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Weather-Induced Mood Effects on Stock Returns

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Abstract

Weather effects exist, as weather influences investors' mood, compelling them to raise or lower asset prices. These effects are indirect, as weather affects returns via mood – weather does not directly affect returns. Weather effects are, in fact, weather-induced mood effects. In this study, I estimated a model of weather-induced mood effects in its full form, which was the only way to identify and estimate the model. The model in its reduced from had exactly the same form as did the direct weather-effect model.

Using the daily returns on Thailand's stock index portfolios, this study found that all weather variables – air pressure, cloud cover, ground visibility, rainfall, relative humidity, temperature, and wind speed – significantly affected mood. The mood effects on the returns were time varying; they were wandering and significant in the early sample period – up to 2009 – but disappearing in the later period – from 2010 onward. The findings help to explain why previous studies reported insignificant effects on returns from certain weather variables even though the psychological literature suggested that these variables were important.

Keywords

Instrumental Variable Estimation, Mood Effects, Weather Effects

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Introduction

Weather effects—the effects of the weather in the areas where markets are located on asset returns—have been studied extensively for national and international markets. Reviews are given by Cao and Wei (2005) for early studies and Furhwirth and Sogner (2015) for recent studies. Most studies have treated weather variables as being exogenous and related the returns linearly with the variables, implying a direct effect of weather on returns. Ordinary least squares (OLS) estimates were best linear unbiased estimates. Significant slope coefficients were used as evidence of the effects.

Weather effects exist in an inefficient market, as weather influences investors' moods (e.g., Howarth & Hoffman, 1984), compelling them to raise or lower asset prices. Although the fundamentals of the assets remain unchanged, rational investors are unable to trade against weather-sensitive investors and drive away the effects. Given this mechanism, the effects cannot be direct; rather, they must be indirect from weather to mood and, finally, from mood to returns. Weather effects are, in fact, weather-induced mood effects.

Furhwirth and Sogner (2015) developed a model that considered the transmission channel from weather to returns via mood. Because mood could not be observed, the researchers treated mood variables as latent variables. The model's reduced form was exactly the same as that of the direct-effect model. The researchers also showed that the indirect effect model in its reduced form had endogeneity problems; the direct- and reduced-form, indirect-effect models were estimated differently by OLS and instrumental-variable (IV) regressions, respectively.

Recently, Khanthavit (2017) estimated the direct weather effect model for the Stock Exchange of Thailand (SET). Noticing that the weather variables were measured with errors and that certain influential variables were potentially omitted, the researcher employed IV regressions to overcome endogeneity problems and to obtain consistent estimates.

When endogeneity problems result from indirect weather effects (Furhwirth & Sogner, 2015) and from errors-in-variables (EIV) and omitted-variables (OV) problems (Khanthavit, 2017), both direct and indirect effect models must be estimated by IV regressions, implying that the indirect model cannot be differentiated from the direct one by using IV regressions over OLS regressions.

I agree with Furhwirth and Sogner (2015). The correct model for weather effects must be a weather-induced mood effect model. In this study, I estimate the model in its full form. The study is important. It is the first study to estimate the full model for weather-induced mood effects. In previous studies (e.g., Dowling & Lucey, 2008; Lu & Chou, 2012), all weather variables were carefully chosen with respect to psychological studies to ensure that they were important for mood. However, only a limited number of these variables showed significant effects on returns. The full-model estimation enables me to examine explicitly how and how much weather affects mood and mood affects returns. Any insignificant findings will be explained.

The full model fits well in a state-space framework. The relationship between returns and the unobserved mood variable is described by the measurement equation, while that between the unobserved mood variable and weather variables is described by the transition equation. I improve the model further in two important ways. First, when the sample period is long, it is unlikely that the relationship between returns and mood and other variables remain fixed over the period. To avoid misspecification from a fixed-effect assumption, I allow the coefficients in the measurement equation to move randomly. This specification is general. It implies fixed effects if the volatilities of the coefficients are small.

I treat the unobserved random coefficients as latent or state variables and describe their behaviors in the transition equations. When the coefficients are random, the model is complicated because the returns have a nonlinear relationship with the mood coefficient and mood variables. I estimate the nonlinear state-space model with extended Kalman filtering.

Second, although the full model is estimated, endogeneity problems still exist. Weather variables are measured with errors, and some influential variables may be omitted. I follow Dooley and Mathieson (2007) to correct the problems and obtain consistent parameter estimates by substituting IV variables for the weather variables.

Using the SET, SET 50, and Market for Alternative Investment (mai) index returns from the Stock Exchange of Thailand and seven weather variables – air pressure, cloud cover, ground visibility, rainfall, relative humidity, temperature, and wind speed – this study found that the weather-induced mood effects on returns changed randomly. Significant effects were found frequently in the early sample period, that is, until 2009. They were less volatile and insignificant in the later period, that is, from 2010 onward. All the weather variables had significant effects on mood. These findings are important. They help to explain insignificant effects of certain weather variables reported by previous studies, even though the psychological literature suggested that these variables were important. Insignificance was caused by the fact that mood effects were time-varying and could be insignificant in certain periods over the full sample; it was not caused by the weather variables' lack of an impact on mood.

Methodology

The Model

I follow Furhwirth and Sogner (2015) to relate the return $\tilde{r}_t$ on day t with its lag r_{t-1} and the mood variable $\tilde{\mu}_t$, as in equation (1).

$$\tilde{r}_t = \tilde{\rho}_t r_{t-1} + \tilde{\beta}_t \tilde{\mu}_t + \tilde{e}_t. \quad (1)$$

$\tilde{\rho}_t$ is the return's autocorrelation coefficient, $\tilde{\beta}_t$ is the mood-effect coefficient, and $\tilde{e}_t$ is the error term. The symbol " $\tilde{}$ " indicates random variables. The error $\tilde{e}_t$ is normally distributed, with a zero mean and σ standard deviation. I assume a zero intercept because the sample data are daily and the mean return is not significantly different from zero. The lagged return is added to describe possible return autocorrelation.

I allow $\tilde{\rho}_t$ and $\tilde{\beta}_t$ to move randomly. The sample period is long. A fixed-coefficient assumption is neither realistic nor supported by the findings in previous studies. For example, Lo (2004) found for U.S. stocks that the autocorrelation coefficients varied over time. In Furhwirth and Sogner (2015), the mood variable was related linearly with weather variables in a mood equation. Substituting the mood equation for the mood variable $\tilde{\mu}_t$ and fixing the coefficients $\tilde{\rho}_t$ and $\tilde{\beta}_t$ makes equation (1) a traditional weather-driven return equation. Researchers (e.g., Saunders, 1993; Yoon & Kang, 2009) found that weather effects were significant in some sample periods but not in others. These findings were not consistent with fixed mood effects.

Equation (2) describes the dynamics of $\tilde{\rho}_t$, $\tilde{\beta}_t$, and $\tilde{\mu}_t$.

$$\begin{bmatrix} \tilde{\rho}_t \\ \tilde{\beta}_t \\ \tilde{\mu}_t \end{bmatrix} = \begin{bmatrix} \rho_{t-1} \\ \beta_{t-1} \\ c_1 W_t^1 + \cdots + c_M W_t^M \end{bmatrix} + \begin{bmatrix} \tilde{u}_t \\ \tilde{v}_t \\ \tilde{w}_t \end{bmatrix}. \quad (2)$$

W_t^m is the weather variable m. c_m is the coefficient for the effect of W_t^m on mood. $m = 1, \ldots, M$. The normal-error vector $[\tilde{u}_t \quad \tilde{v}_t \quad \tilde{w}_t]'$ has a zero mean vector and covariance matrix Q. I assume a random walk for $\tilde{\rho}_t$ and $\tilde{\beta}_t$ because the coefficients should move gradually (Rockinger & Urga, 2000). As in Furhwirth and Sogner (2015), the mood variable $\tilde{\mu}_t$ is related linearly with the weather variables $W_t^{m=1,\ldots,M}$.

Equations (1) and (2) relate weather indirectly to the return via investors' mood. Furhwirth and Sogner (2015) assumed a fixed mood effect, while I allow the effect to vary over time. The time-variation specification is important. When the effect is time-varying, Furhwirth and Sogner's (2015) fixed-mood-effect model is misspecified.

Estimation

Extended Kalman Filtering

The model fits within a state-space framework. Equation (1) is the measurement equation. The unobserved variables $\tilde{\rho}_t$, $\tilde{\beta}_t$, and $\tilde{\alpha}_t$ are treated as state variables, whose random behaviors are described by the transition equation (2).

In equation (1), the return $\tilde{r}_t$ is a non-linear, multiplication function of the state variables $\tilde{\beta}_t$ and $\tilde{\alpha}_t$. The model can be studied by extended Kalman filtering. The multiplication function is linearized around the means $b_{t|t-1}$ and $a_{t|t-1}$, respectively, of $\tilde{\beta}_t$ and $\tilde{\alpha}_t$, conditioned on the observed variables up to time t-1. Then, the linearized measurement equation in equation (3) approximates the non-linear equation (1) (Harvey, 1989, pp. 160-162).

$$\tilde{r}_t \cong \tilde{\rho}_t r_{t-1} + \tilde{\beta}_t a_{t|t-1} + b_{t|t-1}\tilde{\alpha}_t - b_{t|t-1}a_{t|t-1} + \tilde{e}_t. \qquad (3)$$

Equations (3) and (2) constitute a linear state-space model, which is estimated by linear Kalman filtering.

Endogeneity Problems

Endogeneity problems still exist in the full-model estimation. In equation (2), the weather variables are measured with errors; it is likely the M weather variables are not all the influential variables (Khanthavit, 2017).

Weather variables can be missing due to faulty equipment or missed observations. External data need to be imputed in order to complete the series. The imputed data necessarily contained errors. Even if the variables are not missing, they still have measurement errors. The weather variables are observed at a weather station located near the market. Because the areas surrounding the market in which investors' trade can be very large, these variables cannot affect investors uniformly. They are proxies, and they contain errors.

In this study, there are M = 7 variables: air pressure, cloud cover, ground visibility, rainfall, relative humidity, temperature, and wind speed. This set is considered large compared with those of previous studies (e.g., Lu & Chou, 2012). Still, it does not cover all possible influential variables. Some variables are omitted. For example, geomagnetic storms, which were suggested by Dowling and Lucey (2008), are omitted because they are not measured by the Thai Meteorological Department.

Instrumental Variable Estimation

Endogeneity problems in the Kalman filtering estimation can be overcome by substituting IV variables for the weather variables in equation (2) (Dooley & Mathieson, 2007). It is important to choose IVs carefully. The IVs must be informative and valid. Informative IVs are highly correlated with the weather variable W_t^m; valid IVs are uncorrelated with the error $\tilde{w}_t$.

I choose Racicot and Theoret's (2010) two-step IVs. In their study, the adjusted R^2's with the dependent variables could reach eighty percent and the correlation with the error was almost zero. In the first step, I consider the set $\{\mathbf{\iota}_T, \mathbf{z}_D^1, \mathbf{z}_P^1, \cdots, \mathbf{z}_D^M, \mathbf{z}_P^M\}$ of IVs. This set was suggested by Dagenais and Dagenais (1997) due to its small size and good performance. $\mathbf{\iota}_T$ is a unit vector. $\mathbf{z}_D^m$ and $\mathbf{z}_P^m$, Durbin's (1954) and Pal's (1980) cumulant IVs, are conveniently constructed from the weather variable W_t^m as follows.

$$\mathbf{z}_D^m = \mathbf{w}^m * \mathbf{w}^m, \tag{4}$$

$$\mathbf{z}_P^m = \mathbf{w}^m * \mathbf{w}^m * \mathbf{w}^m - 3\mathbf{w}^m \left[E\left(\frac{\mathbf{w}^{m\prime}\mathbf{w}^m}{T}\right) * \mathbf{I}_T\right], \tag{5}$$

where $\mathbf{w}^m$ is the vector of deviations of W_t^m from its mean, $\mathbf{I}_T$ is the identity matrix of size T, and * denotes the Hadamard matrix multiplication operator. In the second step, W_t^m is regressed on $\{\mathbf{\iota}_T, \mathbf{z}_D^1, \mathbf{z}_P^1, \cdots, \mathbf{z}_D^M, \mathbf{z}_P^M\}$ and the regression residual is treated as the IV for W_t^m in the estimation.

The Data

Sample Market

I chose the SET. The market is well qualified for the sample market for a weather study. The SET is rapidly growing and represents one of the most important emerging markets in the world. It is now considered an advanced emerging market (FTSE Russell, 2016).

In weather studies, it is hypothesized that returns are driven by the trading of weather-sensitive investors who domicile in the area surrounding the market. Located in Bangkok, the SET is Thailand's only stock market. Stock News Online (2015) reported that there were 1,134,500 open stock accounts in February 2015, and 88% of these accounts were in the Bangkok metropolitan area. Thus, Bangkok weather affects most investors.

Bangkok is much larger than New York City. It covers an area of 1,569 square kilometers, while New York City covers only 789 square kilometers. Bangkok weather variables are measured by the Thai Meteorological Department's weather station at Don Muang Airport. The airport is 25 kilometers from the SET's former location and 22 kilometers from its current location. It is important to note that some weather variables, such as geomagnetic storms, are not measured by the weather station. Moreover, some measured variables are missing at times. These conditions for Thailand's SET constitute measurement errors and omitted variables for the weather in equation (2), thereby leading to endogeneity problems in the estimation, even though the model is in its full form. The endogeneity problems enable me to demonstrate the ability of the proposed technique to correct the existing problems.

Sample Stock Returns

The stock returns are daily, computed from log differences of the closing SET, SET 50, and mai indexes. The SET index is a broad-based, value-weighted index of all stocks on the SET; the SET 50 index is the value-weighted index of the fifty largest and most actively traded stocks; and the mai index is the value-weighted index of all stocks on the mai. The SET, SET 50, and mai index returns began on January 2, 1991, August 17, 1995, and September 3, 2002, respectively. All index returns ended on December 30, 2015. The indexes were retrieved from the SET's database.

Approximately 58% and 96% of the trading volumes of SET and mai stocks are from small, individual investors, and the remainder are from local institutes, proprietary traders, and foreign investors. The SET index is chosen to represent the overall market, while the SET 50 and mai indexes represent the parts of the market that are dominated by large investors and individuals, respectively.

Weather Variables

The weather data are for Bangkok weather and are 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, 2015. I retrieved the data from the Thai Meteorological Department's database. In equation (2), I considered M=7 weather variables: air pressure (hectopascal), cloud cover (decile), ground visibility (k.m.), rainfall (m.m.), relative humidity (%), temperature (°C), and wind speed (knots per hour). These variables are a collection of weather variables that have also been considered in previous studies (e.g., Dowling & Lucey, 2008) However, the set is not complete. Certain variables, such as geomagnetic storms, are not in the set because the weather station does not measure them.

I follow Hirshleifer and Shumway (2003) to calculate the daily weather variables by their average levels from 6.00 to 16.00. Significant weather effects may be spurious due to weather and return seasonality. I de-seasonalized the variables with their averages for each week of the year over the 1991-2015 sample period. I imputed zero in the missing cases because it is the unconditional mean of de-seasonalized variables.

Descriptive Statistics

The descriptive statistics of the index returns and untreated weather variables are reported in Table 1, panel 1.1. The daily mean returns are small relative to their standard deviations. The return skewnesses are almost zero; the excess kurtoses are very large. The return autocorrelations are significant. Although the Jarque-Bera (JB) tests reject the normality hypothesis for the three indexes, Kalman filtering returns minimum mean square linear estimates (Kellerhals, 2001).

Temperature, cloud cover, humidity, and ground visibility are negatively skewed; rainfall, wind speed, and air pressure are positively skewed. All variables except for cloud cover have fat-tailed distributions. The normality hypothesis is rejected for the seven weather variables. The AR(1) coefficients are significant. The number of weather observations is not equal for either calendar or trading days, creating measurement errors in the weather variables; therefore, imputation is needed.

Weather variables can be highly correlated; highly correlated regressors cause multicollinearity problems in estimation (Worthington, 2009). To ensure that multicollinearity problems were not present, I computed the correlations and variance inflation factors (VIFs) of the de-seasonalized weather variables. On one hand, the correlations were computed from the data on non-missing calendar days. On the other hand, however, the VIFs were computed from the imputation series for trading days because these series were used in the estimation.

The statistics are reported in Table 1, panel 1.2. The largest absolute correlation is 0.5014. All the correlations, except those for air pressure-ground visibility and air pressure-rainfall pairs, are significant. The largest VIF is 1.4861 and is much smaller than the 10-level threshold. The small sizes of correlations and VIFs do not suggest multicollinearity.

Informativeness and Validity of the Instrumental Variables

The last row of Table 1, panel 1.2 reports the R^2's of the regressions of weather variables on their two-step IVs. For the sample period from 1991 to 2015, the R^2's are high, ranging from 0.6012 to 0.9170. Because I could not observe the mood variable in equation (2), the error $\tilde{w}_t$ was not available in this stage. I proceeded to compute the validity R^2, using the regression errors of the SET index returns on weather variables. The validity R^2 of 1.68E-6 is practically zero. Based on these R^2's, I conclude that the two-step IVs are informative and valid.

Empirical Results

In the estimation, all return and weather variables were standardized. The parameter estimates for the full-form model are reported in Table 2. The standard deviations σ and q_{jj}, where $j = \rho$, β, and μ are highly significant, suggesting that the model is estimated precisely for the three index returns. All weather coefficients, except for the temperature for the SET index return and wind speed for the SET 50 index return, are significant. This finding is important. It shows for the first time, based on financial-market data, that weather variables significantly influenced mood, as the psychological literature suggests.

A significant effect of weather on mood was established; the question remains whether mood could drive stock returns away from their fundamental levels. The significant weather-induced mood effects could be inferred from the significant mood coefficient $\tilde{\beta}_t$. Although the coefficient was unobserved, its filtered and smoothed estimates were the outputs of Kalman filtering. I considered the smoothed estimate for $\tilde{\beta}_t$ because it was conditioned on all the observations in the sample period. It was more precise than the filtered one, which was conditioned on some of the observed variables from day one to day t.

Table 1 Descriptive Statistics

Panel 1.1 Index Returns and Untreated Weather Variables

Statistics	Index Returns[1]			Untreated Weather Variables[2]						
	SET	SET 50	mai	Air Pressure (hectopascal)	Cloud Cover (decile)	Ground Visibility (k.m.)	Rainfall (m.m.)	Relative Humidity (%)	Temperature (°C)	Wind Speed (knots/hour)
Mean	1.21E-04	-4.14E-05	5.07E-04	96.8359	5.4684	8.8597	0.3415	65.9481	29.9739	5.6941
S.D.	0.0160	0.0184	0.0159	29.7429	1.4240	1.4502	1.5404	10.5586	2.1562	2.3735
Skewness	0.0284	0.2149	-0.1347	0.3750	-0.5623	-1.1244	7.9375	-0.4709	-0.8150	1.0708
Excess Kurtosis	6.8443	7.1564	110.2023	0.0041	-0.2794	1.2496	84.6261	2.9606	2.8484	1.8259
Minimum	-0.1606	-0.1723	-0.3234	0.0000	0.0909	2.5091	0.0000	4.0909	8.1000	0.2727
Maximum	0.1135	0.1259	0.3269	250.5455	8.0000	14.2727	27.5500	97.3636	36.3455	18.8182
JB Stat.	11,954***	10,687***	1,649,645***	209***	494***	2,443***	2,746,116***	3,588***	4,004***	2,927***
AR(1)	0.0919***	0.0856***	-0.0761***	0.9095***	0.7099***	0.6667***	0.1031***	0.8066***	0.7993***	0.7335***
Trading Days	6,124	4,990	3,260	6,124	6,124	6,124	6,124	6,124	6,124	6,124
Miss. T-Days	0	0	0	141	200	185	163	140	140	176
Miss. T-Intervals	0	0	0	11	27	14	7	10	10	23
Calendar Days	N.A.	N.A.	N.A.	9,131	9,131	9,131	9,131	9,131	9,131	9,131
Miss. C-Days	N.A.	N.A.	N.A.	211	296	272	241	209	209	262
Miss. C-Intervals	N.A.	N.A.	N.A.	13	34	15	7	11	11	31

Note: *** = significance at the 99% confidence level. N.A. = not applicable. [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	-0.1044***	1.0000					
Ground Visibility	-0.0047	-0.1206***	1.0000				
Rainfall	0.0034	0.1821***	-0.1620***	1.0000			
Relative Humidity	-0.1073***	0.5014***	-0.2253***	0.2681***	1.0000		
Temperature	-0.3420***	-0.3286***	0.1414***	-0.2628***	-0.2899***	1.0000	
Wind Speed	-0.1029***	-0.0443***	0.1875***	-0.0813***	-0.1319***	0.0872***	1.0000
Variance Inflation Factors (VIF)	1.2434	1.4438	1.1023	1.1376	1.4861	1.4351	1.0602
Informativeness R^2	0.9170	0.7971	0.9055	0.7658	0.8914	0.7019	0.6012

Note: *** = significance at the 99% confidence level. [1] and [2] = statistics are computed from the de-seasonalized observed data on calendar days (8,742 observations) and imputed, de-seasonalized observed data on trading days (6,124 observations), respectively.

Table 2 Parameter Estimates for Weather-Induced Mood Effects on Stock Returns

Parameters	SET	SET 50	mai
σ	0.4579***	0.3719***	0.2646***
$q_{\rho\rho}$	2.04E-04**	1.35E-3***	3.05E-03***
$q_{\beta\beta}$	2.24E-03***	2.30E-3**	4.58E-03***
$q_{\mu\mu}$	0.7723***	0.5744**	0.5515***
$q_{\rho\beta}$	-0.9487***	0.9025***	-0.6629***
$q_{\rho\mu}$	0.0745	-0.2848***	0.4395***
$q_{\beta\mu}$	-0.3860***	0.1406***	0.0554***
c_1	0.8647***	-0.4518**	0.3252***
c_2	0.0457	0.5803**	0.8730***
c_3	0.3824***	-0.7280**	0.7538***
c_4	0.0881*	0.1557**	0.0961**
c_5	-1.8989***	-0.1758**	-0.7466***
c_6	0.0633	-0.1479**	-0.2564***
c_7	1.6616***	-0.0277	0.9413***

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. Subscripts i and j = ρ, β, and μ for the covariance q_{ij} denote the return autocorrelation, mood-effect coefficient, and mood variable, respectively. Subscripts m = 1,… , 7 for the weather coefficient c_m denote air pressure, cloud cover, ground visibility, rainfall, relative humidity, temperature, and wind speed variables.

Figure 1 shows the T statistics of mood coefficients for the SET, SET 50 and mai index returns. The statistics suggest that the coefficients were not fixed, as they moved randomly over the sample periods. The movement of the coefficients was similar for the three index returns. The coefficients wandered back and forth between positive and negative values. The statistics were significant many times during the early sample periods until 2009. From 2010 onward, they were less volatile and hardly significant. This finding leads me to conclude that weather-driven mood effects existed and were time-varying.

Discussion

Insignificant Effects of Weather Variables in Previous Studies

In previous studies, the weather variables were chosen carefully with respect to the psychological literature. However, certain variables showed no significant effects on returns, or their significance existed only in some sample periods. What can explain these insignificant results?

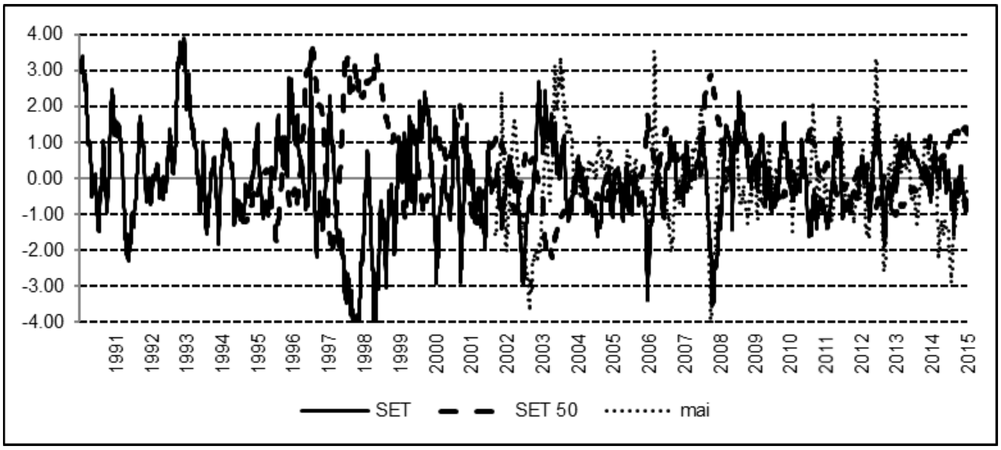

Figure 1 T-Statistics for Weather-Induced Mood Effects

Recently, Khanthavit (2016a) estimated a direct-weather model with random weather effects for Thailand's government bond market. The researcher reported that the direct weather effects were wandering. They were significant only for certain times, especially during the early sample period. The researcher added that a direct model with random weather effects could be interpreted as an indirect model with fixed mood coefficients.

When all the weather variables had significant impacts on mood, as was found by this study, the implied, fixed mood coefficients in Khanthavit (2016a) had to be significant. However, when the mood coefficient was time-varying and significant only in some periods, the insignificant effects of certain weather variables in some periods reported by previous studies should have come from the insignificant response of returns to mood in those periods.

The Traditional Linear Weather Model

This study was motivated by Furhwirth and Sogner (2015), who argued that returns were driven indirectly by weather via mood. The traditional weather model had to be a linear, reduced-form, indirect weather model. The researchers showed that the reduced-form model had endogeneity problems. Recently, Khanthavit (2017) added that endogeneity problems could also result from measurement errors and omitted variables. IV regressions had to be used to obtain consistent estimates.

I estimated the traditional linear weather model for the SET, SET 50, and mai index returns by OLS and IV regressions in order to understand the impacts of endogeneity problems. The results are reported in Table 3. The significant results agreed only for the mai index return. For the SET and SET 50 index returns, the results disagreed for ground visibility and temperature effects, respectively. The results support Furhwirth and Sogner (2015) and Khanthavit (2017)'s recommendation that IV regressions should always be used.

Table 2 OLS and IV Estimates for the Traditional Linear Weather Model

Coefficients	**SET**		**SET 50**		**mai**	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**
Lagged Return	0.0902***	0.0900***	0.0835***	0.0831***	-0.0762***	-0.0762***
Air Pressure	-0.0214	-0.0226	-0.0314**	-0.0347**	0.0104	0.0103
Cloud Cover	0.0153	0.0136	0.0136	0.0181	0.0094	0.0022
Ground Visibility	0.0248*	0.0146	0.0103	-0.0052	-0.0139	-0.0186
Rainfall	-0.0088	4.00E-5	-0.0079	-0.0026	-0.0263	-0.0041
Relative Humidity	-0.0055	-0.0011	0.0068	0.0008	0.0180	0.0187
Temperature	-0.0251*	-0.0271*	-0.0263	-0.0285*	0.0076	0.0064
Wind Speed	-0.0059	-0.0010	-0.0024	0.0077	-0.0077	-0.0076

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

In the reduced-form indirect weather model of Furhwirth and Sogner (2015), the coefficients were assumed fixed. The time-varying coefficients in Figure 1 suggested that the fixed-effect assumption was incorrect; the fixed-effect, indirect model was misspecified. Time-varying effects can be accommodated by treating the coefficients as a random variable, as done in this study, breaking a long sample period into one-year sub-periods as in Khanthavit (2017), or estimating one-year sub-periods' coefficients in a comprehensive model, as in Doyle and Chen (2009).

Inconsistent Signs of Correlations and Weather Coefficients

In Table 2, some correlations and weather coefficients for the SET, SET 50, and mai index returns were inconsistent in their signs. This result was possible because the correlation signs depended on how Kalman filtering returned the state variables. While the fit of the model remained unchanged, the signs reversed if a state variable was multiplied by -1.

The inconsistent signs of weather coefficients for the three returns could be due to their different sample periods. The samples overlapped partly; the investors did not share the same weather conditions during the non-overlapping periods. Denissen, Butalid, Penke, and van Aken (2008) explained that mood reactions to day-to-day weather fluctuations might not be generalized to reactions to seasonal fluctuations. Watson (2000) added that whether the good or bad weather was temporary or prolonged was important for both investors and their moods.

Mood-Driven Weather Effects and Market Efficiency

Researchers (e.g., Hirshleifer & Shumway, 2003) considered weather effects as the evidence against market efficiency, while others (e.g., Yoon & Kang, 2009) interpreted significant effects in early sample periods and insignificant effects in later periods as the evidence for improving market efficiency. Khanthavit (2016b) reported that the efficiency of Thailand's stock market improved over time, while this study found that the T statistics of the mood coefficient $\tilde{\beta}_t$ was smaller in recent years. It is interesting to examine whether weather-induced mood effects moved with the market's efficiency level.

In equation (2), the autocorrelation $\tilde{\rho}_t$ and mood coefficient $\tilde{\beta}_t$ were I(1) variables. If the variables moved together, they had to be co-integrated. Engle and Granger's (1987) two-step tests were conducted. The test statistics for the SET, SET 50, and mai index returns are -1.9378, -2.2569, and -2.7805, respectively. The two variables were not co-integrated. Improved informational efficiency did not explain the insignificant mood effects on the SET in recent years.

Conclusion

Weather effects are behavioral. Significant weather effects imply market inefficiency. The fact that asset returns are driven by both fundamental and behavioral factors calls for behavioral asset pricing models. Based on the effects, traders can trade against weather-sensitive investors for abnormal profits.

Furhwirth and Sogner (2015) argued that the correct model of weather effects had to be an indirect weather model in which returns were driven by weather via investors' mood.

In this study, I estimated the full-form indirect model in a state-space framework. A full-form model enabled me to separate the effects of weather on mood and mood on returns, while a reduced-form model studied by Furhwirth and Sogner (2015) combined these two effects for weather-induced mood effects.

Using the daily returns on SET, SET 50 and mai index portfolios and seven weather variables, this study found that all the weather variables had significant impacts on mood. However, the response of the returns to mood was not fixed but moved randomly over the sample periods. Significant weather-induced mood effects were found frequently during the early sample periods (up to 2009). The effects disappeared from 2010 onward. These findings offer insightful understanding of significant and insignificant effects reported by previous weather studies. Weather variables can influence mood in significant ways, as suggested by the psychological literature. Insignificance tended to result from the insignificant average of time-varying return response to mood during the sample period.

In this study, I allowed the mood coefficient $\tilde{\beta}_t$ in equation (1) to move randomly, but I assumed a fixed weather coefficient c_m. Mood reacts to weather differently each day (Denissen et al., 2008), and whether the weather is temporary or prolonged affects mood (Watson, 2000). Therefore, the weather coefficient c_m can be time-varying as well (Khanthavit, 2016a). Allowing the weather coefficient c_m in equation (2) to move randomly makes the estimation more complicated than it already is. I leave the estimation of a model with random mood and weather coefficients for future research.

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