

WEATHER-DRIVEN STOCK-RETURN CORRELATIONS

Anya Khanthavit*

Abstract

The coordinated trading of weather-sensitive investment drives stock returns and links the return correlations with weather variables. This study tested whether the correlations in the Stock Exchange of Thailand can be explained by Bangkok's weather variables. Using daily data from September 3, 2002, to December 29, 2017, it was found that the correlation of the returns on the Stock Exchange of Thailand 50 and the Market for Alternative Investment index portfolios has a significant relationship with Bangkok's weather. The significant variables are a subset of those variables that drive return volatility.

Keywords: Investor Sentiment; Noise Traders; Pairwise Correlation; Weather Effects

INTRODUCTION

Pairwise stock-return correlations are one of the key inputs for asset pricing, risk management, asset allocation, and correlation trading. It is important to understand the factors that drive the correlation levels and their movement. In the traditional discounted cash flow model (Fisher, 1930; Williams, 1938), in a frictionless market with rational investors, stock prices are the present value of the expected future cash flows,

discounted by market discount rates. The volatility and correlation are necessarily determined by those economic fundamentals that affect cash flow and discount rates (e.g., Campbell, 1991). Barberis, Shleifer, and Wurgler (2005) explained that when the market has friction, information can be incorporated more quickly into some stocks than others. Although stocks share the same set of economic fundamentals, correlations are high among stocks that incorporate information at similar rates.

*Anya Khanthavit is Distinguished Professor of Finance and Banking at the Faculty of Commerce and Accountancy, Thammasat University, Bangkok, Thailand. He holds a Ph.D. in International Business and Finance from New York University's Leonard N. Stern School of Business. He thanks the Faculty of Commerce and Accountancy, Thammasat University for the research grant, and thanks the Thai Meteorological Department for the weather-variable data. Email: akhantha@gmail.com

Previous empirical studies reported that correlations could not be exhaustively explained by economic fundamentals. For example, Pindyck and Rotemberg (1993) found excess return co-movements when they used the latent variable model to capture the unobserved expectations of economic fundamentals. Barberis et al. (2005) reported that stocks' betas with the S&P 500 Index rose after the stocks were included in the index calculation. Peng, Xiong, and Bollerslev (2007) found that the return correlations rose with the arrival of macroeconomic news but fell significantly in the days following the news. Kumar and Lee (2006) found that systematic retail trading explained the return co-movements for stocks with high retail concentration, while Kumar, Page, and Spalt (2013) found that retail investors generated excess co-movements, in stock returns surrounding stock-split and corporate-headquarter-change events. Tang and Xiong (2012) reported that high exposure to common shocks for commodities and other asset classes was influenced more by investor sentiment than by macroeconomic fundamentals. Recently, Hendershott, Menkveld, Praz, and Seasholes (2018) studied stocks on the New York Stock Exchange and found that pricing errors were long-lived. These errors led to a return correlation which could not be explained by economic fundamentals.

Behavioral-finance theories help to explain the return correlations. According to Barberis and Shleifer (2003), investors group assets into categories to simplify investment decisions. If some investors are noise traders with correlated sentiment, the coordinated trading of all

or a subset of stocks in the categories constitutes a nonfundamental common factor for the co-movement of stock returns (Barberis et al., 2005). Gorban, Smirnova, and Tyukina (2010) explained the rising return correlations during bear markets, by the tension-driven model in which individual investors adapted to common stress factors. David and Simonovska (2016) proposed that investors' beliefs were correlated. Hence, the trades of imperfectly informed investors could drive return correlations to be higher than those obtained from fundamentals. Hendershott et al. (2018) developed a model in which some investors were more attentive to the information than other investors. The presence of infrequent, inattentive traders led to long-lived pricing errors and low return correlations.

Weather conditions can affect investor moods (Watson, 2000). Prices and returns rise or fall with the weather due to risk preference, which leads marginal investors to lower or raise discount rates (Mehra & Sah, 2002). Additionally, mood misattribution causes marginal investors to incorrectly associate good or bad weather and mood, with the good or bad prospects of assets (Hirshleifer & Shumway, 2003). According to Barberis et al. (2005), correlated, weather-induced moods can explain return correlations.

Moods also cause investors to have limited attention, poor memory, and a low capacity to process information (e.g., Bohner, Crow, Erb, & Schwarz, 1992; Forgas, Goldenberg, & Unkelbach, 2009; Forgas, 2017). The trades of inattentive investors induce return correlations (Peng et al., 2007; Hendershott et al., 2018),

establishing the causal relationship between weather and return correlations. Goetzman, Kim, Kumar, and Wang (2015) found that for the U.S. market, stocks exposed to the weather-induced moods of similar investors showed a strong correlation.

In this study, the effects of weather on return correlations in the Stock Exchange of Thailand (SET) were empirically examined. Using daily samples from September 3, 2002, to December 29, 2017, it was found that the correlation between returns on the SET 50 index and the Market for Alternative Investment (mai) portfolios is time-varying. Such movement is significantly explained by Bangkok's air pressure, relative humidity, and temperature. These three weather variables are a subset of the variables that explain stock volatility (Khanthavit, 2017a).

The contributions of this study are as follows. First, while weather studies have been conducted for returns and volatilities in national and international markets (e.g., Hirshleifer and Shumway, 2003; Symeonidis, Daskalakis, & Markellos, 2010), correlation studies are lacking (Goetzman et al., 2015). This study adds to the literature and improves researchers' understanding of the relationship between weather conditions and stock-return correlations.

Second, the SET is Thailand's only stock market and is located in Bangkok, where most stock investors live and trade. 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. This fact

allows for the employment of a simple, traditional approach for weather studies (e.g., Dowling & Lucey, 2005), to directly relate the return correlations with Bangkok's weather variables. Goetzman et al. (2015) constructed a proxy for weather-induced moods to aggregate the moods of investors in dispersed locations in the U.S. Moreover, all of Bangkok's available weather variables are considered jointly, while Goetzman et al. (2015) considered only the cloud-cover variable. Denissen, Butalid, Penke, and van Aken (2008) reported that the relationship between moods and weather conditions was strong when all the weather variables are jointly considered.

Third, most weather studies suffer from mis-specified, fixed-effect assumptions and endogeneity problems. In this study, the estimation method proposed by Khanthavit (2017b) is used to mitigate such problems.

METHODOLOGY

The Model

Weather variables are related linearly with the stock-return correlation as in equation (1).

$$P_t = a_0 + \sum_{m=1}^M a_m W_t^m + a_{M+1} r_t^{SET} + a_{M+2} \sigma_t^{SET} + a_{M+3} V_t^{SET} + e_t, \quad (1)$$

where ρ_t is the return correlation, $W_t^{m=1, \dots, M}$ is the weather variable, and e_t is the regression error. The linear relationship is similar to those in weather studies for stock returns and volatilities

(e.g., Hirshleifer and Shumway, 2003; Symeonidis et al., 2010). r_t^{SET} , σ_t^{SET} , and V_t^{SET} are the market return, market volatility, and market volume turnover, respectively. These variables were added into the analysis as they control for possible spurious relationships and proxy the fundamental and nonfundamental factors that explain the correlation.

Market return helps to control this spurious relationship. The stock returns rise and fall with market return. In the rising (falling) market, the stock volatilities fall (rise) due to the Black (1976) leverage effects. Loretan and English (2000) showed that the correlation estimate could rise or fall with the volatilities, even if its true value was fixed.

Market return and volatility, proxy the common fundamental and nonfundamental factors that drive stock returns. Market return is one of the common risk factors in most capital asset pricing models (e.g., Fama & French, 1993), while studies of the multivariate conditional heteroscedasticity behavior of stock returns (e.g., Knif, Kolari, & Pynnonen, 2005) reported that market return and volatility were the determinants of return correlations.

Nonfundamental sentiment factors, other than weather-driven factors, can influence return correlations (Berberis et al., 2005). Therefore, in equation (1), market volatility and volume turnover were added to control the impacts of these sentiment factors. The two variables are indirect sentiment measures commonly used in investor sentiment studies (Baker & Wurgler, 2007).

Model Estimation

Estimation Problems and Mitigation

The relationship between weather conditions and the return correlation results from their relationship with investor moods and limits attention. The linear relationship is the linear projection of weather variables onto the unobserved moods and attention limits of potential investors. This projection leads to endogeneity problems in the estimation (Fruhworth & Sogner, 2015). The problems are worsened due to problems of omitted-variables and errors-in-variables (Khanthavit, 2017b). Moreover, the correlation ranges from -1.00 to 1.00 and cannot be normally distributed. To correct the effects of endogeneity and nonnormality, Hansen's (1982) generalized methods of moments (GMM) was used to estimate equation (1). GMM does not require normally distributed variables. This approach is an instrumental variable (IV) approach, with estimators that are consistent, asymptotically normal, and efficient among the class of estimators that use no information beyond moment conditions.

The estimation, test, and analysis based on long-sample data may suffer from an incorrect, fixed-effect assumption. To mitigate the effects of this incorrect assumption, Khanthavit (2017b) was followed, by estimating the model and testing the hypotheses using a sample period of one year at a time.

The Choice of Instrumental Variables

The IVs are a constant, as with Racicot and Theoret's (2010) two-step

IVs for the weather variables, market return, market volatility, and volume turnover. The Racicot-Theoret IVs were constructed by first computing Pal's (1980) cumulant IVs for the regressing variables. In the second step, the regressing variables were regressed on their Pal IVs. The Racicot-Theoret IVs were the regression residuals.

Estimation of Return Correlations

The return correlation for the day is not observed and must be estimated from the observed stock prices. The correlation $\hat{\rho}_t$ for stocks i and j was estimated, from the relationship $\hat{\rho}_t = \frac{\sigma_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$, where $\sigma_{ij,t}$ is the covariance, and $\sigma_{i,t}$ and $\sigma_{j,t}$ are the standard deviations of the stocks.

Covariance $\sigma_{ij,t}$ was estimated using the method of Rogers and Zhou (2008). This estimator uses not only the closing prices but also daily high and low prices, resulting in a low variance of the estimate. Let $H_{k,t}$, $L_{k,t}$, and $S_{k,t}$ be the high, low, and closing logged price of stock $k = i, j$, respectively. $\sigma_{ij,t} = 0.5S_{k,t}S_{j,t} + 2.1987(H_{i,t} + L_{i,t} - S_{i,t})(H_{j,t} + L_{j,t} - S_{j,t})$.

Although Rogers, Satchell, and Yoon (1994) recommended the method of Rogers and Satchell (1991) for variance estimation when the returns had drifts, the method of Parkinson (1980) was chosen. Sometimes, the Rogers-Satchell method obtains zero variance. The Parkinson variances are unbiased and always positive; the Parkinson variance for stock k is $\sigma_{k,t}^2 = 0.1733(H_{k,t} - L_{k,t})^2$.

The correlation estimate $\hat{\rho}_t$ may fall beyond the $[-1.00, 1.00]$ range (Brunetti & Lildholdt, 2002). Therefore, in the estimation, ρ_t was set in equation (1) equal to $\text{Max}\{-1.0, \text{Min}(1.0, \hat{\rho}_t)\}$.

Hypothesis Tests

The effects of weather conditions on return correlations were tested. In association with equation (1), the hypothesis for a significant weather variable W_t^m is $a_m = 0$, and the joint hypothesis for M significant variables, $W_t^{m=1,\dots,M}$, is $a_1 = \dots = a_M = 0$. Under the null hypotheses, the Wald statistics are distributed as chi-square variables with 1 and M degrees of freedom. The Wald statistic is computed from Newey and West's (1994) heteroscedasticity and autocorrelation consistent covariance matrix.

The statistics for a full-sample test are the sum of the statistics for all τ years in the full period (Doyle & Chen, 2009). Hence, the statistics for the individual- and joint-hypothesis tests are chi-square variables with τ and $(\tau \times M)$ degrees of freedom.

THE DATA

The correlation between the returns on the SET 50 and mai index portfolios from September 3, 2002, to December 29, 2017 (3,748 trading-day observations) was studied. The high, low, and closing SET 50- and mai-index data are the daily data from the SET database that were used in the study.

The correlation between the returns on the SET 50 and mai index portfolios

was chosen because the structures of the investor groups for these two portfolios are very different. The SET 50 index is the value-weighted index of the fifty largest and most actively trading stocks, whereas the mai index is the value-weighted index of all stocks on the mai. Approximately 58% and 96% of the trading volume of SET and mai stocks are from retail investors, while the remainder are from local institutes, proprietary traders, and foreign investors (Khanthavit & Chaowalerd, 2016). It is likely that the percentage share of retail investors for the SET 50 stocks is not above 58%. While the SET index is intended to represent the overall market, the SET 50 and mai indexes can represent parts of the market that are dominated by large institutional investors and small retail investors, respectively. Inexperienced retail investors are more likely than professional, institutional investors to be sensitive to sentiment (Baker & Wurgler, 2007). The correlated weather-induced sentiment and different degrees of investor sensitivity link the return correlation with the weather through investors' moods and their limited attention.

Market returns are the log differences of the closing SET indexes. The SET index is the broad-based, value-weighted index of all stocks on the SET. Market volatility is the Parkinson (1980) standard deviation computed from the daily high, low and closing SET indices, and market volume turnover is the SET trading volume divided by the SET market capitalization. The SET index, volume, and market capitalization data are from the SET database.

Seven weather variables were considered, consisting of air pressure (hectopascal), cloud cover (decile), ground visibility (kilometers), rainfall (millimeters), relative humidity (%), temperature (°C), and wind speed (knots per hour). These variables were taken from the Bangkok weather variables, measured by the Thai Meteorological Department's weather station at Don Muang Airport. The weather data start on January 1, 1991, and end on December 31, 2017 (9,862 calendar-day observations). The weather data were retrieved from the Thai Meteorological Department's database.

Following Hirshleifer and Shumway (2003), the daily weather variables were calculated by their average level between 06:00 to 16:00. Seasonality in the weather variables was removed by using averages for each week over the 1991-2017 sample period. The deseasonalized variables were then standardized by their standard deviations.

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

Table 1 reports the descriptive statistics of the stock market and weather variables. The Jarque-Bera tests reject the normality hypothesis for all variables. This finding supports the use of GMM as such a technique does not require normal variables.

Weather variables can be highly correlated; highly correlated regressors cause multicollinearity problems in estimation (Worthington, 2009). Khanthavit (2017a) reported that

Bangkok weather affected the SET index return and volatility. In the U.S., Loughran and Schultz (2004) reported that weather affected the trading volume of investors. Therefore, market return, volatility, and volume turnover can also be highly correlated with weather variables.

Table 2 reports the correlations for the weather- and stock-market variable pairs. All of the correlations for all of the weather-variable pairs are significant, except for those for air pressure with ground visibility and rainfall. None of the correlations of market return with the weather variables are significant; all the correlations of market volatility with the weather variables, except for air pressure, are significant; the volume turnover correlations with temperature and wind speed are not significant, while the remaining correlations are significant. Because of the significant correlations among the regressors, the variance inflation factors were computed to check for multicollinearity. The statistics are presented in the last row of Table 2. Their maximum value is 1.7761 for the relative-humidity variable, which is much smaller than the threshold level of 10. Thus, the multicollinearity problem is not present in this estimation.

EMPIRICAL RESULTS

The effects of the weather conditions on stock correlations are reported in Table 3. The joint hypothesis test for the full sample rejects the hypothesis of no weather effects on the return correlation at the 99% confidence level. The significant weather variables are air pressure, relative humidity, and temperature, with

significance levels of 90%, 95%, and 95%, respectively.

In equation (1), market return, volatility, and volume turnover are considered to control for possible spurious relationships and to represent influential fundamental and nonfundamental factors. The three stock market variables are significant.

The year 2002 has only 81 observations. The joint test reports a Wald statistic of 43.4212. However, none of the weather variables were significant in 2002. These findings raise an important question as to whether the significance result for the full sample is spurious due to the statistics from the year 2002. The summed Wald statistic for the period from 2003 to 2017 (15 years) was recalculated as 144.9167, which is a chi-square variable with 105 degrees of freedom under the null hypothesis. The joint test for this sample period identifies the significance of weather effects at the 99% confidence level.

DISCUSSION

Weather as a Nonfundamental Factor that Drives Stock-Return Correlations

For the U.S. market, Goetzman et al. (2015) reported significant weather effects on stock-return correlations. Stocks experiencing similar weather-induced moods showed strong return correlations. Using a different approach in which the correlation was linked linearly and directly with weather variables, a similar result was found for the Thai market. Thus, weather effects are significant. The weather, via the investors' moods and limited attention, is

TABLE 1: Descriptive Statistics

Statistics	Stock Market Variables ¹				Weather Variables ²						
	Correlation of SET 50 and mai Index Returns	Market Return	Market Volatility	Market Volume Turnover (Times)	Air Pressure (hectopascal)	Cloud Cover (decile)	Ground Visibility (meters)	Rainfall (millimeters)	Relative Humidity (%)	Temperature (°C)	Wind Speed (knots/hour)
Average	0.4645	4.24E-04	0.0076	0.0036	97.0589	5.4800	8,910.0515	0.3467	66.1626	29.9808	5.8016
Standard Deviation	0.6638	0.0126	0.0052	0.0017	29.7507	1.4028	1,421.7535	1.5458	10.5438	2.1484	2.5164
Skewness	-0.9773	-0.8522	5.2858	2.4534	0.3972	-0.5737	-1.2002	7.7876	-0.4401	-0.7839	1.6545
Excess Kurtosis	-0.3659	13.5721	75.9760	10.2483	0.0484	-0.2306	1.4604	81.5708	2.7896	2.5274	6.9920
Minimum	-1.0000	-0.1606	0.0016	0.0007	0.0000	0.0909	2,509.0909	0.0000	4.0909	8.1000	0.2727
Maximum	1.0000	0.1058	0.1233	0.0188	250.5455	8.0000	14,272.7273	27.5500	98.0000	36.3455	30.5455
Jarque-Bera Statistic	1,214***	29,673***	936,356***	23,922***	254.7168***	545.8528***	3,154.4846***	2.76E+06***	3,441.4408***	3,569.0631***	2.39E+4***
AR(1)	0.0116	0.0298*	0.5452***	0.7919***	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Observations	3,748	3,748	3,748	3,748	9,651	9,566	9,590	9,621	9,653	9,683	9,600

Note: * and *** = significance at the 90% and 99% confidence levels, respectively. N.A. = not applicable because of missing observations. ¹ = the statistics are computed from the observed data on trading days from September 9, 2002, to December 29, 2017. ² = the statistics are computed from the observed data on calendar days from January 1, 1991, to December 31, 2017.

TABLE 2: Correlations and Variance Inflation Factors of De-seasonalized Weather Variables and Control Variables¹

Weather and Control Variables	Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	Market Return	Market Volatility	Market Volume Turnover
Air Pressure	1.0000									
Cloud Cover	-0.0811***	1.0000								
Ground Visibility	0.0215	-0.1102***	1.0000							
Rainfall	-0.0056	0.2001***	-0.2185***	1.0000						
Relative Humidity	-0.1082***	0.5764***	-0.2657***	0.3378***	1.0000					
Temperature	-0.3825***	-0.3148***	0.1958***	-0.2844***	-0.3088***	1.0000				
Wind Speed	-0.0572***	-0.0679***	0.2277***	-0.0387**	-0.1210***	0.1238***	1.0000			
Market Return	-0.0158	0.0109	0.0002	-0.0258	0.0091	0.0088	-0.0113	1.0000		
Market Volatility	-0.0142	-0.0347**	-0.0282*	-0.0325**	-0.0426***	-0.0497***	-0.0416**	-0.2369***	1.0000	
Market Volume Turnover	-0.0245*	-0.0660***	-0.0989***	-0.0291*	0.0756***	-0.0042	0.0241	0.0807***	0.4054***	1.0000
Variance Inflation Factor	1.2869	1.6000	1.1758	1.2047	1.7761	1.5345	1.0769	1.1082	1.3416	1.3015

Note: ***, **, and * = significance at the 90%, 95%, and 99% confidence level, respectively. ¹ = the statistics are computed from the observed data on trading days from September 9, 2002, to December 29, 2017.

TABLE 3: Tests for the Effects of Weather Conditions on Stock-Return Correlation¹

Year	Weather Variables							Stock Market Variables			Joint Hypothesis Test: Weather Coefficients are Zero. (χ^2_7)
	Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	Market Return	Market Volatility	Market Volume Turnover	
2002	0.1418	-0.0145	0.0311	-0.0286	0.1243	-0.0471	-0.1410	0.1376*	0.1475	-0.0893	43.4212***
2003	0.0199	0.0168	0.0015	-0.0973	-0.0519	-0.0864	-0.0212	0.1000***	0.1108*	-0.0664	3.8515
2004	0.0275	-0.0611	-0.0093	0.0379	0.0135	-0.0766*	0.0667*	0.0629	0.1707***	0.0055	16.2673**
2005	-0.0175	0.0577	0.0769	0.0027	0.0758	0.0997	-0.1029**	-0.0575	0.0122	0.0812	13.4494*
2006	0.0597	0.0794	0.0449	0.1758	-0.1532	0.0160	0.0577	0.0359	0.2407*	-0.1079	7.2366
2007	-0.0771	0.0831	-0.0141	0.1937**	-0.1981***	0.0518	-0.0118	0.1663***	0.0880*	0.0090	15.7669**
2008	0.1274***	-0.0729	0.0148	0.0781	0.1400**	0.1220**	0.0671	-0.0539	0.0385	0.1268**	13.7081*
2009	0.0421	-0.0321	0.0782	0.0699	0.0732	0.0371	0.0547	0.1547***	0.1438***	0.0866*	6.4786
2010	0.0680	-0.0617	0.0366	0.0649	0.1225**	0.0564	0.0185	0.1254**	0.1281**	0.0496	9.6490
2011	-0.0737	0.0355	-0.0275	-0.1309	-0.1212	-0.1902	-0.1006	0.1594***	0.2187***	-0.0004	7.4488
2012	0.0439	0.0082	-0.0179	0.1588	0.0058	0.1427*	0.0456	0.1999***	0.1638***	0.0228	5.5783
2013	-0.0471	-0.0932*	-0.0184	-0.1294	0.0346	-0.1076**	0.0084	0.1017***	0.1308***	0.0136	10.2738
2014	0.0737	0.0081	-0.0729**	0.0110	0.0264	0.0431	-0.0206	0.1434***	0.1895***	-0.1082***	9.9430
2015	-0.0656	-0.0307	0.0397	-0.0750	0.0693	-0.0321	0.0193	0.0473	0.1638***	0.0019	2.8679
2016	0.0183	-0.0111	0.0040	0.1418	-0.0021	0.0849	-0.0224	0.1125**	0.0657	0.0424	2.9651
2017	0.0530	0.0663	0.1590**	0.0651	0.0323	0.0572	-0.0904	0.0865*	0.0811	-0.0822	19.4323***
Joint Hypothesis Test: Coefficients are Zero in Full Sample. ($\chi^2_{D.F.}$)	24.0452*	14.3246	16.2109	18.7957	28.5324**	28.3883**	22.2515	107.7250***	95.9231***	28.0132**	188.3379***
Degrees of Freedom (D.F.)	16	16	16	16	16	16	16	16	16	16	112

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence level, respectively. ¹ = the statistics are computed from the observed data on trading days from September 9, 2002, to December 29, 2002, to December 29, 2017.

one unobserved nonfundamental factor that explains the excess co-movement of stock returns (e.g., Pindyck & Rotemberg, 1993).

Market volatility and volume turnover are also significant explanatory variables and are indirect proxies for sentiment. Their significance suggests that their correlations are driven not only by weather-induced sentiment but also by the sentiment induced by other variables.

Biased Correlation Estimates

Previous studies, e.g., Knif et al. (2005), have consistently found that return correlations rise in a falling market. This finding suggests that the coefficient for market returns in equation (1) is negative. However, variance estimates may bias correlation estimates (Loretan & English, 2000), therefore leading to a positive coefficient. From Table 3, it can be seen that the coefficient is positive and significant for most years. This result leads to the conclusion that bias exists and is dominant, implying that econometricians should add market return to control for the bias in studies of return correlations.

Common Weather Variables

In studies on correlation-driving factors, researchers, e.g., Kwan (1996), raised an interesting question, as to whether the factors that drive the correlations are related to the ones that drive the returns or volatility. In this study, air pressure, relative humidity, and temperature were shown to drive the return correlation in SET. Recently, Khanthavit (2017a) found that the SET

index return was explained by air pressure and rainfall, while the volatility was explained by air pressure, relative humidity, temperature, and wind speed. Therefore, this correlation is driven by the weather variables that are prominently related to volatility.

Weather Coefficients Change Signs

The coefficients for individual weather variables are significantly positive, negative, or zero over the full sample period. This result suggests that the effects of individual weather variables on the return correlation are time-varying, which supports the approach of estimating the model one year at a time. Denissen et al. (2008) explained the changing signs: mood reactions to day-to-day weather fluctuations might not be generalized to cover reactions to seasonal fluctuations. Watson (2000) added that whether good or bad weather was temporary or prolonged was important for both investors and their moods.

Trending Correlations

The time-varying return correlations are rising over time (e.g., Ren & Zhou, 2014). In the meantime, temperature, rainfall, and other weather variables can be trending due to global warming (e.g., Wentz, Ricciardulli, Hilburn, & Mears, 2007). Therefore, it is possible that the significant relationship between the return correlations and weather variables in Table 3 is explained by a common time trend and not by investors' moods or limited attention. To ensure that the time trend is not the explanation for this finding, equation (1) was re-estimated

with the time trend included. For the full sample period, the coefficient for the time trend is significant at the 90% confidence level. The Wald statistic for the joint hypothesis test for no relationship is 150.1047. The hypothesis is therefore rejected at the 99% confidence level. When the year 2002 is not included in the sample, the Wald statistic is 130.5183, and the hypothesis is rejected at the 95% confidence level. These findings lead to the conclusion that the significant relationship between the return correlations and weather variables does not result from a common time trend.

CONCLUSION

In addition to fundamental factors, investor sentiment helps to explain pairwise stock-return correlations. In this study, the correlations were related with weather conditions due to the weather effects on investors' moods and limited attention. For the Thai market, the relationship between the correlation of the SET 50 and mai index returns and Bangkok's weather is significant. Despite this significance, the average R^2 is 5.82%. Thus, it is interesting to question which nonfundamental factors, other than weather, explain these correlations. This question falls to future research.

REFERENCES

- Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2), 129–152.
- Barberis, N., & Shleifer, A. (2003). Style investing, *Journal of Financial Economics*, 68(2), 161–199.
- Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement, *Journal of Financial Economics*, 75(2), 283–317.
- Black, F. (1976). Studies of stock price volatility changes. In *Proceedings of the 1976 Meeting of the American Statistical Association, Business and Economic Statistics Section*, Washington D.C., 177–181.
- Bohner, G., Crow, K., Erb, H., & Schwarz, N. (1992). Affect and persuasion: Mood effects on the processing of message content and context cues and on subsequent behaviour. *European Journal of Social Psychology*, 22(6), 511–530.
- Brunetti, C., & Lildholdt, P. (2002). *Return-based and range-based (co)variance estimation - with an application to foreign exchange markets*, Working Paper, Board of Governors of the Federal Reserve System. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=296875
- Campbell, J. Y. (1991). A variance decomposition of stock returns, *Economic Journal*, 101(405), 157–179.
- David, J. M., & Simonovska, I. (2016). Correlated beliefs, returns, and stock market volatility, *Journal of International Economics*, 99(Supplement 1), S58-S77.
- Denissen, J. J. A., Butalid, L., Penke, L., & van Aken, M. A. G. (2008). The effects of weather on daily mood: A multilevel approach. *Emotion*, 8(5), 662–667.

- Doyle, J. R., & Chen, C. H. (2009). The wandering weekday effect in major stock markets. *Journal of Banking and Finance*, 33(8), 1388–1399.
- Dowling, M. & Lucey, B. M. (2005). Weather, biorhythms, beliefs and stock returns—Some preliminary Irish evidence. *International Review of Financial Analysis*, 14(3), 337–355.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics*, 33(1), 3–56.
- Fisher, I. (1930). *The Theory of Interest, as Determined by Impatience to Spend Income and Opportunity to Invest It*. New York: Macmillan.
- Forgas, J. P. (2017). Can sadness be good for you?: On the cognitive, motivational, and interpersonal benefits of mild negative affect, *Australian Psychologist*, 52(1), 3–13.
- Forgas, J. P., Goldenberg, L., & Unkelbach, C. (2009). Can bad weather improve your memory?: An unobtrusive field study of natural mood effects on real-life memory, *Journal of Experimental Social Psychology*, 45(1), 254–257.
- Fruhworth, M., & Sogner, L. (2015). Weather and SAD related effects on the financial market. *Quarterly Review of Economics and Finance*, 57, 11–31.
- Goetzman, W. N., Kim, D., Kumar, A., & Wang, Q. (2015). Weather-induced mood, institutional investors, and stock returns, *Review of Financial Studies*, 28(1), 73–111.
- Gorban, A. N., Smirnova, E. V., & Tyukina, T. A. (2010). Correlations, risk and crisis: From physiology to finance, *Physica A: Statistical Mechanics and its Applications*, 389(16), 3193–3217.
- Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50(4), 1029–1054.
- Hendershott, T., Menkveld, A. J., Praz, R., & Seasholes, M. S. (2018). *Asset price dynamics with limited attention*, 23rd Australasian Finance and Banking Conference 2010 Paper. DOI: 10.2139/ssrn.1651098
- Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *Journal of Finance*, 58(3), 1009–1032.
- Khanthavit, A. (2017a). *Weather, investor sentiment, and stock returns in the Stock Exchange of Thailand*, Working Paper, Thammasat University, DOI: 10.13140/RG.2.2.29145.21606
- Khanthavit, A. (2017b). 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. & Chaowalerd, O. (2016). Revisiting the Day-of-the-week effect in the Stock Exchange of Thailand, *Journal of Business Administration*, 39(151), 73–89.
- Knif, J., Kolari, J., & Pynnonen, S. (2005). *What drives correlation between stock market returns? International evidence*. Working Paper, University of Vaasa. Retrieved from <https://www.univaasa.fi/fi/research/>

- publications/publicationseries/old/knif_ym_fullpaper.pdf
- Kumar, A., & Lee, C. M. C. (2006). Retail investor sentiment and return comovements, *Journal of Finance*, 61(5), 2451–2486.
- Kumar, A., Page, J. K., & Spalt, O. G. (2013). Investor sentiment and return comovements: Evidence from stock splits and headquarters changes, *Review of Finance*, 17(3), 921–953.
- Kwan, S. H. (1996). Firm-specific information and the correlation between individual stocks and bonds, *Journal of Financial Economics*, 40(1), 63–80.
- Loretan M., & English, W. B. (2000). Evaluating changes in correlations during periods of high market volatility, *BIS Quarterly Review*, (June), 29–36.
- Loughran, T., & Schultz, P. (2004). Weather, stock returns, and the impact of localized trading behavior, *Journal of Financial and Quantitative Analysis*, 39(2), 343–364.
- Mehra, R., & Sah, R. (2002). Mood fluctuations, projection bias, and volatility of equity prices. *Journal of Economic Dynamics and Control*, 26(5), 869–887.
- Newey, W. K. & West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *Review of Economic Studies*, 61(4), 631–653.
- Pal, M. (1980). Consistent moment estimators of regression coefficients in the presence of errors in variables. *Journal of Econometrics*, 14(3), 349–364.
- Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return, *Journal of Business*, 53(1), 61–65.
- Peng, L., Xiong, W., & Bollerslev, T. (2007). Investor attention and time-varying comovements, *European Financial Management*, 13(3), 394–422.
- Pindyck, R. S., & Rotemberg, J. J. (1993). The comovement of stock prices, *Quarterly Journal of Economics*, 108(4), 1073–1104.
- 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.
- Ren, F., & Zhou, W. (2014). Dynamic evolution and cross-correlations in the Chinese stock markets, *PLoS ONE*, 9(5), e97711.
- Rogers, L. C. G., & Satchell, S. E. (1991). Estimating variance from high, low, and closing prices, *Annals of Applied Probability*, 1(4), 504–512.
- Rogers, L. C. G., Satchell, S. E., & Yoon, Y. (1994). Estimating the volatility of stock prices: a comparison of methods that use high and low prices, *Applied Financial Economics*, 4(3), 241–247.
- Rogers, L. C. G., & Zhou, F. (2008). Estimating correlation from high, low, opening and closing prices, *Annals of Applied Probability*, 18(2), 813–823.
- Symeonidis, L., Daskalakis, G., & Markellos, R. N. (2010). Does the weather affect stock market

- volatility?, *Finance Research Letters*, 7(4), 217–223.
- Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities, *Financial Analysts Journal*, 68(6), 54–74.
- Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations, *Journal of Business and Economic Statistics*, 20(3), 351–362.
- Watson, D. (2000). *Mood and Temperament*. London: Guilford Press.
- Wentz, F. J., Ricciardulli, L., Hilburn, K., & Mears, C. (2007). How much more rain will global warming bring? *Science*, 317(5835), 233–235.
- Williams, J. B. (1938). *The Theory of Investment Value*. Massachusetts: Harvard University Press.
- Worthington, A. (2009). An empirical note on weather effects in the Australian stock market, *Economic Papers*, 28(2), 148–154.