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Disappearing Weather Effects:
Evidence from Thailand (2011 – 2016)

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Abstract

As the efficiency of the market improves, it is possible that weather effects cannot be detected by traditional, daily return tests. The effects may not exist at all, or they appear briefly but are traded against and disappear within the day. This study more closely examined weather effects, using intraday returns for the Thai stock market from 2011 to 2016, to identify the true cause of the disappearing effects in daily returns. It found no effects for the morning or afternoon trading sessions. Nor did it find any effects for the first and second fifteen minutes of the two sessions. The weather effects completely disappeared from the Thai stock market in recent years.

Keywords: *endogeneity problems, instrumental-variables estimation, intraday stock returns, Thai stock market, weather effects*

Introduction

In an efficient market, weather effects—the conditions in which weather influences stock returns via investors' changing moods (Howarth & Hoffman, 1984), cannot exist because the conditions do not affect the fundamentals of firms. However, significant weather effects had been reported for national and international markets (e.g., Cao & Wei, 2005; Furhwirth & Sogner, 2015).

For the Thai market, significant effects were reported, for example, by Khanthavit (2017a). As the efficiency of the market improved (Khanthavit, 2016), Khanthavit (2017b) found, for daily stock returns, that the effects were disappearing from the market in recent years. It is interesting and important to ask whether these effects completely disappeared in recent years, or whether they existed but disappeared quickly during the trading hours, similar to what was found for the U.S. market by Chang et al. (2008) and the Chinese market by Lu and Chou (2012). Nonexistence of weather effects even in intraday returns provides additional evidence to support the improved efficiency of the Thai market; the existence but quick disappearance of the effects suggests remaining inefficiency and profit opportunities for rational traders to trade against weather-sensitive investors during some trading hours.

In this study, I used recent intraday returns on the SET index portfolio from 2011 to 2016 to test for weather effects in trading sessions. The estimation followed the approach suggested by Khanthavit (2017a) to ensure that the results were not driven by incorrect fixed-effect assumptions and endogeneity problems present in most weather studies.

Methodology

The Regression Model

I related the trading session return linearly with M weather variables, as in equation (1).

$$\mathrm{r}_{\mathrm{t}}^{\mathrm{s}} = \beta_1^{\mathrm{s}} \mathrm{W}_{1,\mathrm{t}}^{\mathrm{s}} + \cdots + \beta_{\mathrm{M}}^{\mathrm{s}} \mathrm{W}_{\mathrm{M},\mathrm{t}}^{\mathrm{s}} + \mathrm{e}_{\mathrm{t}}^{\mathrm{s}}, \tag{1}$$

where $\mathrm{r}_{\mathrm{t}}^{\mathrm{s}}$ is the return for trading session s on day t, $\mathrm{W}_{\mathrm{m,t}}^{\mathrm{s}}$ is the weather variable m immediately at or prior to trading session s on day t, $\beta_{\mathrm{m}}^{\mathrm{s}}$ is the coefficient for weather variable m, and $\mathrm{e}_{\mathrm{t}}^{\mathrm{s}}$ is the regression error. $\mathrm{m} = 1, 2, \ldots, \mathrm{M}$.

In equation (1), I did not add lagged return $\mathrm{r}_{\mathrm{t}-1}^{\mathrm{s}}$, as was practiced earlier by Chang et al. (2008). I did not estimate the intercept coefficient because all the variables were standardized by their averages and standard deviations.

The fact that $\beta_{\mathrm{m}}^{\mathrm{s}}$ is different from zero suggests the significance of weather variable m. Moreover, if the weather effect exists for trading session s, the joint hypothesis in equation (2) must be rejected.

$$\beta_1^{\mathrm{s}} = \cdots = \beta_{\mathrm{M}}^{\mathrm{s}} = 0 \tag{2}$$

The hypotheses are tested by Wald statistics. Under the null hypotheses of zero $\beta_{\mathrm{m}}^{\mathrm{s}}$ and of no weather effects, the statistics are distributed as chi-square variables with one and M degrees of freedom, respectively. All analyses are based on heteroscedasticity and autocorrelation consistent covariance (HAC) matrices to correct the problems from possible heteroskedastic and autocorrelated $\mathrm{e}_{\mathrm{t}}^{\mathrm{s}}$.

Model Estimation

Estimation Problems and Mitigation

Khanthavit (2017a) noted that the model estimation and test of equation (1) by traditional ordinary least squares regressions on long-sample data relied on an incorrect, fixed-effect assumption. It also suffered endogeneity problems induced by the measurement errors in those M weather variables and the omission of significant variables beyond the M variables.

To lessen effects of the incorrect assumption, I estimated the model and computed chi-square statistics using a sample period of one year at a time. The statistics for a full sample test is the sum of statistics for all the N years in the full period. Under the null hypothesis, the statistics for the $\beta_{\mathrm{m}}^{\mathrm{s}}$ test are chi-square variables with N degrees of freedom, while the statistics for the tests for weather effects are chi-square variables with $(\mathrm{N} \times \mathrm{M})$ degrees of freedom (Doyle & Chen, 2009). I mitigated the endogeneity problems by Hansen's (1982) generalized method of moments (GMM). Being considered as an instrumental-variables approach, GMM makes use of the orthogonality conditions to allow for efficient estimation. GMM 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

Desirable informative variables (IVs) must be informative and valid, meaning they are highly correlated with the weather variable $\mathrm{W}_{\mathrm{M,t}}^{\mathrm{s}}$ and uncorrelated with the error term $\mathrm{e}_{\mathrm{t}}^{\mathrm{s}}$. In this study, I chose a two-step approach in Racicot and Theoret (2010) to construct the IVs. In the first step, I considered the set $\left\{\boldsymbol{\iota}_{\mathrm{T}}, \mathbf{z}_{\mathrm{P}}^{1}, \cdots, \mathbf{z}_{\mathrm{P}}^{\mathrm{M}}\right\}$ of IVs because of its small size in addition to informativeness and validity performance (Khanthavit, 2017a). $\boldsymbol{\iota}_{\mathrm{T}}$ is a unit vector. $\mathbf{z}_{\mathrm{P}}^{\mathrm{m}}$ is Pal's (1980) cumulant IV; it is conveniently derived from the weather variable $\mathrm{W}_{\mathrm{m,t}}^{\mathrm{s}}$, as follows.

$$\mathbf{z}_{\mathrm{P}}^{\mathrm{m}} = \mathbf{w}^{\mathrm{m}} * \mathbf{w}^{\mathrm{m}} * \mathbf{w}^{\mathrm{m}} - 3\mathbf{w}^{\mathrm{m}}\left[\mathrm{E}\left(\frac{\mathbf{w}^{\mathrm{m}\prime}\mathbf{w}^{\mathrm{m}}}{\mathbf{T}}\right) * \mathbf{I}_{\mathrm{T}}\right], \tag{3}$$

where $\mathbf{w}^{\mathrm{m}}$ is the vector of deviations of $\mathrm{W}_{\mathrm{m,t}}^{\mathrm{s}}$ from its mean, $\mathbf{I}_{\mathrm{T}}$ is the identity matrix of size T—the number of observations in the full sample, and * denotes the Hadamard matrix multiplication operator. In the second step, $\mathrm{W}_{\mathrm{m,t}}^{\mathrm{s}}$ was regressed on $\left\{\boldsymbol{\iota}_{\mathrm{T}}, \mathbf{z}_{\mathrm{P}}^{1}, \cdots, \mathbf{z}_{\mathrm{P}}^{\mathrm{M}}\right\}$ and the regression residual was treated as the IV for $\mathrm{W}_{\mathrm{m,t}}^{\mathrm{s}}$ in the estimation.

The Data

The stock price data are the intraday Stock Exchange of Thailand index (SET index), covering a period from January 4, 2011 to December 30, 2016 (1,466 observations). These data are from the Stock Exchange of Thailand and Phatra Securities, PLC.

The study examined the effects in the morning and afternoon returns; it also took a closer look into the first and second fifteen-minute returns of the two trading sessions:

(i) from the morning opening time to the morning opening time plus fifteen minutes,

(ii) from the morning opening time plus fifteen minutes to the morning opening time plus thirty minutes,

(iii) from the afternoon opening time to the afternoon opening time plus fifteen minutes, and

(iv) from the afternoon opening time plus fifteen minutes to the afternoon opening time plus thirty minutes.

The returns are log differences of the SET indexes at the ending and opening times of the sessions. The analyses of these early session returns are important. As the Thai market's efficiency improves, the weather effects can still exist. However, they are traded against, disappear within a few minutes, and never show in daily, full morning, or full afternoon returns. Chang et al. (2008) reported for the U.S. market that the effects existed but disappeared within the first fifteen minutes of the morning session; Lu and Chou (2012) reported for the Chinese market that the effects from extreme weather conditions such as snow existed only in the first thirty minutes of the morning session.

In this study, the weather variables are air pressure (hectopascal), cloud cover (decile), ground visibility (km), rainfall (mm), relative humidity (%), temperature (°C), and wind speed (knots per hour). These variables are the same ones considered by previous studies for the Thai stock market (e.g., Khanthavit, 2017a; 2017b); they are Bangkok weather variables, measured by the Thai Meteorological Department's weather station at Don Muang Airport. The data coverage began on January 1, 1991, and ended on December 31, 2016. I retrieved the data from the Thai Meteorological Department's database.

During the sample period, the SET's trading hours are from a random morning opening time (between 9.55 and 10.00) to 12.30 and from a random afternoon opening time (between 14.25 and 14.30) to a random closing time (between 16.35 and 16.40). Following Chang et al. (2008), I estimated and tested the model for the morning and afternoon sessions and fifteen-minute sub-sessions by the weather variables measured at 10.00 and 14.00, respectively, so that the measurement times were approximately at and immediately prior to the opening times (Chang et al., 2008).

Weather conditions are seasonal. Due to faulty equipment or missed observations, some observations are missing. I deseasonalized the weather variables, as in Hirshleifer and Shumway (2003), with their averages for each week of the year over the 1991-2016 sample period. Zero was imputed in the missing cases, as in Khanthavit (2017a), because it was the unconditional means of deseasonalized variables.

Table 1 reports the descriptive statistics of the standardized returns and weather variables. The Jarque-Bera tests rejected the normality hypothesis for all the variables; all the variables, except for the first fifteen-minute returns in the morning and afternoon, showed significant AR(1) coefficients. To note, the GMM results are not affected by non-normality. The significant AR(1) coefficients support the use of HAC covariance matrices in the analyses.

Weather variables can be highly correlated and cause multicollinearity problems in estimation (Worthington, 2009). To ensure that the problems did not exist, I computed the variance inflation factors (VIFs) for the weather variables at 10.00 and 14.00 and reported them in Table 2. The largest VIF is 2.6961, which is much smaller than the significance threshold of 10.00.

Table 1. Descriptive Statistics of Standardized Returns and Weather Variables

Session		Statistics			
		Skewness	Excess Kurtosis	Jarque-Bera Statistic	AR(1) Coefficient
Open-to-Close Daily Return		-0.5195	2.7562	5.30E+02***	-0.0511*
Morning Return	Morning Open to Morning Close	-2.2857	22.3856	3.19E+04***	0.0822***
	Open to Open+15 Mins.	-0.6332	3.2961	7.62E+02***	-0.0415
	Open+15 Mins. to Open+30 Mins.	-1.0537	6.4307	2.80E+03***	0.0083
Afternoon Return	Afternoon Open to Afternoon Close	0.0596	5.0189	1.54E+03***	-0.0869***
	Open to Open+15 Mins.	0.7803	6.8972	3.05E+03***	0.0054
	Open+15 Mins. to Open+30 Mins.	0.1011	8.6003	4.52E+03***	0.1062***
Weather Variable at 10.00	Air Pressure	-0.0288	0.5709	20.1121***	0.7520***
	Cloud Cover	-0.0787	0.3537	9.1555**	0.3227***
	Ground Visibility	-1.4364	4.9796	2.02E+03***	0.4085***
	Rainfall	12.2299	1.83E+02	2.09E+06***	0.0828***
	Relative Humidity	0.4421	0.5033	63.2253***	0.4843***
	Temperature	-1.5404	5.5112	2.44E+03***	0.5944***
	Wind Speed	13.7414	2.94E+02	5.33E+06***	0.0897***
Weather Variable at 14.00	Air Pressure	0.0258	0.4481	12.4298***	0.7262***
	Cloud Cover	-0.1023	0.2587	6.6460**	0.3728***
	Ground Visibility	-4.3147	26.6893	4.81E+04***	0.1339***
	Rainfall	12.1267	1.76E+02	1.94E+06***	0.1678***
	Relative Humidity	1.1212	2.3662	6.49E+02***	0.4084***
	Temperature	-1.4731	4.6245	1.84E+03***	0.4747***
	Wind Speed	0.0104	0.2995	5.5057*	0.1843***

*, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively.

Table 2. Test for Multicollinearity among Weather Variables

Weather Variable	Variance Inflation Factor	
	At 10.00	At 14.00
Air Pressure	1.2192	1.2455
Cloud Cover	1.5055	1.5406
Ground Visibility	1.1074	1.1477
Rainfall	1.1471	1.1587

Relative Humidity	1.7142	2.6961
Temperature	1.4842	2.3641
Wind Speed	1.0350	1.0236

Informative and valid IVs are important for GMM estimation. I checked for the informativeness and validity quality. For informativeness in Table 3, Panel 3.1, the R^2s of the IVs with their corresponding weather variables are high. The averages for the morning and afternoon sessions are 0.7196 and 0.7545, respectively; even the minimums are still high at 0.3036 and 0.3146. In Table 3, Panel 3.2, the small R^2s of the error terms with the IVs ensure the validity.

Table 3. Quality of Instrumental Variables

Panel 3.1 Informativeness

Weather Variable	**R^2 of Weather Variable with Corresponding IV**	
	At 10.00	**At 14.00**
Air Pressure	0.9540	0.9652
Cloud Cover	0.9601	0.9587
Ground Visibility	0.7359	0.5226
Rainfall	0.3036	0.3146
Relative Humidity	0.9314	0.7978
Temperature	0.7872	0.7561
Wind Speed	0.3647	0.9666
Average	0.7196	0.7545
Maximum	0.9601	0.9666
Minimum	0.3036	0.3146

Panel 3.2 Validity

Session		**R^2 of Regression Error with IVs**
Morning	Open to Open+15 Mins.	0.0006
	Open+15 Mins. To Open+30 Mins.	0.0008
	Morning Open to Morning Close	0.0022
Afternoon	Open to Open+15 Mins.	0.0045
	Open+15 Mins. To Open+30 Mins.	0.0009
	Afternoon Open to Afternoon Close	0.0015

Empirical Results

Tests for Weather Effects

Before I proceeded with the test results for intraday returns, I checked for significant effects in daily returns from 2011 to 2016. To be comparable with previous studies, the weather variables for this daily return test were the averages of the variables from 6.00 to 16.00, rather than the variables at 10.00 or 14.00 for the intraday-return tests. In Table 4, row 3, the daily return result supported Khanthavit (2017b). The weather effects in daily returns were not significant.

In the intraday results in Table 4, rows 4 to 9, the effects were not significant for the morning or the afternoon sessions. Neither were they significant for their two early fifteen-minute sub-sessions.

Robustness Checks

The intraday-return tests relied on the weather variable exactly at 10.00 and 14.00. It is important to recall that weather effects are driven by weather-sensitive investors. If the investors are not exposed to the weather conditions at 10.00 or 14.00, the tests will not be able to detect the effects. For example, the investors may arrive at their trading rooms early in the morning at 7.00; they may leave for lunch and return at 13.00.

I checked for robustness of the results in Table 4 by substituting the weather at 10.00 by the average weather from 6.00 to 10.00, and the weather at 14.00 by the average weather from 13.00 to 14.00. In Table 5, I found similar results. There were no weather effects in the intraday returns.

Based on the findings in Tables 4 and 5, I concluded that the weather effects did not exist even briefly during the day. They disappeared completely from the Thai stock market in recent years.

Table 4. Test Results for Weather Effects

Session		Significant Weather Variable (χ^2_6)							Significant Weather Effects (χ^2_{42})
		Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	
Traditional Full Day Close to Close[a]		9.3060	7.4353	7.3971	1.9107	5.6373	2.3132	6.5829	47.4041
Morning[b]	Morning Open to Morning Close	7.2153	3.6376	1.9189	7.8288	4.1909	8.4126	3.2397	32.6991
	Open to Open+15 Mins.	5.7946	6.4871	10.0770	11.6364*	4.6756	3.6220	0.7882	49.0806
	Open+15 Mins. to Open+30 Mins.	1.1249	14.4798**	2.5687	3.6887	1.8032	3.5374	3.5124	31.8241
Afternoon[c]	Afternoon Open to Afternoon Close	4.4274	8.9816	2.0176	2.3891	1.9308	7.2536	7.1679	41.0430
	Open to Open+15 Mins.	10.1477	9.0471	2.4452	9.9045	4.7001	9.8804	2.6147	52.3957
	Open+15 Mins. to Open+30 Mins.	4.5706	4.0004	10.0158	2.2622	4.2206	7.7831	4.6335	39.5100

Note: [a] = average weather variables from 6.00 to 16.00. [b] and [c] = weather variables at 10.00 and 14.00. * and ** = significance at the 90% and 95% confidence levels, respectively.

Table 5. Robustness Checks

Session		Significant Weather Variable (χ^2_6)							Significant Weather Effects (χ^2_{42})
		Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	
Morning[a]	Morning Open to Morning Close	7.1062	2.8010	0.5680	6.5857	2.0403	7.9042	4.7392	40.6267
	Open to Open+15 Mins.	2.9783	2.8574	6.3232	9.5345	3.7420	2.0800	3.5264	52.8592
	Open+15 Mins. to Open+30 Mins.	2.4163	9.3791	3.6506	6.0953	3.0751	5.2493	0.7561	27.3653
Afternoon[b]	Afternoon Open to Afternoon Close	4.8139	10.6671*	1.5244	2.8177	3.4792	7.6746	3.4113	43.1492
	Open to Open+15 Mins.	10.4417	9.3693	1.7344	8.3973	5.3256	9.0005	3.5485	50.3551
	Open+15 Mins. to Open+30 Mins.	5.6217	4.6404	8.2278	2.2700	5.1457	10.4207	4.0258	37.9639

Note: [a] and [b] = Average Weather variables from 6.00 to 10.00 and from 13.00 to 14.00. * = significance at the 90% confidence level.

Discussion

Chang et al. (2008) and Lu and Chou (2012) reported significant weather effects in the intraday returns during the first fifteen and thirty minutes of morning trading session. Significant weather effects suggest market inefficiency. Why had the effects existed in the U.S. and Chinese markets but not in the Thai market?

First, the U.S. market is considered. Although the U.S. market is much more developed than the Thai market, three explanations for significant weather effects are possible. First, the sample returns in Chang et al. (2008) were old, dating from January 1, 1994 to December 31, 2004. Due to the old sample, the significant results could reflect the inefficiency of the U.S. market in the distant past. Second, the sample covered a total of eleven years, and Chang et al. (2008) used the full sample in estimation. Even if the U.S. market gained efficiency and the effects disappeared in the later subsample, the full-sample effects were from the dominant early subsample effects. Third, as in most weather studies, Chang et al. (2008) suffered fixed-effect assumption and endogeneity problems; the significance could be induced by those problems.

Next, the Chinese market is considered. Lu and Chou (2012) tested for the effects for China from 2003 to 2008, while I did so for Thailand from 2011 to 2016. The Chinese and Thai markets are both emerging markets. Therefore, one possible explanation could be the efficiency level of the Chinese market in those past years. Another possible explanation is the third explanation I proposed for Chang et al. (2008).

Conclusion

Weather effects are an indication of market inefficiency. Therefore, they should be weaker and disappear as the efficiency improves. Traditional weather studies relied on daily return tests, resulting in their inability to detect the significant effects if they still arise but are traded against and disappear quickly within a few minutes. Alternatively, the inability to detect the effects in daily returns results from the effects completely disappearing from the market. In this study, I tested for the effects for the Thai stock market using intraday returns from 2011 to 2016. The findings led me to conclude that the effects had disappeared completely from the Thai stock market.

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References

Cao, M., & Wei, J. (2005). Stock market returns: A note on temperature anomaly. *Journal of Banking and Finance*, *29*(6), 1559-1573.

Chang, S., Chen, S., Chou, R. K., & Lin, Y. (2008). Weather and intraday patterns in stock returns and trading activity, *Journal of Banking and Finance*, *32*(9), 1754-1766.

Doyle, J. R., & Chen, C. H. (2009). The wandering weekday effect in major stock markets. *Journal of Banking and Finance*, *33*(1), 1388-1399.Durbin, J. (1954). Errors in variables. *Review of the International Statistical Institute*, *22*(1/3), 23-32.

Furhwirth, M., & Sogner, L. (2015). Weather and SAD related effects on the financial market. *Quarterly Review of Economics and Finance*, *57*, 11-31.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(3), 1029–1054.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *Journal of Finance, 58*(3), 1009-1032.

Howarth, E., & Hoffman M. S. (1984). A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology, 75*(1), 15-23.

Khanthavit, A. (2016a). The fast and slow speed of convergence to market efficiency: A note for large and small stocks on the Stock Exchange of Thailand. *Social Science Asia*, *2*(2), 1-6.

Khanthavit, A. (2017a). Instrumental-variable estimation of Bangkok-weather effects in the Stock Exchange of Thailand. *Asian Academy of Management Journal of Accounting and Finance*, *13*(1), 83-111.

Khanthavit, A. (2017b). Weather-induced mood effects on stock returns, *Thammasat Review*, *20*(1).

Lu, J., & Chou, R. K. (2012). Does the weather have impacts on returns and trading activities in order-driven stock markets? Evidence from China, *Journal of Banking and Finance*, *19*(1), 79-93.

Pal, M. (1980). Consistent moment estimators of regression coefficients in the presence of errors in variables. *Journal of Econometrics*, *14*(3), 349-364.

Racicot, F. E., & Theoret, R. (2010). Optimal instrumental variables generators based on improved Hausman regression, with an application to hedge fund returns. *Journal of Wealth Management*, *13*(1), 103-123.

Worthington, A. (2009). An empirical note on weather effects in the Australian stock market, *Economic Papers*, *28*(2), 148-154.