

Investors' Weather-Related Moods and the Stock Market

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Abstract

To test for weather effects on stock returns and volatility, weather-related mood indexes were constructed from the principal components (PCs) of weather variables to obtain clean measures of investors' moods. Using the daily data on the Stock Exchange of Thailand portfolio index and Bangkok weather variables from February 17, 1992, to December 30, 2016, significant weather effects were found on both stock returns and volatility. Returns were driven by the rainfall-related, fourth PC, while the fifth PC—most sensitive to ground visibility and wind speed—drove volatility. However, the first PC was not significant.

Keywords: *principal component; return behavior; sentiment index; weather effects*

Introduction

Investors' moods at the time that they make decisions influence their behavior; therefore, investors' moods can cause stock returns and volatility to deviate from their fundamental values (Loewenstein, 2000). Prices and returns rise or fall due to changing risk preferences, which lead marginal investors to lower or raise discount rates (Mehra & Sah, 2002), or due to mood misattribution, which cause marginal investors to incorrectly associate good or bad weather and mood with good or bad prospects for the assets (Hirshleifer & Shumway, 2003). Stock volatility changes because social moods create a 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).

Weather conditions can affect investors' moods (Watson, 2000). Because moods cannot be observed while weather conditions can, tests for the effects of moods on stock returns and volatility rely on observed weather variables, such as ground visibility, rainfall, and wind speed. The significant relationship of weather variables with stock returns and volatility constitutes the *weather-related mood effects* or, more commonly, ***weather effects*** in the behavioral finance literature (Furhworth & Sogner, 2015).

Khanthavit (2017) tested and found that for Thailand, different weather variables affected returns in the same or different years, but none did for the full sample. Beer and Zouaoui (2013, p. 53) suggested that "perhaps the best empirical approach is to condense several imperfect indicators onto an aggregate index", and given these findings for Thailand, this appears to be a suitable approach.

In this study, I constructed aggregate weather-related mood indexes to test for weather effects on the Stock Exchange of Thailand (SET). These indexes are the principal components (PCs) of weather variables. They are considered clean measures of unobserved moods because idiosyncratic noise in weather variables is averaged out (Brown & Cliff, 2004; Baker & Wurgler, 2007).

Methodology

The Model

I used the vector autoregressive (VAR) model to describe the dynamics of returns and volatility. To test for weather effects, I added the weather-related, k^{th} PC mood index to the model. Because weather variables are exogenous (Vlady & Tufan, 2011), so are the corresponding PCs. The resulting model is a VAR

model with exogenous variables (VAR-X). Equation (1) shows the VAR-X (p, q) model with p lags for the endogenous return (r_t) and volatility (σ_t^2) and q lags for the exogenous, k^{th} PC mood index (c_t^k).

$$\mathbf{X}_t = A_0 + \sum_{i=1}^p A_i \mathbf{X}_{t-i} + \sum_{j=0}^q B_j \mathbf{C}_{t-j} + \boldsymbol{\varepsilon}_t, \quad (1)$$

where the variable vectors $\mathbf{X}'_{t-i} = [r_{t-i}, \sigma_{t-i}^2]$ and $\mathbf{C}'_{t-j} = [c_{t-j}^k, c_{t-j}^k]$, and the residual vector $\boldsymbol{\varepsilon}'_t = [\varepsilon_t^r, \varepsilon_t^{\sigma^2}]$. $\boldsymbol{\varepsilon}_t$ has a zero mean vector and Ω covariance matrix. The intercept-coefficient vector A'_0 is $[a_0^r, a_0^{\sigma^2}]$, while the (2×2) slope-coefficient matrix A_i is $\begin{bmatrix} a_i^{r,r} & a_i^{r,\sigma^2} \\ a_i^{\sigma^2,r} & a_i^{\sigma^2,\sigma^2} \end{bmatrix}$ and B_j is $\begin{bmatrix} b_j^r & 0 \\ 0 & b_j^{\sigma^2} \end{bmatrix}$.

Equation (1) relates the k^{th} PC linearly with returns and volatility. Lee, Jiang, and Indro (2002) cautioned that this empirical model risked misspecification and incompleteness because it was not based on a rigorous theory. I argue that the model is well specified. By the Wold decomposition theorem, a VAR(p) model sufficiently describes the dynamics of endogenous returns and volatility. Adding exogenous variables to the model cannot make it misspecified or incomplete (Ocampo & Rodriguez, 2012).

Lag Selection

The lag orders p and q are unknown. I chose the Bayesian information criterion (BIC) approach over the Akaike information criterion (AIC) approach for estimation. Zivot and Wang (2006) noticed that the AIC asymptotically overestimated an order, while the BIC gave an order consistently under general conditions. The optimal lag orders were computed in two steps. In the first step, the optimal order p^* was identified by the minimum BIC statistic for the VAR($\hat{p}$) models of orders $\hat{p} = 1, \dots, 10$. In the second step, I fixed the order $p = p^*$. I then chose the optimal order q^* for the exogenous variable by the minimum BIC statistic for the VAR-X($p^*, \hat{q}$) models of orders $p = p^*$ and $\hat{q} = 1, \dots, 10$.

Construction of Weather-Related Mood Indexes

I constructed M weather-related mood indexes from the PCs of M weather variables (Brown & Cliff, 2004; Baker & Wurgler, 2007). The desired indexes are the unobserved components of the variables that influence investors' moods. Although the first PC is able to capture the common variation of these variables, this ability does not necessarily translate to its influence on moods. For this reason, I considered all the M indexes, one at a time, in equation (1). In the past, Brown and Cliff (2004) considered the first and second PCs.

Model Estimation

The Generalized Method of Moments

The variable c_t^k is the unobserved component of the weather variables that influence moods. It is proxied by the k^{th} PC. The estimation of equation (1) suffers from endogeneity problems. The variable c_t^k is measured with errors from the k^{th} PC proxy. Moreover, the underlying M weather variables were also measured with errors (Khanthavit, 2017).

To mitigate these problems, I estimated equation (1) with Hansen's (1982) generalized methods of moments (GMM). GMM is an instrumental-variable (IV) approach, whose estimators are consistent, asymptotically normal, and efficient among the class of estimators that do not use any information beyond moment conditions. Moreover, GMM does not require normally distributed variables.

The Choice for Instrumental Variables

The IVs are a constant, lagged return and volatility, and Racicot and Theoret's (2010) two-step IVs for the current and lagged k^{th} PC. The two-step IVs were used only for the current and lagged PC because of their measurement errors. I was aware that volatility was also measured with errors. However, the variable itself was used for its IV because the endogeneity problem from this source was readily accounted for by the VAR specification.

I constructed the Racicot-Theoret IVs by first computing Pal's (1980) cumulant IV for the PC. The second step took the Racicot-Theoret IV from the regression residuals of the PC on the Pal IV. The resulting two-step IVs had good informativeness and validity performance (Khanthavit, 2017).

Hypothesis Tests

From equation (1), if weather-related moods affect stock returns and volatility, the tests must reject the $b_1^r = \dots = b_q^r$ and $b_1^{\sigma^2} = \dots = b_q^{\sigma^2}$ hypotheses, respectively. Under the null hypotheses, the Wald statistics are a chi-square variable with q degrees of freedom. For the joint test of the $b_1^r = \dots = b_q^{\sigma^2}$ hypothesis in which moods affect both returns and volatility, the Wald statistic is a chi-square variable with $2q$ degrees of freedom. The Wald statistics are computed from Newey and West's (1994) heteroscedasticity and autocorrelation consistent covariance matrix.

The Data

Stock returns are the logged differences of the closing indexes of the SET portfolio index. Volatility is the realized daily variances computed by Rogers and Satchell's (1991) adjusted extreme-value estimator. The stock data were retrieved from the SET database and are from February 17, 1992, to December 30, 2016 (6,091 trading-day observations).

The mood indexes are the principal components of Bangkok's seven weather variables—air pressure (hectopascal), cloud cover (decile), ground visibility (kilometers), rainfall (millimeters), relative humidity (%), temperature (°C), and wind speed (knots per hour). These variables were 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). The Thai Meteorological Department provided the weather data to me.

I followed Khanthavit's (2017) strategy to treat seasonality and missing-variable problems in the weather series. First, I used Hirshleifer and Shumway's (2003) approach to remove seasonality from the weather variables by their averages for each week of the year over the 1991-2016 sample period. Next, the deseasonalized variables were standardized by their averages and standard deviations. Then, I imputed the missing cases with zero because zero was the unconditional means of deseasonalized variables. Finally, the seven PCs were computed from the treated weather variables on trading days from February 17, 1992, to December 30, 2016.

Table 1 reports the descriptive statistics of the return, volatility, and weather variables. From Panel 1.1, all of the variables are skewed or fat-tailed. The Jarque-Bera statistics reject the normality hypothesis. Non-normality does not damage the estimation. GMM does not rely on the normality assumption.

Panel 1.2 reports the correlation of the treated weather variables. The correlation coefficients of all the pairs are highly significant, except for the (air pressure, ground visibility) and (air pressure, rainfall) pairs. When the variables are correlated, it is appealing to extract their common components (Brown and Cliff, 2004). The significant correlation coefficients support the use of PCs to construct the weather-related mood indexes.

Table 1 Descriptive Statistics**Panel 1.1** Index Return, Volatility, and Raw Weather Variables

Statistics	Return ¹	Volatility ¹	Raw Weather Variables ²						
			Air Pressure (hectopascal)	Cloud Cover (decile)	Ground Visibility (kilometers)	Rainfall (millimeters)	Relative Humidity (%)	Temperature (°C)	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

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 Correlations¹ of Treated 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

Note: *** = significance at the 99% confidence level. ¹ = statistics are computed from the de-seasonalized observed data on calendar days (9,108 observations).

Table 2 reports the percentages of the total variance of the weather variables explained by each PC. The first PC explained 30.35%, while the seventh PC explained 6.10%. The PCs are orthogonal to one another, that is, they are weighted averages of the seven weather variables. Table 3 reports the weighting of standardized weather variables for PC construction. Because the variables are standardized, large absolute weights suggest significant relationships between the variables and the PCs (Finter, Ruenzi, & Ruenzi, 2012).

Table 2 Total Variance Explained

Principal Component	Total Variance Explained (%)
1	30.35
2	18.25
3	15.54
4	12.18
5	10.75
6	6.66
7	6.10

Table 3 Weighting for Standardized Weather Variables

Principal Component	Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed
1	0.0346	0.3299	-0.2095	0.2567	0.3700	-0.3041	-0.1368
2	-0.7010	0.2429	0.0069	0.0165	0.2250	0.3782	0.1964
3	0.1493	0.2444	0.5747	0.0096	0.0936	-0.2827	0.6466
4	-0.0360	-0.4215	-0.2306	0.8651	-0.1576	0.0534	0.4060
5	-0.1554	-0.0009	0.7977	0.4931	-0.0698	0.0538	-0.6464
6	0.8324	0.4542	0.0149	0.2205	0.2620	1.0617	0.0459
7	0.0892	-0.9428	0.2304	-0.1885	1.1621	0.0825	0.0017

Empirical Results

I estimated the VAR model for stock returns and volatility of orders 1 to 10. The BIC statistics suggested the optimal lag order of $p^* = 7$. Fixing the optimal order $p^* = 7$, I computed the BIC statistics for the VAR-X(7, $\hat{q} = 1, \dots, 10$) models. The optimal order q^* equals 1 for all of the exogenous PCs $c_t^{k=1, \dots, 7}$. Hence, the hypothesis tests were performed against the VAR-X(7,1) model.

Table 4 reports the test results. For the first PC, weather-related mood effects are not significant for the return nor for the volatility. Neither is it for the joint hypothesis test. These insignificant results are also found for the second, third, sixth, and seventh PCs.

Table 4 Hypothesis Tests

Component	Effect Coefficients for		Joint Effect (χ^2_2)
	Return	Volatility	
1	0.0150	-0.0053	1.3992
2	0.0105	-0.0016	0.6864
3	0.0170	-0.0063	1.7990
4	-0.0249*	0.0097	3.8761
5	0.0152	-0.0498***	18.3265***
6	-0.0167	-0.0049	2.4217
7	-0.0099	0.0161	2.1052

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

The fourth PC has a significant effect on returns. Its p-value is 0.0513; however, the fourth PC does not affect volatility. The fifth PC significantly affects volatility but not returns. The p-values for the individual and joint tests are 0.0000. These findings lead me to conclude that weather-related mood effects on the stock return and volatility exist in the SET.

Discussion

Weather-Related Mood Indexes that Drive Stock Returns and Volatility

The significant effects found in this study are consistent with the findings of previous studies on the SET (e.g., Khanthavit, 2017). Furthermore, it is interesting and important that returns and volatility are driven by two different PCs. Because the fourth and fifth PCs are uncorrelated, return-driving moods and volatility-driving moods must differ.

The fourth PC is so sensitive to rainfall that the return-driving moods could be considered as rainfall-related moods. With respect to Wurtman and Wurtman (1989), the lack of sunlight associated with rainy days caused serotonin levels to fall, which led to bad moods. This explanation is consistent with the negative slope coefficient for the fourth PC in Table 4 and the positive weight for the rainfall variable in Table 3.

The absolute weights of the ground-visibility and wind-speed variables are largest for the fifth PC. The volatility-driving moods are driven by the unobserved components in these two weather variables. Visibility degradation derived from poor sunlight can cause falling serotonin levels and bad moods (Wurtman & Wurtman, 1989). Charry and Hawkinshire (1981) reported that ions created by wind might prompt changes in mood states. The changing mood states induced by ground visibility and wind speed support the significant relationship of the fifth PC with the volatility.

Implications for Studies on Sentiment Indexes

The first PC was chosen for the index in most sentiment studies (e.g., Baker & Wurgler, 2007; Chen, Leung, & She, 2014) and can best explain the common variation in the proxies. In this study, the

variance explained by the first PC is about the same level as the 30% level in Finter, Ruenzi, and Ruenzi's (2012) study of the German market, and higher than the 25% level in Stambaugh, Yu, and Yuan's (2012) study of the U.S. market. Nonetheless, the percentage is lower than those in other studies, such as the 49% level in Baker and Wurgler (2006).

I did not find a significant relationship between the first PC and returns or volatility, implying that the first PC is not necessarily the best choice for the mood measure. The implication extends to sentiment studies. Researchers should be careful when they choose a PC for the sentiment index.

Conclusion

Weather affects investors' moods and, in turn, causes stock returns and volatility to deviate from their fundamental levels. In this study, I tested for weather-related mood effects on stock returns and volatility in Thailand. I constructed weather-related mood indexes with the principal-component approach. The PCs are clean measures of mood because the idiosyncratic noise in weather variables is averaged out. I found that the first PC had no relationship with returns or volatility. The effects of the fourth and fifth PCs were significant for returns and volatility, respectively. Because the fourth and fifth PCs were uncorrelated, the moods that drove returns and volatility had to differ. Further investigation related the fourth PC to rainfall and the fifth PC to ground visibility and wind speed. These findings offer an important implication for sentiment studies: the first PC may not be the best sentiment measure.

Acknowledgments

The author thanks the Faculty of Commerce and Accountancy, Thammasat University, for the research grant. He thanks Sumridh Sudhibrabha, Somchai Sanplang, and the Thai Meteorological Department for the weather-variable data.

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