WEATHER, INVESTOR SENTIMENT, AND STOCK RETURNS IN THE STOCK EXCHANGE OF THAILAND

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Abstract

A well-specified and complete empirical model for weather effects, based on a rigorous noise-trader-risk theory, was developed. Using the daily data on the Stock Exchange of Thailand index portfolio and Bangkok weather variables from February 17, 1992 to December 30, 2016, significant effects of weather on both stock returns and volatility were found. Further investigation revealed that the effect on stock returns was temporary. Because weather effects were driven by sentiment, the significant effect suggested the important role of noise traders in price formation in the Stock Exchange of Thailand.

Keywords: Investor Sentiment; Model Misspecification; Noise Traders; Return Behavior; Weather Effects

INTRODUCTION

Weather influences investor sentiment and thereby drives stock returns and volatility away from their fundamental values. On the one hand, weather affects the moods (e.g., Howarth & Hoffman, 1984) and risk preferences of investors (Mehra & Sah, 2002) whose trading, in turn, raises or lowers stock prices and returns, without changing the fundamentals of the stocks. On the other hand, weather-induced moods affect stock volatility because social moods create divergence of opinions among investors with respect to stock prices (Shalen, 1993) and because investors in good moods tend to trade more stocks (Statman, Thorley, & Vorkink, 2006).

Previous tests for weather effects did not incorporate rigorous pricing theories relating to investor sentiment to construct empirical models; they heuristically related the returns and volatilities linearly and directly with the weather variables. For example, when studying national stock markets around the world,

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Hirshleifer and Shumway (2003) related stock returns with respect to cloudiness and precipitation, whereas Symeonidis, Daskalakis, and Markellos (2010) related stock volatility with cloudiness, precipitation, and temperature. Recently, studying national stock markets in south Asia using a GARCH framework, Sheikh, Shah, and Mahmood (2017) related both stock returns and volatility with temperature, humidity, cloudiness, air pressure, ground visibility, wind speed, and precipitation. However, in the absence of a rigorous theory, the empirical models in the above mentioned studies involve risks of misspecification or incompleteness (Lee, Jiang, & Indro, 2002).

In this study, weather effects on the Stock Exchange of Thailand were tested. An empirical model was constructed, based on the theoretical model of noise-trader risk by DeLong, Shleifer, Summers, and Waldmann (1990) and Thomas and Wang (2013), thereby ensuring a complete and well-specified model. When weather variables served as proxies for investor sentiment, the theory predicted that weather would directly affect conditional volatility. As for the expected returns, weather effects consisted of temporary and permanent components. The temporary component was driven directly by the weather, whereas the permanent component was driven indirectly by the weather via the weather-driven volatility risk.

For estimation, daily returns on the Stock Exchange of Thailand (SET) index portfolio were used, alongside seven weather variables: air pressure, cloud cover, ground visibility, rainfall, relative humidity, temperature, and wind speed. The estimation technique was applied, as suggested by Khanthavit (2017) to mitigate the effect of a misspecified, fixed-effect assumption and to correct the endogeneity problems commonly present in traditional weather studies. Significant weather effects on stock returns and volatility were found. A further investigation revealed that only the temporary component contributed to the significant effect of weather on stock returns.

METHODOLOGY

The Model

In DeLong et al. (1990) and Thomas and Wang (2013), the expected stock return is the sum of the temporary component, $\mu_t(\Omega_{t-1}, \mathbf{W}_t)$, and the permanent component, $\delta\sigma_t^2(\Omega_{t-1}, \mathbf{W}_t)$, so that the return $\tilde{r}_t$ is the expected return plus the random component $\tilde{u}_t$ as in equation (1).

$$\widetilde{R}_t = \mu_t(\Omega_{t-1}, \mathbf{W}_t) + \delta\sigma_t^2(\Omega_{t-1}, \mathbf{W}_t) + \tilde{u}_t. \quad (1)$$

The conditional variance of $\tilde{u}_t$ is $\sigma_t^2(\Omega_{t-1}, \mathbf{W}_t)$. The coefficient δ indicates the response of the return to the risk level $\sigma_t^2(\Omega_{t-1}, \mathbf{W}_t)$. Ω_{t-1} is the information available to investors at time $t-1$ for forming the conditional expected return and variance. The components μ_t and σ_t^2 are also driven by investor sentiment. In this study, the weather vector $\mathbf{W}_t$ appears in $\mu_t(\Omega_{t-1}, \mathbf{W}_t)$ and $\sigma_t^2(\Omega_{t-1}, \mathbf{W}_t)$ because it serves as a proxy for investor sentiment.

Because $\mu_t(\Omega_{t-1}, \mathbf{W}_t)$ is unobserved, it is projected linearly onto the observed r_{t-1} and $\mathbf{W}_t$, as in Equation (2).

$$M_t(\Omega_{t-1}, \mathbf{W}_t) = a_0 + a_r r_{t-1} + a_1 W_t^1 + \cdots + a_M W_t^M + e_t^\mu, \tag{2}$$

where $W_t^{m=1,..,M}$ is the element m of the vector $\mathbf{W}_t$. r_{t-1} is chosen among the conditioning information in Ω_{t-1} because in previous weather studies, e.g., Sheikh et al. (2017), r_{t-1} commonly appeared in the return equation. $a_{j=0,r,1,\ldots,M}$ is the projection coefficient.

The conditional variance $\sigma_t^2(\Omega_{t-1}, \mathbf{W}_t)$ is also unobserved. The realized variance s_t^2 is used as a proxy because s_t^2 is considered as the most accurate representation of the unobserved variance process (Symeonidis et al., 2010). The proxy used implies that $s_t^2 = \sigma_t^2(\Omega_{t-1}, \mathbf{W}_t) + e_t^\sigma$, where e_t^σ is the error in the proxy s_t^2. Next, the realized variance s_t^2 was projected linearly onto its lag s_{t-1}^2 and the weather variables $W_t^{m=1,..,M}$, as in Equation (3).

$$s_t^2 = b_0 + b_s s_{t-1}^2 + b_1 W_t^1 + \cdots + b_M W_t^M + e_t^s, \tag{3}$$

where $b_{j=0,s,1,\ldots,M}$ is the projection coefficient and e_t^s is the projection error. The variance in Equation (3) is similar to that of the variance equations in previous weather studies on stock volatility (e.g., Symeonidis et al., 2010; Sheikh et al., 2017).

Combining Equations (1), (2), and (3) and collecting terms gives

$$\tilde{r}_t = a_0 + a_r r_{t-1} + a_1 W_t^1 + \cdots + a_M W_t^M + \delta(b_0 + b_s s_{t-1}^2 + b_1 W_t^1 + \cdots + b_M W_t^M) + \tilde{u}_t + e_t^\mu + \delta e_t^s - e_t^\sigma \tag{4.1}$$

$$= \alpha_0 + a_r r_{t-1} + \beta_s s_{t-1}^2 + \alpha_1 W_t^1 + \cdots + \alpha_M W_t^M + \tilde{v}_t, \tag{4.2}$$

where $\alpha_0 = a_0 + \delta b_0$, $\beta_s = \delta b_s$, $\alpha_{m=1,\ldots,M} = a_{m=1,\ldots,M} + \delta b_{m=1,\ldots,M}$, and $\tilde{v}_t = \tilde{u}_t + e_t^\mu + \delta e_t^s - e_t^\sigma$.

Hypothesis Tests

The hypothesis test for the weather effect on stock returns is $\alpha_1 = \cdots = \alpha_M = 0$; the test for the corresponding effect on stock volatility is $b_1 = \cdots = b_M = 0$. Under the null hypothesis of no weather effect, the Wald statistics are distributed as chi-squared variables with M degrees of freedom.

The weather effect on returns can be decomposed into temporary and permanent components. It is interesting and important to check for the significant contribution of each component. Because $\delta = \frac{\beta_s}{b_s}$, it follows from Equations (3) and (4.2) that the hypothesis for a significant permanent component is $\frac{\beta_s}{b_s} b_1 = \cdots = \frac{\beta_s}{b_s} b_M = 0$ and the hypothesis for a significant temporary component is $a_1 - \frac{\beta_s}{b_s} b_1 = \cdots = a_M - \frac{\beta_s}{b_s} b_M = 0$. Under the null hypothesis of no contribution, the Wald statistics are distributed as chi-squared variables with M degrees of freedom.

Model Estimation

All the variables in Equations (3) and (4.2) were observed. For the tests and analyses of the weather effects, Equations (3) and (4.2) were estimated.

Estimation Problems and Mitigation

Equations (3) and (4.2) constitute a system of two linear regression equations, for which estimation, test, and analysis based on long-sample data may suffer from an incorrect, fixed-effect assumption. In addition, the results may suffer from endogeneity problems induced by the measurement errors in the M weather variables and the omission of significant variables beyond the regressors being considered. To lessen the effects of the incorrect assumption, the work of Khanthavit (2017) was followed, by estimating the model and computing chi-square statistics using a sample period of one year at a time. The statistic for a full-sample test is the sum of statistics for all the N years in the full period. Hence, the statistics for the tests of the weather-effect hypothesis and the significant-contribution hypothesis are chi-square variables with $(N \times M)$ degrees of freedom (Doyle & Chen, 2009). To address the endogeneity problems, Hansen's (1982) generalized method of moments (GMM) was referred to. GMM is an instrumental-variable (IV) approach, whose estimators are consistent, asymptotically normal, and efficient among the class of all estimators that do not use any information beyond the moment conditions.

The Choice for Instrumental Variables

For Equation (3), the IVs are a constant and Racicot and Theoret's (2010) two-step IVs for the weather variables and a lagged variance. For Equation (4.2), the IVs are a constant, a lagged return, the Racicot-Theoret IVs for the weather variables and a lagged variance. I considered the Racicot-Theoret IVs for the weather and lagged-variance regressors, but not for the lagged-return regressor, because these variables were measured with errors.

To construct the Racicot-Theoret IVs, Pal's (1980) cumulant IVs for the weather variables and lagged variance were first computed.

Khanthavit (2017) found that their resulting two-step IVs had good informativeness and validity performance. In the second step, the weather variables and the lagged variance were regressed on the Pal IVs. The Racicot-Theoret IVs were the regression residuals.

THE DATA

The stock returns are daily returns on the SET index portfolio from February 17, 1992 to December 30, 2016 (6,091 trading-day observations). The returns are log differences of the closing indexes. The realized daily variances are computed by Rogers and Satchell's (1991) adjusted extreme-value estimator. This estimator is efficient, simple, and general. The computation requires data on opening, closing, maximum, and minimum indexes readily observed during the day. The SET opening, closing, maximum, and minimum indexes were taken from the SET database.

The weather variables used were air pressure (hectopascal), cloud cover (decile), ground visibility (kilometers), rainfall (millimeters), relative humidity (%), temperature (°C), and wind speed (knots per hour). These variables are identical to the ones used in previous studies for the Thai stock market (e.g., Khanthavit, 2017). They are Bangkok weather variables, measured by the Thai Meteorological Department's weather station at Don Muang Airport. The weather data started on January 1, 1991 and ended on December 31, 2016 (9,497 calendar-day observations). I obtained the weather data from the Thai Meteorological Department.

Weather is seasonal. Following Hirshleifer and Shumway (2003), the seasonality in the weather variables was removed, using averages for each week over the 1991-2016 sample period. The deseasonalized variables were then standardized by their standard deviations.

Some weather observations were missing because of faulty equipment or missed observations. Because zero was the unconditional mean of the deseasonalized variables, a value of zero was inputted to the missing cases.

Table 1, Panel 1.1 reports the descriptive statistics of the return, variance, and raw weather variables. The return is not serially correlated. This may result from the fact that efficiency of the Thai market has improved over time (Khanthavit, 2016) so that the significant serial correlation in the early sample period is averaged out by the insignificant correlation in the more recent sample period. The improving market efficiency supports the approach of estimating the model sequentially using one-year daily sample intervals each time.

The serial correlation of variance is significant. This finding is consistent with volatility clustering, found by previous studies for the

Thai and other national markets (e.g., Dowling & Lucey, 2008). The significant serial correlation of the variance justifies using the lagged variance as a regressor in Equation (4.2).

For the weather variables, the statistics were computed from the usable raw observations. Their autocorrelation coefficients are high and significant. The missing observations are from 179 to 296 observations; a value of zero is the input for the missing cases after the series is deseasonalized and standardized.

The Jarque-Bera statistics rejected the normality hypothesis for all variables. The GMM approach does not require normality. The parameter estimates and tests are unaffected by the non-normality. The significant serial correlation and heteroscedasticity in Table 1, Panel 1.1 suggest using Newey and West's (1994) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix in the tests and analysis.

Worthington (2009) cautioned that weather variables are highly correlated and could cause multicollinearity. As shown in Table 1, Panel 1.2, the data were checked for significant correlations among the weather variables and for potential multicollinearity problems. It was found that all the correlations, except for those of the air pressure and ground visibility, and the air pressure and rainfall pairs, were significant. The variance inflation factors (VIFs) were much smaller than the significance threshold of 10.00. No multicollinearity problems were found.

For the IV estimation, it is important that the IVs are informative and valid. To ensure that the IVs in this study possessed these properties, the informativeness and validity of R^2 values were computed as reported in Table 2. The informativeness of R^2 values was obtained by regressing the regressors on all the IVs, while the validity of R^2 values was obtained by regressing the error terms in Equations (3) and (4.2) on all the IVs. The informativeness of R^2 values was very high, ranging from 0.5085 to 0.9823. The validities of R^2 values were smaller than 1%. This finding leads to the conclusion that the IVs are informative and valid.

EMPIRICAL RESULTS

Table 3, Panel 3.1 reports the test results for the aggregate weather effect on stock returns. The Wald statistics for the years are presented in the last column. They are chi-square variables with 7 degrees of freedom. The statistic for the full sample is the sum of all the statistics. It is a chi-square variable with 175 ($=7 \times 25$) degrees of freedom. For the Thai stock return, the weather effect is significant. A further analysis reveals that the effect is time-varying.

Table 1: Descriptive Statistics

Panel 1.1: Index Returns and Raw Weather Variables

Statistics	Return	Variance	Raw Weather Variables[2] Air Pressure (hectopascal)	Cloud Cover (decile)	Ground Visibility (kilometers)	Rainfall (millimeters)	Re. 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
xcess Kurtosis	6.7979	24.4938	0.0168	-0.2461	1.3509	83.9827	2.8797	2.4997	4.8165
Minimum	-0.1487	0.0000	0.0000	0.0909	2,509.0909	0.0000	4.0909	8.1000	0.2727
Maximum	0.0912	0.1078	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***
AR(1) Coefficient	-0.0042	0.3918***	0.9107***	0.7076***	0.6684***	0.1004***	0.8044***	0.8090***	0.6892***
Observations	6,091	6,091	9,286	9,201	9,225	9,256	9,288	9,318	9,235

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[1] and Variance-Inflation Factors[2] of Imputed, De-seasonalized Weather Variables

Weather Variables	Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed
Air Pressure	1.0000						
Cloud Cover	-0.1010***	1.0000					
Ground Visibility	0.0008	-0.1152***	1.0000				
Rainfall	0.0031	0.1828***	-0.1603***	1.0000			
Relative Humidity	-0.1092***	0.5036***	-0.2198***	0.2702***	1.0000		
Temperature	-0.3440***	-0.3189***	0.1339***	-0.2562***	-0.2838***	1.0000	
Wind Speed	-0.1011***	-0.0446***	0.1924***	-0.0819***	-0.1253***	0.0991***	1.0000
Variance Inflation Factors (VIF)	1.2408	1.4905	1.1306	1.1441	1.6278	1.4522	1.0639

Note: *** = significance at the 99% confidence level. [1] and [2] = statistics are computed from the de-seasonalized observed data on calendar days (9,108 observations) and imputed, de-seasonalized observed data on trading days (6,091 observations), respectively.

Table 2: Informativeness and Validity of the Instrumental Variables

Panel 2.1: *Informativeness*

Instrumental Variable	Informativeness R^2
Lagged Variance	0.8322
Air Pressure	0.9600
Cloud Cover	0.9717
Ground Visibility	0.8737
Rainfall	0.5085
Relative Humidity	0.9823
Temperature	0.9091
Wind Speed	0.9111

Panel 2.1 *Validity*

Equation	Validity R^2
Return	0.0010
Variance	0.0015

It is significant only in certain years including 1992, 1998, 1999, 2002, and 2003. In the last row, Columns 4 to 10 show the Wald statistics for the significant contribution of the individual weather variables. The statistics, chi-square variables with 25 degrees of freedom, suggest that only the air pressure and rainfall variables have a significant contribution.

The relationship between the return and its lagged variance is significant at the 90% confidence level, implying that the response coefficient δ of the return to its conditional variance in Equation (4.2) is significant.

The return has a significant relationship with its first lag in the full sample test. The fact that the significance appears in the early sample but not in the recent sample supports the hypothesis that the efficiency of the SET is improving (Khanthavit, 2016).

The test results for the effects on volatility are presented in Table 3, Panel 3.2. The effect is significant in the full sample test. The year results suggest that the effect on volatility is also time-varying. The effect is significant for the years 1992, 1996, 1998, 2000, 2008, 2011, and 2015. The air pressure, cloud cover, relative humidity, temperature, and wind speed contribute significantly to the joint effect, whereas the ground visibility and rainfall do not.

The autocorrelation coefficients of the variance are much smaller than 1.00, satisfying the stationarity property of the variance process. The significant autocorrelation b_s in a full-sample test helps to ensure that $\delta = \frac{\beta_s}{b_s}$ can be recovered from the β_s and b_s estimates.

Table 3: Test for Weather Effects

Panel 3.1: Effects in Return

Year	Lagged Variables		Weather Variables							Joint Weather Effects
	Return	Variance	Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	$\chi^2(7)$
1992	0.0222	0.1145	-0.0670	0.1299	-0.0443	-0.0827*	-0.0628	-0.0276	-0.0541	19.0135***
1993	0.2233***	0.1200	0.1399*	0.0430	0.0531	0.0493	-0.0334	0.0933	0.0261	8.5638
1994	0.0761	0.0854	-0.0367	0.0810	0.1029	0.0264	-0.1334	-0.1635	-0.0194	8.8267
1995	0.2231***	0.1895***	0.1093	0.0948	0.1669**	0.0085	-0.0277	-0.0591	-0.0701	8.1157
1996	0.1003	-0.0640	-0.0775	-0.0132	-0.0958	0.1155	-0.1461	0.0207	0.0909	7.8911
1997	0.1759**	-0.1352	0.0739	0.1508**	-0.0395	-0.0091	-0.0278	0.1129	0.0575	7.3922
1998	0.1521*	-0.0251	-0.0880	-0.1435**	-0.0203	0.1118**	0.0755	-0.0455	-0.0330	15.0416**
1999	0.1304**	0.0269	-0.1131	0.1429	-0.0412	-0.0809	-0.0335	-0.1324*	-0.0230	12.9190*
2000	-0.0281	0.1496**	-0.0707	0.0404	0.0347	-0.0471	-0.0855	-0.0993	0.0409	4.4406
2001	0.0541	-0.0412	-0.0966	-0.0239	-0.0166	-0.0007	-0.0414	-0.1458	0.0024	5.3331
2002	0.0996**	0.0471	-0.1024	-0.1205*	0.0132	0.1837***	0.0973	0.0010	0.0899	20.1336***
2003	0.1623***	0.0979	0.1456**	0.0844	-0.0036	-0.1100*	0.0317	-0.0095	0.0413	14.7365**
2004	-0.0386	-0.0489	0.1149	-0.0615	0.0792	-0.1339	0.1159	0.0908	0.0454	10.0240
2005	0.0918	0.0039	-0.1395	0.0252	0.2211	-0.3722	-0.0351	-0.1842	-0.0099	5.8760
2006	2.1994	4.0626	0.0131	0.3076	-0.1033	0.0035	0.0135	0.8045	-0.3369	0.6574
2007	0.1325*	0.0682	-0.0291	0.0768	0.0421	0.0072	-0.0651	-0.0985	-0.0351	2.8385
2008	0.0618	0.0180	-0.1890**	0.1088	-0.0302	-0.1956	-0.0818	-0.0912	0.0011	8.4303
2009	-0.0389	0.0439	-0.0838	0.0145	-0.0865	-0.0764	-0.0531	0.0197	0.0339	7.7650
2010	-0.0068	-0.0642	-0.0099	-0.0603	-0.0409	0.0251	-0.1571	-0.0532	-0.0955	8.7623
2011	0.0989*	0.1186	0.0814	0.0284	0.0149	0.0912	0.1891	0.0669	0.1287*	10.7190
2012	-0.0158	0.0125	-0.0177	-0.1574**	-0.1085*	-0.0899	0.1466	0.0162	0.0436	10.8293
2013	0.0534	0.0854	0.1469**	0.0292	-0.0019	-0.1312	0.0489	0.1011	-0.0354	9.4644
2014	0.0853	0.1209	-0.1111**	0.0659	0.0892	0.0401	-0.0203	-0.0159	-0.0245	11.5556
2015	0.0370	0.1252*	0.0022	0.0297	-0.0820	0.0079	-0.0227	-0.0374	0.0043	2.3849
2016	0.0505	0.1592	-0.0090	0.0084	0.0064	-0.0301	-0.0390	-0.0397	-0.1209	1.7224
Joint Hypothesis	55.9406***	35.3494*	41.6824**	32.3221	19.2564	37.9869**	21.9866	20.8508	14.0993	223.4366***
χ^2(d.f.)	(25)	(25)	(25)	(25)	(25)	(25)	(25)	(25)	(25)	(175)

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. d.f. = degrees of freedom.

Panel 3.2 *Effects in Volatility*

Year	Lagged Variance	Weather Variables							Joint Weather Effects $\chi^2(7)$
		Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	
1992	0.0409	0.0440	0.1098	0.0717	-0.1131***	0.1047	0.1025	-0.1448**	15.0772**
1993	0.1195**	0.1261**	-0.0787	0.0167	0.0245	0.0321	0.0814	0.0918	9.4829
1994	0.2155**	0.0218	0.0489	-0.0852	-0.0087	0.0180	0.1137	0.0017	4.2690
1995	0.3349***	-0.0278	-0.0142	-0.0641	0.0349	0.0234	0.1291	0.0297	8.2069
1996	0.1498**	0.2418***	-0.0305	-0.1170*	-0.1332**	0.1912***	0.0991	0.0506	19.3070***
1997	0.1622**	0.0073	-0.0805	-0.1369*	-0.0486	0.1459**	0.0147	0.1044*	10.8962
1998	0.0552	-0.1837**	0.0508	0.0011	-0.1215*	0.1724	0.0698	0.0596	22.5689***
1999	0.1329*	0.1252*	-0.0888	-0.0255	0.0016	0.0855	0.0663	0.0261	5.9863
2000	-0.4501	0.0521	-0.1752**	0.1168	-0.0586	0.1191*	-0.2888***	0.1187*	12.0982*
2001	0.1715**	0.0225	0.0999	-0.1277	-0.0852	-0.1132	-0.0229	0.0683	9.6351
2002	0.3763***	0.0298	-0.1100	0.0138	0.1017	0.1319	0.0552	0.0972	5.5196
2003	0.1538*	-0.0188	-0.0087	0.0468	-0.0068	0.0235	-0.0773	-0.0490	2.6221
2004	0.1111	-0.0653	0.1569**	0.0145	-0.0322	-0.1206	0.1578	-0.0277	8.0594
2005	0.2950***	0.1052**	0.0120	0.0271	-0.0185	-0.0777	0.0939	-0.0628	8.6428
2006	0.0766	-0.0964	-0.0909	-0.0758	-0.2405*	0.0210	-0.1190	0.0561	5.3013
2007	0.1442**	-0.2095**	0.0247	0.0292	0.0211	-0.0717	-0.1268	-0.0381	8.9801
2008	0.1714***	-0.0284	-0.1456**	0.1408*	0.0154	-0.0356	-0.0775*	-0.0348	12.1540*
2009	-0.0024	0.0963	-0.0326	0.0066	0.0454	0.0497	0.0607	-0.0743	5.2753
2010	0.4546***	-0.0249	-0.0615	0.0361	-0.0089	0.1027*	-0.0849	-0.0545	10.1182
2011	0.0409	0.0440	0.1098	0.0717	-0.1131***	0.1047	0.1025	-0.1448**	15.0772**
2012	0.1195**	0.1261**	-0.0787	0.0167	0.0245	0.0321	0.0814	0.0918	9.4829
2013	0.2155**	0.0218	0.0489	-0.0852	-0.0087	0.0180	0.1137	0.0017	4.2690
2014	0.3349***	-0.0278	-0.0142	-0.0641	0.0349	0.0234	0.1291	0.0297	8.2069

2015	0.1498**	0.2418***	-0.0305	-0.1170*	-0.1332**	0.1912***	0.0991	0.0506	19.3070***
2016	0.1622**	0.0073	-0.0805	-0.1369*	-0.0486	0.1459**	0.0147	0.1044*	10.8962
Joint Hypothesis χ^2(d.f.)	200.4069*** (25)	44.3160** (25)	43.7116** (25)	33.8212 (25)	31.4038 (25)	46.9457*** (25)	47.4364*** (25)	44.3809*** (25)	265.4606*** (175)

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. d.f. = degrees of freedom.

The weather effect on stock returns is a weather-driven sentiment effect. It consists of an indirect, permanent component $\frac{\beta_s}{b_s} b_{m=1,..,M}$ and a direct, temporary component $a_{m=1,...,M} - \frac{\beta_s}{b_s} b_{m=1,...M}$. The roles of these two components was examined, as reported in Table 4.

From Table 4, Panel 4.1, the response coefficient δ —recovered from $\frac{\beta_s}{b_s}$, is not significant except for the year 2000. Neither the individual nor the joint contribution is significant. In Table 3, Panels 3.1 and 3.2, β_s and b_s are significant. Therefore, it is likely that the insignificance of δ results from the fact that δ was recovered imprecisely from the non-linear relationship $\delta = \frac{\beta_s}{b_s}$.

The permanent contributions are $\delta b_{m=1,..,M}$. The fact that they are not significant may stem from the imprecision of δ or from the small $b_{m=1,..,M}$. Recall that $\beta_s = \delta b_s$ and that b_s are significant. So, if $b_{m=1,..,M}$ is large, $\delta b_{m=1,..,M}$ should be significant. Checking the sizes of $b_{m=1,..,M}$ in Table 3, Panel 3.2, it can be found that $b_{m=1,..,M}$ values are much smaller than b_s. Furthermore, when checking the individual and joint contributions of the Wald statistics in the last row and column of Table 4, Panel 4.1, it is found that they are very small. Their p values were 0.99 or greater. The analysis leads to the conclusion that the indirect, permanent component is small and insignificant.

The significant aggregate effect in Table 3, Panel 3.1, together with a small and insignificant, indirect, permanent component in Table 4, Panel 4.1, implies a significant direct, temporary component. The temporary components $a_{m=1,...,m} - \frac{\beta_s}{b_s} b_{m=\,1,...,M}$ were estimated as reported in the results, Table 4, Panel 4.2. It was found that they were significant in the years 1998 and 2002. This component was not significant for the full sample test. It

Table 4: Decomposition of Weather Effects in Return

Panel 4.1: Permanent Components

Year	Response Co-efficient	Weather Variables							Joint Contribution $\chi^2(7)$
		Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	
1992	0.2986	0.2175	0.2233	0.2734	0.1671	0.2681	0.2861	0.2448	0.3331
1993	0.8981	0.5165	0.0204	2.0788	0.1197	0.8526	1.7416	1.6661	1.1699
1994	0.2803	0.5287	0.0020	0.3348	0.0128	0.0009	0.7664	0.0015	0.3614
1995	1.9980	0.2882	1.6280	0.1238	0.0469	0.9006	0.7486	0.0017	2.3039
1996	1.1738	0.0885	0.1019	0.1132	0.1142	0.1233	0.1018	0.1170	1.0417
1997	2.6350	0.1218	0.0922	0.0325	0.0704	0.0716	0.1076	0.1147	2.0646
1998	0.1229	0.1103	0.3549	0.8472	0.0257	0.0593	1.1478	0.0007	0.1401
1999	0.1222	0.0921	0.0309	0.1288	0.1596	0.0654	0.1808	0.0947	0.1460
2000	2.8905*	0.4897	0.1455	0.3841	0.4344	0.4673	0.3949	0.2160	1.5762
2001	0.2197	0.0127	0.6006	0.8082	0.3905	0.9038	0.0403	0.7273	0.2429
2002	0.5309	0.1626	0.0979	0.0003	0.1548	0.1734	0.1894	0.1590	0.5115
2003	1.2826	0.0052	0.0051	0.0044	0.0001	0.0051	0.0050	0.0050	1.0688
2004	0.1702	0.1934	0.1482	0.1808	0.1000	0.1635	0.1514	0.1588	0.2178
2005	0.0052	0.0744	0.1873	0.2182	0.2395	0.1979	0.0621	0.1486	0.0054
2006	0.1556	0.0407	0.0513	0.0333	0.0409	0.0495	0.0473	0.0456	0.3823
2007	0.2773	0.0341	0.0076	0.1920	0.0141	0.0405	0.1238	0.2159	0.3153
2008	0.0465	0.1988	0.3857	0.0444	0.1423	0.2818	0.3324	0.1605	0.0620
2009	0.1830	1.3498	0.0236	0.1425	0.0267	0.5271	0.9192	0.6559	0.2587
2010	0.4583	0.0373	0.0313	0.0336	0.0346	0.0188	0.0350	0.0321	0.4716
2011	1.5902	0.3284	0.0728	0.1905	0.0136	0.2038	0.2897	0.0871	1.7168
2012	0.0332	0.3194	0.6060	0.7171	0.2002	0.2548	0.5904	0.2971	0.0410
2013	0.4292	0.0012	0.0013	0.0009	0.0012	0.0013	0.0013	0.0012	0.5771
2014	0.9255	0.1390	0.7668	0.8970	0.0422	1.3480	1.0590	0.3059	0.8182
2015	0.0012	0.2175	0.2233	0.2734	0.1671	0.2681	0.2861	0.2448	0.0016
2016	2.1375	0.5165	0.0204	2.0788	0.1197	0.8526	1.7416	1.6661	1.8392
Joint Hypothesis χ^2(d.f.)	18.8653 (25)	6.3844 (25)	6.8638 (25)	8.0959 (25)	2.9847 (25)	7.1457 (25)	10.6676 (25)	5.9827 (25)	17.6670 (175)

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. d.f. = degrees of freedom.

Panel 4.2: Temporary Components

Year	Weather Variables							Joint Contribution $\chi^2(7)$
	Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	
1992	0.3266	0.5521	4.2006**	0.0571	0.5463	2.2287	2.3798	6.2141
1993	0.6197	0.0271	1.9986	1.4625	2.7781*	0.0057	1.3253	5.9334
1994	0.4225	4.7911**	0.0540	0.0956	0.8979	0.0259	0.7769	4.2419
1995	0.2917	0.1174	0.0280	0.0395	0.5000	0.0072	0.1943	5.6179
1996	1.4249	1.9463	0.2522	1.8570	0.1586	2.6023	0.1990	7.4646
1997	1.5139	0.0051	0.8673	0.2282	1.1467	2.0163	0.1994	6.5222
1998	1.9420	0.1193	0.0702	0.0058	0.2577	1.8589	0.0063	12.4899*
1999	1.2863	1.8315	0.1703	6.6206**	0.1139	0.0774	0.6386	5.3786
2000	2.6327	1.3490	0.3169	0.7487	0.1826	0.0313	0.0452	5.1529
2001	0.0133	0.0095	0.7035	0.6608	0.5261	0.8627	0.5088	5.7240
2002	1.8073	0.0676	0.4291	0.4241	0.1479	0.4150	0.0038	18.9441***
2003	0.1553	0.1689	0.2190	0.1236	0.1666	0.2033	0.1497	9.0048
2004	0.1725	0.0865	0.3207	0.2484	0.0180	0.6341	0.3452	7.6868
2005	5.1394**	1.7785	0.1063	2.2456	1.0957	1.5990	0.0033	5.2697
2006	0.4959	0.0208	1.9663	0.8871	0.2435	0.1323	0.3009	0.3669
2007	0.2019	0.0386	0.3181	0.0083	1.9346	0.0662	1.8409	2.1961
2008	0.2129	0.0540	0.0025	0.3544	2.0821	0.0772	3.9643**	8.5319
2009	0.0003	1.8930	0.9674	0.0425	2.2133	0.0917	0.1474	6.1452
2010	1.2055	0.0220	0.0491	0.3793	0.3204	0.9698	0.0111	11.4613
2011	1.6759	1.3583	0.0034	0.2602	0.0022	0.1072	3.41E-07	8.6730
2012	0.0012	0.0012	0.0005	0.0012	0.0012	0.0012	0.0012	8.2360
2013	9.52E-06	0.1170	0.0091	0.1174	0.5758	0.0113	0.3961	3.4587
2014	0.3266	0.5521	4.2006**	0.0571	0.5463	2.2287	2.3798	7.7895
2015	0.6197	0.0271	1.9986	1.4625	2.7781*	0.0057	1.3253	0.0021
2016	0.4225	4.7911**	0.0540	0.0956	0.8979	0.0259	0.7769	1.7401
Joint Hypothesis χ^2(d.f.)	24.9614 (25)	19.1954 (25)	14.3633 (25)	18.0446 (25)	17.1348 (25)	17.9173 (25)	14.0466 (25)	164.2459 (175)

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. d.f. = degrees of freedom.

is likely that the insignificance stems from the imprecise estimation of δ from $\frac{\beta_s}{b_s}$. Despite being insignificant, the Wald statistic of 164.2459 was high compared to the statistic for the permanent component of 17.6670.

DISCUSSION

The Misspecification of Weather Tests for Returns

The empirical results support Lee et al. (2002). In a weather test, the return equation necessarily includes the variance, if the variance is time-varying or conditionally time-varying.

Those studies, such as Symeonidis et al. (2010), did not consider time-varying variances; they were thus misspecified.

The misspecification does not always affect the analyses and tests. The fact that the time-varying variance does not appear in the return equation constitutes an omitted-variable problem. This problem can be addressed by an IV estimation (Furhwirth & Sogner, 2015; Khanthavit, 2017).

The Weather-Driven, investor sentiment Effect

In traditional sentiment studies, popular proxies include sentiment-survey indicators, trading volumes, and option open interests. However, these proxies are caused by stock returns and volatilities (Wang, Keswani, & Taylor, 2006), so that the results from those studies are questionable. From a sentiment-study perspective, the weather variables in this study are the sentiment proxy. The possibility that the returns or volatility affect the weather variables is therefore excluded. The significant weather effects on stock returns and volatility provide evidence of the role of noise traders in price formation in the Stock Exchange of Thailand.

CONCLUSION

In this study, weather effects were attributed to a weather-induced investor sentiment that affects stock returns and volatility; the test of weather effects therefore was based on a rigorous theory to ensure that the empirical model was well-specified and complete. To this end, the noise-trader-risk model of DeLong et al. (1990) and Thomas and Wang (2013) was used. The weather affected the return directly and indirectly. The direct effect was temporary. The indirect effect was permanent, via the response of stock returns to the weather-driven variance.

Using daily data on the SET index portfolio and Bangkok weather variables, significant weather effects were found on both stock returns and volatility. Further investigation revealed that only the direct, temporary component contributed to the effect on stock returns. The indirect, permanent component was small and insignificant.

From a sentiment-study perspective, weather effects are caused by a weather-driven sentiment. The findings provide evidence that support the role of noise traders in price formation in the Stock Exchange of Thailand.

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