations), both Granger causality and directed acyclic graph causality tests revealed bi-directional relationships of the weather with returns and volatility. Despite the bi-directional relationships, the analyses led to the conclusion that there were weather-caused effects on returns and volatility.

Keywords: *Causality tests, stock return behavior, weather effects*

Introduction

Weather influences mood (e.g., Howarth & Hoffman, 1984) and risk preferences of investors (Mehra & Sah, 2002) whose trading, in turn, drives stock prices and returns. Meanwhile, weather affects stock volatility because social moods create a divergence of opinions among investors with respect to stock prices (Shalen, 1993), and because investors in a good mood tend to trade more stocks (Statman, Thorley, & Vorkink, 2006). The relationship is causal from weather to mood, as well as from mood to returns and volatility, thereby establishing that there are weather effects on stock markets.

Weather effects were tested and found for national markets around the world (e.g., Hirshleifer & Shumway, 2003; Sheikh et al., 2017; Kathiravan et al., 2019). The significance of the weather effects was based on the significant correlation of weather variables with returns and volatility. Stock returns and volatility cannot cause weather; causality necessarily runs from weather to returns and volatility (Vlady & Tufan, 2011).

A significant correlation does not necessarily imply causality. Jacobsen and Marquering (2008) found that for 48 national stock markets, temperature and seasonal affective disorder effects disappeared once the tests were controlled for other variables with a strong seasonal pattern. The researchers cautioned that the significant correlation could be spurious. The conclusion of weather-caused effects could be incorrect.

Three groups have conducted causality tests for weather effects. All relied on Granger causality tests. Tufan and Hamarat (2003) found that cloudiness did not Granger predict the Turkish Istanbul Securities Exchange 100 index returns. Recently, Tuna and Bektur (2015) found that temperature Granger values predicted the Turkish Borsa Istanbul 100 index returns. For the Australian market, Vlady and Tufan (2011) reported a Granger causality of humidity on the S&P/ASX All Australian 200 index returns.

Granger causality tests for weather effects are important and useful. The tests were developed considering the fact that weather causes necessarily precede market return and volatility effects, but not vice versa (Granger, 1969). Because they are predictive (Diebold, 2006), the tests are able to capture the lagged responses of the investors and, therefore, the mood-driven returns and volatility responses to weather variables (Persinger, 1975). Nevertheless, the tests possess a major weakness. They cannot detect the incidents where weather contemporaneously causes returns and volatility within the same sampling interval (Awokuse et al., 2009).

In this study, two tests were applied—a Granger causality test and a directed acyclic graph (DAG) contemporaneous causality test, for the weather effect on stock returns and volatility. These tests ensure that the significant correlation in weather studies resulted from weather causality. I revisited the

Granger causality tests because the above-mentioned weather-causality studies did not test for the effect on volatility. I estimated a multivariate system of return, volatility, and weather variables. The multivariate causality test is more powerful than the univariate test performed in the previous studies (Gelper & Croux, 2007).

Contemporaneous causality was tested using the DAG technique. The methodology is general. As opposed to Granger causality, the DAG allows for non-time sequence causal relations of weather to returns and volatility.

Thailand was chosen as the sample market. It is one of the world's most important emerging economies. The Stock Exchange of Thailand (SET)—the country's only stock exchange, is located in Bangkok; most investors live and trade in the Bangkok metropolitan area, and therefore, Bangkok weather is able to move Thai stocks.

Methodology

Granger Causality of Weather to Returns and Volatility

The Vector Autoregressive Model

The dynamics of return, volatility, and weather variables was modelled using a multivariate vector autoregression (VAR). Let r_{t-i}, σ^2_{t-i}, and W^m_{t-i} denote the return, volatility, and weather variables $m = 1, \dots, M$ on day $t - i$. The VAR equation of order p is in equation (1).

$$\mathbf{X}_t = A_0 + \sum_{i=1}^{p} A_i \mathbf{X}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where the variable vector $\mathbf{X}'_{t-i} = \left[r_{t-i}, \sigma^2_{t-i}, W^1_{t-i}, \dots, W^M_{t-i}\right]$ and the residual vector $\boldsymbol{\varepsilon}'_t = \left[\varepsilon^r_t, \varepsilon^{\sigma^2}_t, \varepsilon^{W^1}_t, \dots, \varepsilon^{W^M}_t\right]$. $\boldsymbol{\varepsilon}_t$ has a zero mean vector and Ω covariance matrix. The intercept-coefficient vector A'_0 is $\left[a^r_0, a^{\sigma^2}_0, a^{W^1}_0, \dots, a^{W^M}_0\right]$, while the ((M+2)×(M+2)), slope-coefficient matrix A_i is $\begin{bmatrix} a_i^{r,r} & \dots & a_i^{r,W^M} \\ \vdots & \ddots & \vdots \\ a_i^{W^M,r} & \dots & a_i^{W^M,W^M} \end{bmatrix}$.

Optimal Lag Selection

The lag order p is not known; it must be estimated. In the literature, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are popular approaches for optimal lag selection. In this study, BIC was chosen over the AIC. The AIC asymptotically overestimates the order, while the BIC gives an order consistently under general conditions (Zivot & Wang, 2006, pp. 385–428). The BIC (ρ) statistic for a system of order ρ equals

$$\mathrm{BIC}(\rho) = Ln|\widehat{\Omega}_\rho| + \frac{(M+2)^2 \times \rho \times Ln(N)}{N}, \tag{2}$$

where $\widehat{\Omega}_\rho$ is the covariance estimate of the system of order ρ, and N is the number of observations. The order p in equation (1) is identified by the order ρ^* whose BIC is smallest among those $\mathrm{BIC}(\rho = 1, 2, \dots, 5)$s.

Granger Causality Tests

From equation (1), if the weather variable m does not Granger cause the returns, it must be that $a_1^{r,W^m} = \dots = a_p^{r,W^m} = 0$. The Wald statistic for the hypothesis tests was used in this study. Under the null hypothesis, the statistic is a chi-square variable with p degrees of freedom. The Granger causality tests for the volatility were conducted vis-à-vis the $a_1^{\sigma^2,W^m} = \dots = a_p^{\sigma^2,W^m} = 0$ hypothesis.

Granger causality was interpreted as predictive causality (Diebold, 2006). With this interpretation, the joint causality of M weather variables on the returns and volatility could be tested. The hypotheses are $a_1^{r,W^1} = \cdots = a_p^{r,W^M} = 0$ and $a_1^{\sigma^2,W^1} = \cdots = a_p^{\sigma^2,W^M} = 0$, respectively. The Wald statistics are chi-square variables with (p×M) degrees of freedom.

Vlady and Tufan (2011) explained that it was not rational to expect a causal link from returns to weather. These researchers, as well as Tufan and Hamarat (2003) and Tuna and Bektur (2015), did not run the tests of causal returns on weather. I argue that these tests are interesting, important, and useful. Significant Granger causality implies investors predict weather and use the prediction to improve their trades. Prediction ability is possible. If the market is an efficient information processor, it incorporates publicly available weather forecasts into stock prices and volatility (Roll, 1984).

The hypotheses for Granger causality of returns and volatility to weather variable m are $a_1^{W^m,r} = \cdots = a_p^{W^m,r} = 0$ and $a_1^{W^m,\sigma^2} = \cdots = a_p^{W^m,\sigma^2} = 0$. The Wald statistics are chi-square variables with p degrees of freedom. I also tested whether the returns and volatility Granger caused all the M weather variables. The corresponding hypotheses are $a_1^{W^1,r} = \cdots = a_p^{W^M,r} = 0$ and $a_1^{W^1,\sigma^2} = \cdots = a_p^{W^M,\sigma^2} = 0$. The test statistics are chi-square variables with (p×M) degrees of freedom.

DAG Causality Tests

Sims (1986) proposed a structural factorization approach to model the structure of contemporaneous causation among the residual via the Ω covariance matrix. Swanson and Granger (1997) are followed here to identify the causal structure by the data-determined DAG approach.

The DAG Theory

Let $Pr(\varepsilon_t^r, \varepsilon_t^{\sigma^2}, \varepsilon_t^{W^1}, \dots, \varepsilon_t^{W^M})$ be the joint density of residuals $\left[\varepsilon_t^r, \varepsilon_t^{\sigma^2}, \varepsilon_t^{W^1}, \dots, \varepsilon_t^{W^M}\right]$. $Pr(\varepsilon_t^r, \varepsilon_t^{\sigma^2}, \varepsilon_t^{W^1}, \dots, \varepsilon_t^{W^M})$ can be modelled by the product decomposition, as in equation (3) (Pearl, 2000).

$$Pr(\varepsilon_t^r, \varepsilon_t^{\sigma^2}, \varepsilon_t^{W^1}, \dots, \varepsilon_t^{W^M}) = \prod_{k=r,\sigma^2,W^1,\dots,W^M} Pr(\varepsilon_t^k | pa^k), \quad (3)$$

where pa^k is the subset of $\left[\varepsilon_t^r, \varepsilon_t^{\sigma^2}, \varepsilon_t^{W^1}, \dots, \varepsilon_t^{W^M}\right]$ that causes ε_t^k. $Pr(\varepsilon_t^k | pa^k)$ is the density of ε_t^k, conditioned on pa^k.

Spirtes et al. (2000) developed a PC causal search algorithm to infer a DAG from the relation in equation (3) and the Pearson correlation estimates for $\left[\varepsilon_t^r, \varepsilon_t^{\sigma^2}, \varepsilon_t^{W^1}, \dots, \varepsilon_t^{W^M}\right]$. Five types of DAG relationships between an (ε_t^j,$\varepsilon_t^{k\neq j}$) pair are possible. They can be represented by graph edges:

1. no edge ($\varepsilon_t^j \quad \varepsilon_t^{k\neq j}$) indicates independent ε_t^j and $\varepsilon_t^{k\neq j}$,
2. undirected edge ($\varepsilon_t^j — \varepsilon_t^{k\neq j}$) indicates their correlation but not causation,
3. uni-directed edge ($\varepsilon_t^j \rightarrow \varepsilon_t^{k\neq j}$) indicates the causality from ε_t^j to $\varepsilon_t^{k\neq j}$,
4. uni-directed edge ($\varepsilon_t^j \leftarrow \varepsilon_t^{k\neq j}$) indicates the causality from $\varepsilon_t^{k\neq j}$ to ε_t^j, and
5. bi-directed edge ($\varepsilon_t^j \leftrightarrow \varepsilon_t^{k\neq j}$) indicates the bidirectional causality between ε_t^j and $\varepsilon_t^{k\neq j}$.

If the weather variable m contemporaneously causes returns and volatility, the PC algorithm must report that ($\varepsilon_t^{W^m} \rightarrow \varepsilon_t^r$) and ($\varepsilon_t^{W^m} \rightarrow \varepsilon_t^{\sigma^2}$), respectively.

The PC algorithm is based on hypothesis testing for significant correlations and partial correlations among the residuals. The significance level needs to be set. In this study, a ten-percent level was chosen because the system of M+2 variables is not large, and the one-year sample of daily observations for the correlation calculation is not long (Glymour et al., 2004). Moreover, 10% is the largest *p*-value this study considers significant.

The PC algorithm assumes joint normality for the residuals. If the assumption is incorrect, it is likely the conclusion is misleading (Teramoto et al., 2014). I mitigated the effects from the incorrect assumption by substituting the Pearson correlation with the adjusted Spearman rank correlation, as was suggested by Harris and Drton (2013) and Teramoto et al. (2014).

The Fixed-Effect Assumption

The model estimation and tests impose the fixed-effect assumption under which relationships among the return, volatility, and weather variables stay fixed over the sample period. For long-sample data, the assumption is hardly correct. To lessen the effects of the assumption, I followed Khanthavit (2017) to estimate the model and test the hypotheses, using a sample period of one year at a time. Therefore, the tests are for each year in the full period. Full sample results were computed by summing the Wald statistics for one-year subsamples. The sums are distributed as chi-square variables with the summed degrees of freedom (Doyle & Chen, 2009).

The Data

Daily returns were considered on the SET index portfolio from February 17, 1992, to December 30, 2016 (6,091 trading-day observations). The returns were the log differences of the closing indexes. The volatility was the realized variance measured by Rogers and Satchell's (1991) adjusted extreme-value estimator. The SET index data were retrieved from the SET database.

The weather variables are Bangkok weather—air pressure (hectopascal), cloud cover (decile), ground visibility (kilometres), rainfall (millimetres), relative humidity (%), temperature (℃), and wind speed (knots per hour). The variables were measured by the Thai Meteorological Department's weather station at Don Mueang Airport. The weather samples began on January 1, 1991, and ended on December 31, 2016 (9,497 calendar-day observations).

Weather is seasonal. I used Hirshleifer and Shumway's (2003) approach to remove the seasonality in the weather variables by subtracting them from the averages for each week over the 1991–2016 period. Missing weather observations were detected. I input a value of zero for the missing cases. Zero was the unconditional mean of the deseasonalized variables.

Table 1, Panel 1.1 reports the descriptive statistics of the return, variance, and raw weather variables. All the distributions are skewed or fat-tailed. Jarque-Bera statistics reject the normality hypothesis for all the variables. This finding supports the use of the adjusted Spearman rank correlation in the PC algorithm for the DAG analyses.

Table 1 *Descriptive Statistics*

Panel 1.1 *Return, Volatility, and Raw Weather Variables*

Statistics	Return[1]	Volatility[1]	Raw Weather Variables[2]						
			Air Pressure (hectopascal)	Cloud Cover (decile)	Ground Visibility (kilometres)	Rainfall (millimetres)	Relative Humidity (%)	Temperature (℃)	Wind Speed (knots per hour)
Mean	-0.0009	0.0084	96.9436	5.4730	8,886.8710	0.3403	66.0036	29.9903	5.7522
Standard Deviation	0.0136	0.0060	29.8185	1.4110	1,435.9828	1.5311	10.5416	2.1542	2.4447
Skewness	-0.1239	3.1737	0.3882	-0.5683	-1.1628	7.8967	-0.4523	-0.7733	1.3835
Excess Kurtosis	6.7979	24.4938	0.0168	-0.2461	1.3509	83.9827	2.8797	2.4997	4.8165
Minimum	0.0912	0.1078	0.0000	0.0909	2,509.0909	0.0000	4.0909	8.1000	0.2727
Maximum	-0.1487	0.0000	250.5455	8.0000	14,272.7273	27.5500	98.0000	36.3455	30.5455
Jarque-Bera Statistic	1.17E+04**	1.62E+05**	233.3975**	518.5471**	2,780.2697**	2.82E+06**	3,525.9827**	3,354.5745**	1.19E+04**
Observations	6,091	6,091	9,286	9,201	9,225	9,256	9,288	9,318	9,235
Augmented Dickey-Fuller Statistic[1]	-71.1186**	-11.6203**	-28.3141**	-23.2441**	-22.9933**	-74.6138**	-14.5218**	-19.4568**	-13.8034**
Optimal Lags[1]	0	11	2	5	5	0	8	6	8

Note. ** = significance at the 99% confidence level. [1] and [2] = statistics are computed from the observed data on trading days and calendar days, respectively

Panel 1.2 *Correlations of Return and Volatility with Weather Variables*[1]

Statistics		Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed
Pearson Correlation	Return	-0.0146	0.0184	0.0195	0.0111	-0.0073	-0.0108	0.0005
	Volatility	0.0161	-0.0439**	-0.0762**	-0.0260*	-0.0043	-0.0125	0.0712**
Spearman Rank Correlation	Return	0.3697**	0.4172**	0.4608**	0.4154**	0.4241**	0.3828**	0.3799**
	Volatility	0.3400**	0.3404**	0.3975**	0.3862**	0.4090**	0.3677**	0.4105**

Note. * and ** = significance at the 95% and 99% confidence levels, respectively. [1] = statistics are computed from imputed, de-seasonalized observed weather data on trading days (6,091 observations).

Table 1, Panel 1.2 reports the Pearson and Spearman correlations of return and volatility with weather variables. The Pearson correlations of the returns are not significant for any of the weather variables, while the correlations of the volatility are significant for cloud cover, ground visibility, rainfall, and wind speed. The insignificant Pearson correlations of the returns with weather variables may result from non-normality, heavy noise, no relationship, or a non-linear relationship. The Spearman rank correlations are non-parametric and general. They can assess the linear or non-linear, monotonic relationships of two variables.

In order to examine the relationship of the return and the variance with the grouped weather variables, canonical correlations were computed. The statistics for the return and the variance were .0458 and .1283. They are significant at the 90% and 99% confidence levels, respectively.

The Spearmen and canonical correlations of the returns and the variance with all the weather variables are significant. The finding is consistent with the results in previous weather studies for Thailand (e.g., Khanthavit, 2017).

Empirical Results

Granger Causality Test Results

The VAR model in equation (1) was investigated by using seemingly unrelated regressions (Zellner, 1962). The BICs suggest the lag order p = 1 is optimal for every year.

I was aware of the fact that the volatility and weather variables had measurement errors. Measurement errors induce endogeneity problems in most weather studies (Khanthavit, 2017). In this study, however, the problems were resolved by the VAR specification (Enders, 1995).

Returns

Table 2, Panel 2.1 reports the estimation and test results for the Granger causality for the returns. The tests for the individual variables reveal that the volatility, air pressure, temperature, and wind speed Granger caused the returns, while the returns Granger caused the volatility and rainfall. In the joint tests, the seven weather variables Granger caused the returns, but the opposite is not true. The finding leads to the conclusion that the Granger causality of the returns and variance is bi-directional, and the weather Granger causes the returns. The evidence of Granger causality for the returns to weather is weak.

Volatility

The results for volatility are reported in Table 2, Panel 2.2. Individually, the returns, cloud cover, relative humidity, temperature, and wind speed Granger cause the volatility, while the volatility Granger causes the returns, ground visibility, and wind speed. The joint tests indicate that the seven weather variables Granger cause the volatility, and the volatility Granger causes all the weather variables. The results indicate bi-directional Granger causality for the volatility and weather.

Table 2 *Granger Causality Tests*

Panel 2.1 *Return*

Year	Volatility or weather does not Granger cause return.								
		Weather							
	Volatility (χ_1^2)	Air Pressure (χ_1^2)	Cloud Cover (χ_1^2)	Ground Visibility (χ_1^2)	Rainfall (χ_1^2)	Relative Humidity (χ_1^2)	Temperature (χ_1^2)	Wind Speed (χ_1^2)	Seven Weather Variables (χ_7^2)
1992	0.8264	0.3379	1.2177	1.5284	2.8729^{a}	0.0065	0.1697	0.5797	5.1615
1993	3.0164^{a}	0.9144	0.0000	0.2191	0.4840	0.0347	5.5551*	10.0444**	16.7290*
1994	2.3856	1.3484	0.0626	1.1964	0.2715	1.6583	7.2393**	0.1085	9.4858
1995	7.0315**	0.4014	0.0145	3.2268^{a}	3.0512^{a}	0.8081	0.0610	0.1167	9.1412
1996	0.5375	1.1685	0.5771	0.0011	0.5434	1.1216	0.0015	1.5241	4.3824
1997	5.9640*	0.3800	1.6276	0.8601	0.1078	0.2413	0.2332	0.6689	5.8278
1998	0.2034	2.1417	1.0667	0.1336	0.1595	0.8086	0.0878	0.0347	3.5413
1999	0.3104	6.9344**	1.6584	0.4131	1.9641	1.8371	6.0362*	2.1360	16.2370*
2000	5.5163*	1.5739	1.2552	1.0874	0.1160	0.0027	0.5477	0.0756	4.1946
2001	3.3911^{a}	3.6414^{a}	0.0058	0.0330	0.5078	0.5003	1.9954	0.7762	6.1908
2002	0.6660	0.5835	1.3422	1.2334	0.7904	2.0188	0.8963	2.2507	9.9550
2003	1.7863	8.2983**	0.5977	1.0306	1.0964	0.2516	1.9625	1.4055	11.4125
2004	0.3201	0.7775	0.3632	4.0536**	1.1193	0.1580	0.1679	1.2604	9.0681
2005	0.0201	0.0761	3.3969^{a}	1.2168	0.0153	0.0124	0.8333	0.5816	6.0521
2006	18.5568**	0.2473	0.7862	0.3818	0.1622	0.0581	0.7816	3.0861^{a}	6.4276
2007	0.3959	0.0943	0.0036	3.4106^{a}	0.3262	0.0196	0.0475	1.1708	5.0472
2008	0.0168	7.9104**	0.0298	0.0682	4.7598*	0.0009	3.8895*	0.0090	15.1354*
2009	0.8709	0.3971	3.0550*	0.6068	3.0707^{a}	1.0908	1.4724	6.2184*	13.9500^{a}
2010	0.9765	1.3170	1.8169	1.1598	0.9307	0.0086	0.1427	0.5397	8.7906
2011	6.2908*	0.5805	0.9074	0.0535	0.0063	0.0012	0.0407	0.9537	5.4786
2012	0.1560	0.1500	1.1355	0.7727	0.0088	3.0870*	2.2674	0.0346	5.1284
2013	1.8599	5.0182*	0.0717	0.0499	0.1123	0.7765	1.5905	1.2464	8.9859
2014	0.4119	0.2810	0.1471	1.8151	0.4665	0.0097	0.3553	0.1241	6.5610
2015	3.8298^{a}	0.1943	1.2915	0.0019	0.0775	0.1908	0.0007	0.5567	2.5468
2016	5.5865*	1.9320	4.9995*	0.5605	0.6700	3.8597**	1.5317	7.4895**	18.2695*
Joint Hypothesis (χ_{df}^2)	70.9271**	46.6997**	27.4297	25.1141	23.6909	18.5630	37.9069*	42.9920*	213.7000*
Degrees of Freedom (*df*)	25	25	25	25	25	25	25	25	175

Year	Return does not Granger causes volatility or weather.								
		Weather							
	Volatility (χ_1^2)	Air Pressure (χ_1^2)	Cloud Cover (χ_1^2)	Ground Visibility (χ_1^2)	Rainfall (χ_1^2)	Relative Humidity (χ_1^2)	Temperature (χ_1^2)	Wind Speed (χ_1^2)	Seven Weather Variables (χ_7^2)
1992	1.5474	1.5372	0.0952	0.2742	2.9185^{a}	0.3383	0.0583	1.4389	6.3379
1993	10.2607**	0.3373	0.4089	0.3736	0.0137	1.5113	0.1642	0.6221	2.9861
1994	0.5594	1.1284	0.1111	0.0424	2.3507	0.2357	0.4604	0.0851	3.5211
1995	0.4547	1.2593	0.0169	0.4174	19.0602**	0.0275	0.3150	1.7901	24.0616**
1996	20.6744**	6.4382*	0.1573	0.5272	0.6087	4.2885*	0.3038	0.9507	17.6408*
1997	2.1749	0.5937	2.5886	0.0354	0.0149	0.1039	0.1758	1.2001	4.3569
1998	31.0495**	0.0331	2.9317*	1.1822	0.7148	1.5401	0.3560	0.5143	4.6542
1999	1.4350	0.0075	0.0396	0.3610	0.7289	1.0043	0.3127	2.5258	8.6474
2000	0.8624	0.4100	4.1394*	0.0410	0.3308	0.7667	0.1358	3.8048^{a}	10.5474
2001	1.6275	2.2227	0.5623	0.0000	0.6845	0.1125	0.0850	0.3284	4.1846
2002	2.1715	0.1865	1.9602	0.0086	0.9653	1.4153	0.0714	0.4187	5.0862
2003	0.2452	0.3016	1.7049	0.5310	2.3864	0.4795	0.9061	2.7202^{a}	12.6066
2004	5.3807*	0.1878	1.5659	2.7100^{a}	2.5548	1.0312	0.8105	2.6132	10.6218
2005	3.9964*	0.2495	0.0107	1.1204	0.1968	0.0212	2.1159	0.4536	6.3607
2006	0.1433	1.5871	0.0448	0.3811	0.9476	0.4985	1.1543	0.0130	9.0013
2007	1.8597	1.0750	3.1163^{a}	1.4812	0.3391	0.7593	0.6533	0.4228	12.1905
2008	4.0678*	0.0000	0.7581	2.4926	0.0881	0.1453	0.1525	0.2914	4.7427
2009	2.7173^{a}	0.5192	0.2308	1.2176	0.0751	0.4845	0.0549	0.1735	4.1924
2010	1.2972	0.2191	0.0348	0.1563	0.2299	0.0000	0.9615	0.3479	3.5765
2011	6.2991*	0.5267	0.3549	0.6408	0.1694	1.2720	0.3788	0.9863	4.6697
2012	0.7731	0.2938	1.2212	0.0343	0.1914	2.9228^{a}	1.4406	2.9756^{a}	7.8978
2013	12.0052**	0.4754	0.4074	1.8964	3.5542^{a}	1.3040	0.7414	3.1482^{a}	11.0414
2014	3.7191^{a}	0.1508	1.2656	1.2835	0.1966	0.0053	0.0030	2.2715	5.4508
2015	8.4442**	2.2272	0.8444	0.0485	0.0548	0.2170	1.0897	0.0265	6.2463
2016	5.5705*	1.1300	0.9080	3.1683^{a}	0.0769	0.0083	2.1010	1.0973	7.1096
Joint Hypothesis (χ_{df}^2)	129.3361**	23.0970	25.4791	25.4791	39.4520*	20.4929	15.0018	31.2199	197.7323
Degrees of Freedom (*df*)	25	25	25	25	25	25	25	25	175

Note. ^{a}, *, and ** = significance at the 90%, 95%, and 99% confidence levels, respectively

Panel 2.2 *Volatility*

	Return or weather does not Granger cause volatility.									Volatility does not Granger causes return or weather.								
		Weather									Weather							
Year	**Return (χ_1^2)**	**Air Pressure (χ_1^2)**	**Cloud Cover (χ_1^2)**	**Ground Visibility (χ_1^2)**	**Rainfall (χ_1^2)**	**Relative Humidity (χ_1^2)**	**Temperature (χ_1^2)**	**Wind Speed (χ_1^2)**	**Seven Weather Variables (χ_7^2)**	**Return (χ_1^2)**	**Air Pressure (χ_1^2)**	**Cloud Cover (χ_1^2)**	**Ground Visibility (χ_1^2)**	**Rainfall (χ_1^2)**	**Relative Humidity (χ_1^2)**	**Temperature (χ_1^2)**	**Wind Speed (χ_1^2)**	**Seven Weather Variables (χ_7^2)**
1992	1.5474	0.8494	2.8053	0.0276	1.7896	3.9957*	0.8496	5.8148*	12.0232	0.8264	0.8348	2.3215	0.5039	0.0240	1.2048	0.0276	0.2293	17.6404*
1993	10.2607**	1.2447	7.8321**	0.0899	1.7182	0.0037	7.3571**	7.0142**	25.1666**	3.0164^{a}	0.4337	0.8496	0.0338	0.0449	0.3882	0.8884	1.3252	9.8771
1994	0.5594	0.0391	0.1545	0.7256	0.6014	6.7172**	6.5848*	1.5600	16.9527*	2.3856	1.6622	0.0237	2.8191^{a}	1.1051	2.6415	0.4735	0.0394	5.3370
1995	0.4547	0.5765	0.4708	3.6179^{a}	0.1819	2.1483	0.6028	0.0386	7.8036	7.0315**	0.3374	10.5754**	2.3844	1.4778	2.5592	1.0493	0.1692	6.6890
1996	20.6744**	3.3436^{a}	0.2064	1.8357	0.4541	0.1610	3.4683^{a}	0.8276	11.0068	0.5375	0.5964	0.7156	0.0463	1.3214	0.2919	0.0286	0.7805	3.7960
1997	2.1749	1.4291	0.9258	0.0032	0.0381	0.4656	4.6173*	0.4117	9.2469	5.9640*	0.0001	0.0116	0.2499	0.3911	0.4751	3.5548^{a}	12.1584**	3.2872
1998	31.0495**	0.2385	0.0018	0.7415	1.4360	0.0185	0.0304	4.1433*	7.0019	0.2034	2.1727	0.5893	0.8088	0.1524	0.6019	0.0001	3.4194	13.6407^{a}
1999	1.4350	1.2308	0.0399	0.0037	0.0440	0.0239	0.0434	1.0019	2.2414	0.3104	0.6446	0.7857	0.8600	0.0427	0.3547	0.0646	1.4180	19.4626**
2000	0.8624	0.0498	0.0509	0.0183	0.0474	0.2848	2.2863	1.8510	6.6938	5.5163*	0.0003	1.5616	0.9033	1.7120	0.6128	0.0022	2.0008	2.2587
2001	1.6275	0.2757	2.5015	0.0155	0.0674	2.0855	0.3427	0.4582	5.2716	3.3911^{a}	1.2020	0.3168	0.0003	0.6602	2.3619	2.0934	0.0018	4.2223
2002	2.1715	2.1667	0.3509	0.1578	0.0001	3.3192^{a}	0.0451	0.0006	7.4330	0.6660	1.2463	0.0024	1.3306	0.0169	0.0860	0.6551	0.0163	10.8389
2003	0.2452	0.2636	5.1877*	2.5564	5.3636*	2.7056^{a}	1.6125	0.0210	15.0503*	1.7863	0.8295	0.0738	4.5683*	1.1531	2.0821	0.6551	3.9831*	7.9094
2004	5.3807*	4.3389*	0.0696	0.0230	2.3725	5.7449*	0.0502	0.3437	16.6784*	0.3201	3.3048^{a}	0.0140	5.7004*	2.6009	0.0067	0.0001	3.8965*	10.4794
2005	3.9964*	0.7787	3.9452*	3.2435^{a}	0.0748	0.9242	0.0112	0.5119	8.9122	0.0201	0.0061	0.1888	0.0538	0.3158	0.7166	1.2018	0.7239	13.0703^{a}
2006	0.1433	0.7845	2.5217	0.7153	0.6137	1.1061	6.6999**	0.4937	12.8732	18.5568**	0.3455	0.3637	0.0626	0.0600	0.0018	0.8320	0.8288	7.8577
2007	1.8597	1.6153	0.4254	2.0753	3.8283^{a}	0.6996	0.2848	6.2802*	14.2401*	0.3959	2.0420	2.1926	0.3564	0.0127	1.0308	1.1034	4.0848*	3.6990
2008	4.0678*	4.2085*	3.1567^{a}	0.4906	1.3571	8.3753**	2.2700	1.3286	10.7442	0.0168	0.1673	1.5470	0.0838	0.4826	0.5131	0.1302	0.4968	9.6009
2009	2.7173^{a}	0.2119	1.3064	2.4785	0.7398	2.4609	1.6387	2.1750	14.5050*	0.8709	0.0025	0.1243	3.0453^{a}	0.0048	0.4818	1.3782	0.4353	7.1392
2010	1.2972	0.0315	2.3404	1.3515	2.6774	1.0237	0.7021	0.7713	10.0086	0.9765	3.0163^{a}	0.8533	2.6203	0.5048	1.5086	3.2947*	0.6623	12.6853^{a}
2011	6.2991*	2.8948	0.9687	0.3970	0.9117	2.4966	2.1345	0.1870	8.1883	6.2908**	0.6916	0.6193	0.4741	0.0067	1.4082	0.1053	0.0301	3.3439
2012	0.7731	0.4428	0.6640	1.0156	0.0097	2.7855^{a}	2.6703	1.2016	8.9654	0.1560	0.0206	0.0132	1.0931	0.5885	0.2465	1.4795	0.4790	17.6404*
2013	12.0052**	5.6487*	0.1278	0.8673	0.2927	0.7005	2.4105	0.2497	7.6552	1.8599	0.8696	1.6791	0.7554	1.2904	0.0001	0.0155	2.9622^{a}	9.8771
2014	3.7191^{a}	0.2912	0.6098	0.4301	0.1407	0.0172	0.0096	1.0963	3.4450	0.4119	0.6768	3.2463^{a}	1.3044	0.7429	0.1622	0.9541	0.2271	5.3370
2015	8.4442**	0.5405	0.5020	1.5194	0.0003	1.5899	0.6730	0.3965	4.7427	3.8298^{a}	0.0169	0.0421	5.9802*	0.4228	1.1974	0.7518	0.5111	6.6890
2016	5.5705*	0.0006	1.1359	0.5898	0.7692	2.2454	0.0040	0.1760	3.3103	5.5865*	1.2689	0.3627	0.0073	1.1311	1.2242	0.8564	0.0627	3.7960
Joint Hypothesis ($\chi^2_{df.}$)	129.3361**	33.4954	38.3010*	24.9900	25.5295	52.0987**	47.3993**	38.3545*	250.1602**	70.9271**	22.3890	29.0733	36.0459^{a}	16.2658	22.1581	21.5957	40.9420*	207.3477*
Degrees of Freedom (*df*)	25	25	25	25	25	25	25	25	175	25	25	25	25	25	25	25	25	175

*Note***.** ^{a}, *, and ** = significance at the 90%, 95%, and 99% confidence levels, respectively.

DAG Causality Test Results

Table 3 reports the DAG edges for contemporaneous causality tests. The edges shown are those that link the variables to the returns or volatility. The linked weather variables are different from one year to another. All their edges are bi-directed, except for 2014 when they are uni-directed from the ground visibility and wind speed to the volatility. For the (returns, volatility) pair, most edges are uni-directed; the directional relationships are not uniform. The bi-directed edges are found in 1993, 2002, and 2012.

Table 3 *DAG Edges*

Year	Return		Volatility	
	Edge	Variable	Edge	Variable
1993	↔	Volatility	↔	Return
	↔	Air Pressure	↔	Cloud Cover
	↔	Wind Speed		
1996	←	Volatility	→	Return
	↔	Relative Humidity		
2000	→	Volatility	←	Return
			↔	Ground Visibility
2002	↔	Volatility	↔	Return
	↔	Rainfall	↔	Air Pressure
2004	→	Volatility	←	Return
			↔	Air Pressure
2009	←	Volatility	→	Return
	↔	Air Pressure		
	↔	Rainfall		
2010	→	Volatility	←	Return
			↔	Temperature
2012	↔	Volatility	↔	Return
	↔	Ground Visibility	↔	Rainfall
2013	→	Volatility	←	Return
			↔	Air Pressure
2014	→	Volatility	←	Return
			←	Ground Visibility
			←	Wind Speed

Discussion

Granger-Causality Fallacy?

Maziarz (2014) cautioned that the relationships among variables revealed by Granger-causality tests could be erroneous due to variable non-stationarity or nonlinear-causal relationship. In this study, I checked for the non-stationarity property of the variables. In Panel 1.1, Table 1, all the variables are stationary.

The causal relationship can be linear or nonlinear. In this study, the return and volatility linearly Granger cause and are linearly Granger caused by the weather variables. Therefore, tests for nonlinear Granger causality were not needed (Pereda et al., 2005).

Granger Causality among Return, Volatility, and Weather Variables

The fact that the weather Granger causes, i.e., leads, the returns and volatility can be explained by the lagged response of investors' moods to weather (Persinger, 1975). This finding has important implications for most weather studies (e.g., Hirshleifer & Shumway, 2003) in which lagged weather variables were not included. Their models were misspecified. To mitigate the effects, the researchers could either add lagged weather variables or apply instrumental-variable estimation techniques.

The Granger causality is bi-directional for volatility and weather. There is evidence that the returns Granger cause data are related to the rainfall. This finding is expected. The informational efficiency in the SET has been improving over time (Khanthavit, 2016). Investors know that weather affects the returns and volatility (DeLong et al., 1990). Accurate weather forecasts are public information. Investors utilize the forecasts to improve their trading strategies. Therefore, the information is incorporated into the predictive returns and volatility (Roll, 1984).

The Granger causality of returns and volatility is also bi-directional. This finding is consistent with the generalized autoregressive conditional heteroscedasticity in mean process found for Thai stocks (e.g., Choudhry, 1996). The finding is explained by the common fundamental and sentiment causes of returns and volatility (DeLong et al., 1990). This explanation extends to the bi-directed edges between the returns and volatility discussed below.

DAG Causality among Return, Volatility, and Weather Variables

Most of the DAGs are bi-directed. Bi-directed edges suggest an unspecified number of common causes of the two variables that they connect (Morgan & Winship, 2007). To determine the common cause, I turned first to the cause of weather. All the weather conditions result from the atmosphere responding to the uneven heating of the earth by the sun (Hines & Halevy, 1997). To be the common cause, the sun must influence investors' moods and, in turn, the returns and volatility. Sun-influenced moods were supported by Cunningham's (1979) study. The researcher reported that the amount of sunshine reaching the earth was significantly related to moods.

The edges are not uni-directed; it is not immediately clear that the weather contemporaneously causes returns and volatility. Because the sun's activities are effectively a weather variable (Krivelyova & Robotti, 2003), I interpreted the bi-directed edges as evidence to support weather causality.

Conclusions

In this study, the causality of weather effects on stock returns and volatility was tested. The tests ensure that significant weather effects are weather-caused mood effects predicted by the psychology literature. Using daily data for Thailand from 1992 to 2016, bi-directional Granger causality and bi-directed DAG contemporaneous causality were found among the Bangkok weather and the SET index returns and volatility.

Stock returns or volatility cannot cause weather. Moreover, the common cause of contemporaneous weather, returns, and volatility is itself a weather variable. Despite the bi-directional relationships, it was concluded that there are weather-caused effects on returns and volatility for Thailand.

Acknowledgments

I thank the Faculty of Commerce and Accountancy, Thammasat University for the research grant; the Thai Meteorological Department for the weather-variable data; and C. Glymour, R. Scheines, P. Spirtes, and J. Ramsey for the TETRAD software and manuals.

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