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Weather-Induced Moods and Stock-Return Autocorrelation*

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Abstract: *Moods affect investors' attention, memory, and capacity to process information. Inattentive investors delay the price adjustment process, thus leading to a positive autocorrelation of asset returns. In this study, I investigate the relationship between weather-induced moods and stock-return autocorrelation in the Stock Exchange of Thailand from January 2, 1991, to December 29, 2017. Only good moods contribute significantly to return autocorrelation.*

Keywords: information processing; moods; limited attention; return autocorrelation; weather effects

JEL classification: G40, G41

Introduction

Significant autocorrelation of stock returns is found in national markets around the world (e.g. Thompson, 2011). It implies return predictability and profitable stock trading. Researchers have attempted to explain why autocorrelation exists. In an inefficient market, return autocorrelation results from the market's inability to disseminate information immediately (Fama, 1970). Its size may vary, and it can disappear at times as the market evolves (Lo, 2004).

Kual and Nimalendran (1990) explained that significant return autocorrelation might be a statistical artifact. If returns were measured with errors, the autocorrelation estimate would be negative. A negative autocorrelation can be found in cases in which the market prices stocks incorrectly; the prices necessarily adjust over time to the correct levels (e.g. De Bondt, 1989). Scholes and Williams (1977) warned that nonsynchronous trading could create spurious positive autocorrelation for returns.

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Return autocorrelation can be generated in models of informed trading and liquidity trading. Informed trading leads to zero or positive autocorrelation (e.g. Kyle, 1985; Boulatov, Hendershott, & Livdan, 2013), whereas liquidity trading generates negative autocorrelation (e.g. Campbell, Grossman, & Wang, 1993; Nagel, 2012).

Moods cause investors' limited attention, poor memory, and low capacity to process information (e.g. Bohner, Crow, Erb, & Schwarz, 1992; Isen, 2001; Forgas, Goldenberg, & Unkelbach, 2009; Forgas, 2017). Inattentive investors delay the price adjustment process, therefore leading to positive autocorrelation of asset returns (Dehaan, Madsen, & Piotroski, 2017). Researchers (e.g. Bogousslavsky, 2016; Hendershott, Menkveld, Praz, & Seasholes, 2018) have developed theoretical limited-attention models in which the market consists of attentive and inattentive investors. In these models, with liquidity shocks, inattentive investors' trades prolong pricing errors and cause positive return autocorrelation.

I investigate whether and how investors' moods contribute to significant return autocorrelation. Moods are not observed but are estimated by weather variables. Therefore, in this study, the moods are weather-induced moods.

This study offers two contributions. First, it adds weather-induced moods to the economic and finance literature as one possible explanation of significant return autocorrelation. Second, it contributes to the psychology literature indirect evidence of mood effects on limited attention, memory, and information-processing capacity.

Methodology

The Model

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

$$\tilde{r}_t = \alpha_0 + \alpha_1 \tilde{M}_t + \rho\left(M_{t-1}, X_{t-1}\right) r_{t-1} + \tilde{e}_t \tag{1}$$

$\rho\left(M_{t-1}, X_{t-1}\right)$ is the autocorrelation coefficient. It is a function of the lagged mood variable, M_{t-1}, and a control variable, X_{t-1}. α_0 and α_1 are the intercept and mood coefficient, respectively. $\tilde{e}_t$ is the error term.

Good and bad moods do not necessarily have symmetric effects. On the one hand, Isen (2001) reported that high positive moods facilitated systematic, careful, cognitive processing, tending to make processing both more efficient and more thorough, while Brand, Reimer, and Opwis (2007) reported that bad moods impaired information-processing ability. Dehaan et al. (2017) found for the U.S. stock market that analysts with bad weather-induced moods were slower or less likely to respond to an earnings announcement than those with good moods. Therefore, only bad moods should contribute to positive return autocorrelation. On the other hand, Bohner et al. (1992) reported that positive moods reduced subjects' motivation to systematically process message content and context cues; Forgas et al. (2009) reported that subjects with negative moods showed better memory and discriminatory ability than subjects with good moods; and Forgas (2017) reported that negative moods promoted optimal performance in cognitive and social tasks. These studies suggest that good moods contribute positively to return autocorrelation, and bad moods contribute less or nothing.

The contributions of good moods and bad moods are measured separately. I assume that the function $\rho\left(M_{t-1}, X_{t-1}\right)$ is linear in its arguments. Two specifications are proposed.

$$\rho\left(M_{t-1}, X_{t-1}\right) = \rho_0 + \rho_1 X_{t-1} + \rho_2^{+} I_{t-1}^{+} + \rho_2^{-} I_{t-1}^{-}. \tag{2.1}$$

$$\rho\left(M_{t-1}, X_{t-1}\right) = \rho_0 + \rho_1 X_{t-1} + \rho_2^{+} I_{t-1}^{+} M_{t-1} + \rho_2^{-} I_{t-1}^{-} \left|M_{t-1}\right|. \tag{2.2}$$

I_{t-1}^{+} and I_{t-1}^{-} are dummy variables. $I_{t-1}^{+} = 1$ ($I_{t-1}^{-} = 1$) if M_{t-1} is greater (smaller) than a threshold value $\tau > 0$ ($-\tau < 0$). Otherwise, $I_{t-1}^{+} = 0$ ($I_{t-1}^{-} = 0$). ρ_2^{+} and ρ_2^{-} indicate the contribution of different mood states to the autocorrelation, while ρ_1 is the coefficient for the control variable X_{t-1}. ρ_0 is a constant. It averages the contributions of influential variables other than M_{t-1} and X_{t-1}.

The threshold value τ should be large enough to discriminate good moods from bad moods. In estimation, the mood variable is standardized. Its mean and standard deviation are 0.00 and 1.00, respectively. Following Kang, Jiang, Lee, and Yoon (2010), $\tau = 1.00$.

The specification in equation (2.1) considers only the mood states. The specification in equation (3.2) considers both the mood states and their degrees. I place $\left|M_{t-1}\right|$ with I_{t-1}^{-} so that ρ_2^{-} can be interpreted straightforwardly.

Combining equation (1) with equations (2.1) and (2.2) and rearranging terms provides the linear regression models for estimation and tests.

$$\tilde{r}_t = \alpha_0 + \alpha_1 \tilde{M}_t + \rho_0 r_{t-1} + \rho_1 X_{t-1} r_{t-1} + \rho_2^{+} I_{t-1}^{+} r_{t-1} + \rho_2^{-} I_{t-1}^{-} r_{t-1} + \tilde{e}_t. \tag{3.1}$$

$$\tilde{r}_t = \alpha_0 + \alpha_1 \tilde{M}_t + \rho_0 r_{t-1} + \rho_1 X_{t-1} r_{t-1} + \rho_2^{+} I_{t-1}^{+} M_{t-1} r_{t-1} + \rho_2^{-} I_{t-1}^{-} \left|M_{t-1}\right| r_{t-1} + \tilde{e}_t. \tag{3.2}$$

Hypothesis Tests

Investors' moods can cause stock returns to deviate from their fundamental values (Loewenstein, 2000). Based on equations (3.1) and (3.2), the hypothesis for the mood effect on return is $\alpha_1 = 0.00$. Under the null hypothesis, the Wald statistic is distributed as a chi-square variable with 1 degree of freedom. The Wald statistic is computed from Newey and West's (1994) heteroscedasticity and autocorrelation consistent covariance matrix.

The significance and sign of α_1 enable me to interpret whether ρ_2^+ and ρ_2^- are the contributions of good moods or bad moods. Prices and returns rise or fall due to changing risk preference, which leads marginal investors to lower or raise discount rates (Mehra & Sah, 2002), or due to mood misattribution, which causes marginal investors to incorrectly associate good or bad weather and mood with good or bad prospects of the assets (Hirshleifer & Shumway, 2003). Therefore, significant and positive α_1 suggests that ρ_2^+ is the contribution of good moods and ρ_2^- is the contribution of bad moods. However, if α_1 is negative and significant, ρ_2^+ and ρ_2^- result from bad moods and good moods, respectively.

The hypotheses for significant contributions to the autocorrelation are $\rho_2^+ = 0.00$ and $\rho_2^- = 0.00$. Moreover, if good and bad moods have equal contributions, $\rho_2^+ = \rho_2^-$. Under each null hypothesis, the Wald statistic is a chi-square variable with 1 degree of freedom.

Model Estimation

Unobserved Moods

The mood variable, $\tilde{M}_t$, is unobserved. Denissen, Butalid, Penke, and van Aken (2008) reported that moods were influenced by weather conditions, and the relationship was strong when all the weather variables were considered jointly. To proceed, I follow Dehann et al. (2017) to a proxy for $\tilde{M}_t$ by the principal component (PC) of a set of weather variables. This proxy is superior to a linear combination of the weather variables considered by previous studies (e.g. Fruhwirth & Sogner, 2015). The model is simple; the chosen principal component summarizes common variations of the weather variables, and it is easy to interpret the coefficients.

Endogeneity Problems

The use of a proxy for $\tilde{M}_t$ causes endogeneity problems in the estimation. The conventional ordinary-least-squares regression gives biased and inconsistent estimates. To mitigate the problems, I use Hansen's (1982) generalized methods of moments (GMM) to estimate equations (3.1) and (3.2). GMM is an instrumental variable (IV) approach whose estimators are consistent, asymptotically normal, and efficient among the class of estimators that use no information beyond moment conditions. Moreover, GMM does not require normally distributed variables.

The Choice of Instrumental Variables

The IV for the mood variable is Racicot and Theoret's (2010) two-step IV. Khanthavit (2017) found that two-step IVs had good informativeness and validity performance. In the first step, I computed Pal's (1980) cumulant IV for the mood variable. In the second step, the mood variable was regressed on the Pal IV. The Racicot-Theoret IV was the regression residual. The IVs for I_{t-1}^{+} and I_{t-1}^{-} were constructed from the mood variable's IV. The remaining IVs were a constant, the lagged return, and control variable.

A Fixed-Effect Assumption

The estimation of the models in equations (3.1) and (3.2) imposes a fixed-effect assumption under which the relationship between the stock return and the regressors is fixed throughout the estimation sample. For a long sample period, the assumption is unlikely. To lessen the effects of the incorrect assumption, I follow Khanthavit (2017) to estimate the models using sample periods of one year at a time. The Wald statistics for a full sample test are the sum of statistics for all the N years in the full period. Hence, they are chi-square variables with N degrees of freedom (Doyle & Chen, 2009).

The Data

The stock returns are the logged differences of the closing indexes of the Stock Exchange of Thailand (SET) portfolio index. The weather variables are Bangkok's seven weather variables – air pressure (hectopascal), cloud cover (decile), ground visibility (meters), rainfall (millimeters), relative humidity (%), temperature (°C), and wind speed (knots per hour). These variables were measured at Don Muang Airport by the Thai Meteorological Department.

I retrieved the stock data from the SET database and the weather variables from the Thai Meteorological Department database. The data started on January 2, 1991, and ended on December 29, 2017. There are 6,612 trading-day observations for the stock and 9,862 calendar-day observations for the weather.

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 1991-2017 sample period. Next, the deseasonalized variables were standardized by their averages and standard deviations. Because some observations were missing, I imputed the missing cases with zero because zero was the unconditional mean of deseasonalized variables.

I chose volume turnover for the control variable X_{t-1}. In the liquidity-trading models, trading volume measures the buying and selling price pressure from liquidity traders (e.g. Campbell et al., 1993), and in the informed-trading models, it is likely that trading volume results from informed traders (e.g. Kyle, 1985).

In addition to the mood channel, weather may contribute to the autocorrelation by other channels (Dehaan et al., 2017). Severe weather affects investors physically. For example, heavy rains and floods interrupt transportation and delay trading, resulting in positive autocorrelation. On severe-weather days, the trading volume tends to be low. The volume turnover also helps to control the physical effects. The volume data were retrieved from the SET database.

I am aware the trading volume cannot control the contributions of factors such as day-of-the-week (DOW) effects (Campbell et al., 1993). Nonetheless, if these effects exist, their contributions are represented by the coefficient ρ_0.

Table 1 reports the descriptive statistics. In Panel 1.1, the variables are not distributed normally. The return is serially correlated at the first order. The non-normality result supports the GMM estimation because GMM does not require normal samples. The autocorrelation result ensures that the autocorrelation issue is valid. It also supports the use of Newey and West's (1994) heteroscedasticity and autocorrelation consistent covariance matrix in the statistical tests. In Panel 1.2, the correlations among the treated weather variables are significant. The PC should well summarize their common variation.

Table 1: Descriptive Statistics

Panel 1.1: Index Return, Volume Turnover, and Untreated Weather Variables

Statistics	Index Return	Volume Turnover	Untreated Weather Variables[2]						
			Air Pressure (hectopascal)	Cloud Cover (decile)	Ground Visibility (meters)	Rainfall (mm.)	Relative Humidity (%)	Temperature (°C)	Wind Speed (knots/hour)
Average	1.59E-04	0.0035	97.0589	5.4800	8,910.0515	0.3467	66.1626	29.9808	5.8016
Standard Deviation	0.0155	0.0020	29.7507	1.4028	1,421.7535	1.5458	10.5438	2.1484	2.5164
Skewness	0.0223	1.8483	0.3972	-0.5737	-1.2002	7.7876	-0.4401	-0.7839	1.6545
Excess Kurtosis	7.3393	5.3284	0.0484	-0.2306	1.4604	81.5708	2.7896	2.5274	6.9920
Minimum	0.1135	0.0188	0.0000	0.0909	2,509.0909	0.0000	4.0909	8.1000	0.2727
Maximum	-0.1606	0.0004	250.5455	8.0000	14,272.7273	27.5500	98.0000	36.3455	30.5455
Jarque-Bera Statistic	1.48E+4***	1.16E+4***	254.7168***	545.8528***	3,154.4846***	2.76E+06***	3,441.4408***	3,569.0631***	2.39E+4***
AR(1)	0.0912***	0.8270	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Observations	6,612	6,612	9,651	9,566	9,590	9,621	9,653	9,683	9,600

Note: *** = significance at the 99% confidence level. N.A. = not applicable because of missing observations. [1] and [2] = statistics are computed from the observed data on trading days and calendar days, respectively.

Panel 1.2: Correlations[1] of Imputed, Deseasonalized Weather Variables

Weather Variables	Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed
Air Pressure	1.0000						
Cloud Cover	-0.1133***	1.0000					
Ground Visibility	0.0111	-0.1151***	1.0000				
Rainfall	-0.0051	0.1826***	-0.1647***	1.0000			
Relative Humidity	-0.1242***	0.5104***	-0.2170***	0.2752***	1.0000		
Temperature	-0.3467***	-0.3170***	0.1189***	-0.2539***	-0.2783***	1.0000	
Wind Speed	-0.0787***	-0.0319***	0.1979***	-0.0525***	-0.1011***	0.0773***	1.0000

Note: *** = significance at the 99% confidence level. [1] = statistics are computed from the observed data on trading days (6,612 observations).

I computed the seven PCs from the treated weather variables. Table 2 reports the percentages of the total variance of the weather variables explained by each PC. The first PC explained 29.34%, while the seventh PC explained 6.39%.

Table 2: Total Variance Explained

Principal Component	Total Variance Explained (%)
1	29.34
2	18.55
3	15.67
4	12.24
5	10.81
6	6.99
7	6.39

In most weather (Dehann et al., 2017) and sentiment (e.g. Baker & Wurgler, 2007) studies, the first PC was chosen because it best explains the common variation of the variables. Recently, Khanthavit (2018) argued that this ability did not necessarily translate to its influence on moods. For the SET, it was the fourth PC that had significant effects on the return. Based on Khanthavit's (2018) evidence, in this study, the proxy for the mood variable is the fourth PC.

Empirical Results

Table 3 reports weather-induced moods' contributions to the stock-return autocorrelation. Panel 3.1 shows the results of the model in which only the mood states were considered. The average mood coefficient, α_1, is -0.0455. In the full sample test, the mood effect is significant at the 90% confidence level. In the last row, I report the results when the full sample was used in the estimation. α_1 is -0.0221. Although it is not significant, its sign is consistent with that of the average. The result for α_1 enables me to associate positive mood variables with bad moods and negative mood variables with good moods.

Table 3: Contributions of Moods to Return Autocorrelation

Panel 3.1: Only Mood States Were Considered.

Sample	Principal Component(t)	Autocorrelation				Ho: Equal Effects (χ_1^2)
		Return(t-1)	Return(t-1) × Volume Turnover(t-1)	Return(t-1) $\times I_{t-1}^{+}$	Return(t-1) $\times I_{t-1}^{-}$	
1991	0.0530	0.0606	-0.1113	0.1975	0.6777***	7.8599***
1992	-0.0775	-0.1204	0.0577	0.2413	0.2955	0.0400
1993	-0.0019	0.1240	-0.0087	0.6467***	0.3096	1.9369
1994	-0.0763	0.0416	-0.0112	0.3168	0.2917*	0.0017
1995	-0.0521	0.1089	-0.1214*	-0.0706	0.9714***	6.3084**
1996	0.1715**	-0.0319	-0.2652**	0.1212	-0.3281**	3.8475**
1997	-0.0782	0.2213**	0.0092	-0.0428	0.8620***	18.2732***
1998	0.0384	0.2450**	-0.1498***	-0.0714	0.9220***	14.2712***
1999	-0.2092	0.0525	0.0460	0.2627	0.0965	0.1919
2000	-0.0723	-0.0069	0.0418	0.1232	-0.1189	0.5929
2001	0.0176	0.0611	0.0241	0.2068	-0.2719	2.8483*
2002	0.1764***	0.0984	-0.0024	0.0833	-0.1129	0.2151
2003	-0.1217**	0.0565	0.0351	0.0157	0.1195	0.1224
2004	-0.0954	-0.0100	-0.0052	-0.0898	0.1389	1.2432
2005	-0.5436	0.0695	-0.1581	0.0927	0.3211	0.2782
2006	-0.0878*	0.1323	-0.1261***	-0.0023	0.2792	1.8269
2007	-0.0072	0.1692	-0.1115	-2.1988	-0.0797	0.6819
2008	-0.1681	0.1923	-0.2428	-0.3604**	-0.2327	0.4361
2009	-0.0117	-0.0331	-0.0151	0.0380	-0.0175	0.0420
2010	0.0140	0.0428	0.0084	-0.1592	-0.0322	0.2748
2011	0.0191	0.1635**	-0.1037	0.0803	-0.2507*	0.9922
2012	0.0525	-0.0645	-0.0415	-0.0490	0.3131*	2.7207*
2013	-0.0690	0.0745	-0.1311	-0.0056	0.1539	0.2362
2014	-0.0176	0.0787	0.1566**	-0.3568	0.6379	2.2117
2015	-0.0079	-0.0046	-0.3668***	0.5840	0.5574*	0.0020
2016	-0.0861*	0.0724	0.0035	-0.3423	-0.4526	0.0372
2017	0.0122	0.1138	-0.1201	-0.2908	0.0504	0.0095
Average Coefficients	-0.0455	0.0706	-0.0633	-0.0381	0.1889	N.A.
Ho: For all years, Coefficients=0 / Equal Effects. (χ_{27}^2)	39.5470*	41.8270**	84.6330***	33.0778	100.0428***	67.4925***
1991-2017	-0.0221	0.1135***	-0.0542**	0.0515	0.0422	0.0095

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

Panel 3.2: Both Mood States and Degrees Were Considered.

Sample	Principal Component(t)	Autocorrelation				Ho: Equal Effects (χ^2_1)
		Return(t-1)	Return(t-1) × Volume Turnover(t-1)	Return(t-1) × I^+_{t-1} × Principal Component(t-1)	Return(t-1) × I^-_{t-1} × |Principal Component(t-1)|	
1991	0.0466	0.0507	-0.1105	0.1576	0.5861***	6.8242***
1992	-0.0819	-0.1056	0.0543	0.1338	0.2035	0.1406
1993	-0.0066	0.1299	-0.0057	0.4401***	0.2734	0.6630
1994	-0.0739	0.0426	-0.0113	0.1554	0.2223*	0.0570
1995	-0.0531	0.1146	-0.1277*	-0.0725	0.7097**	5.2350**
1996	0.1751**	0.0648	-0.1857	-0.0171	-0.2239***	15.9628***
1997	-0.0682	0.2057**	0.0180	0.0402	0.7376***	18.8252***
1998	0.0499	0.2198**	-0.1429***	0.0245	0.6931*	3.5385*
1999	-0.2027	0.0322	0.0381	0.1496	0.1434	6.65E-04
2000	-0.0689	-0.0134	0.0377	0.0386	-0.0511	0.4016
2001	0.0180	0.0596	0.0242	0.1757	-0.2011	2.6236
2002	0.1766***	0.0997	-0.0023	0.0562	-0.1151	0.2935
2003	-0.1225**	0.0621	0.0343	-0.0101	0.0570	0.1094
2004	-0.0927	0.0012	-0.0072	-0.0622	0.0808	2.6627
2005	-0.5329	0.1394	-0.1742	-0.0123	-0.0695	0.0031
2006	-0.0897*	0.1304	-0.1257***	0.0304	0.1999	1.2544
2007	4.33E-04	0.1283*	-0.0573	-0.1493	-0.0553	0.0634
2008	-0.1948	0.1517	-0.2437	-0.1166**	-0.0183	0.0724
2009	-0.0145	-0.0250	-0.0111	-0.0190	-0.0545	0.0250
2010	0.0125	0.0426	-0.0118	-0.0374	0.0288	0.1589
2011	0.0166	0.1719**	-0.1111	-0.0410	-0.1962*	1.5758
2012	0.0543	-0.0678	-0.0424	-0.0648	0.2769**	5.0675**
2013	-0.0697	0.0756	-0.1326	-0.0076	0.1183	0.7041
2014	-0.0201	0.0794	0.1554**	-0.1399	0.5998	2.0538
2015	-0.0123	0.0090	-0.3382***	0.2474	0.4058*	0.2044
2016	-0.0872*	0.0489	0.0139	-0.0742	-0.3065	0.2614
2017	0.0133	0.1189*	-0.1169	-0.1222**	0.0049	0.8675
Average Coefficients	-0.0455	0.0729	-0.0586***	0.0260	0.1500	N.A.
Ho: For all years, Coefficients=0 / Equal Effects. (χ^2_{27})	40.1251**	36.4125	82.7159***	31.8278	92.7047***	69.6494***
1991-2017	-0.0221	0.1118***	-0.0543**	0.0249	0.0522	0.1216

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

The contribution to return autocorrelation of bad moods is -0.0381, while that from good moods is 0.1889. The full sample tests show that only the contribution of good moods is significant. The confidence level is very high at 99%. The effects of bad moods are not significant. The hypothesis of equal contributions is rejected at the 99% confidence level.

Panel 3.2 shows the results for the model in which both mood states and degrees are considered. They are similar to those in Panel 3.1.

Discussion

Good Moods and Positive Autocorrelation

For stock-market studies, my results contradict Dehaan et al.'s (2017) results. The researchers found that U.S. analysts delayed responses to earnings news when they were in bad moods.

Dehaan et al. (2017) were aware that weather-driven moods had both information-processing and psycho-physical effects. The latter effects arise when bad weather induces discomfort and negatively affects analysts' moods. These analysts tended not to report to work and became less productive (Coleman & Schaefer, 1990).

Dehaan et al. (2017) were unable to separate the two effects. In their study, even if superior information processing was associated with bad moods, the psycho-physical effects could be dominant. Analyzing earnings news and writing reports are more physically demanding for analysts than receiving news and information and trading stocks are for investors. In this study, in which investors' trading is considered, the psycho-physical effects should be small.

The Volume Effects and Remainders

The volume turnover in the autocorrelation function served to control the effects of informed-trading, liquidity-trading, and weather-induced physical effects. In Table 3, Panels 3.1 and 3.2, the estimates are negative and significant. This finding supports the liquidity-trading and physical effects.

It is unlikely that moods, liquidity-trading, and physical effects can exhaustively explain the return autocorrelation. The contribution of the remaining factors is captured by the coefficient ρ_0. Its estimates are positive and significant. This result is consistent with the DOW effects in autocorrelation for which the significant positive autocorrelation is present on most weekdays. The coefficient ρ_0 averages the effects. It must be positive. Khanthavit and Chaowalerd (2016) reported significant DOW effects on return autocorrelation for the SET and explained that the effects were caused by positive feedback strategies with respect to foreign investors' trading volume.

I did not control the positive contribution of nonsynchronous trading and the negative contribution of measurement errors. However, their sizes should be small. The two problems are generally present in small, inactive stocks. In this study, I considered the SET portfolio index. It is a value-weighted index, and actively trading large stocks contribute most to its movement.

Nor did I control the negative contribution of weather-induced mispricing. In Table 3, the coefficients ρ_2^+ and ρ_2^- are the contributions of bad and good moods, the net of the mispricing effects. The estimates suggest that the size of the mispricing is small vis-à-vis that for moods.

The First Principal Component's Results

I chose the fourth PC as a proxy for the mood variable because it was the only PC that affected Thai stock returns (Khanthavit, 2018). In previous studies, such as Dehaan et al. (2017), the first PC was commonly used. It is interesting to investigate the results when the first PC is used in the estimation.

Table 4, Panels 4.1 and 4.2, shows that the mood coefficient is positive. Positive and negative mood variables are associated with good and bad moods, respectively. It is important to note that the coefficient is not significant. The results are suggestive and must be interpreted carefully.

Table 4: Contributions of Moods to Return Autocorrelation When the First Principal Component Proxied the Mood Variable

Panel 4.1: Only Mood States Were Considered.

Sample	Principal Component(t)	Autocorrelation				Ho: Equal Effects (χ_1^2)
		Return(t-1)	Return(t-1) × Volume Turnover(t-1)	Return(t-1) × I_{t-1}^+	Return(t-1) × I_{t-1}^-	
Average Coefficients (1991 – 2017)	0.0032	0.0866	-0.0506	-0.0636	-0.0006	N.A.
Ho: For all years, Coefficients=0 / Equal Effects. (χ_{27}^2)	26.6542	45.9408**	75.1367***	30.9414	40.9996**	46.5463**
1991-2017	0.0046	0.0887***	-0.0536**	0.0726	0.1265*	0.4412

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

Panel 4.2: Both Mood States and Degrees Were Considered.

Sample	Principal Component(t)	Autocorrelation				Ho: Equal Effects (χ^2_1)
		Return(t-1)	Return(t-1) × Volume Turnover(t-1)	Return(t-1) × I^+_{t-1} × Principal Component(t-1)	Return(t-1) × I^-_{t-1} × |Principal Component(t-1)|	
Average Coefficients (1991 – 2017)	0.0024	0.0913	-0.0541	-0.0367	-0.0225	N.A.
Ho: For all years, Coefficients=0 / Equal Effects. (χ^2_{27})	26.7019	50.5436***	76.0036***	39.7923*	48.5632***	57.2532***
1991-2017	0.0044	0.0975***	-0.0534**	0.0282	0.0665	0.5909

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

For the case in Panel 4.1 in which only mood states were considered, the bad moods' coefficient is negative and significant, while that of the good moods is negative but not significant. This finding is not inconsistent with that for the fourth PC. Investors in bad moods processed information quickly. The contribution of bad moods with respect to information processing is small. It is likely that the negative autocorrelation associated with bad moods results from mispricing effects. The results in Panel 4.2 are similar.

Limited-Attention Models

In Table 3, investors with good moods are inattentive and associated with positive autocorrelation. Bad moods cause attentive investors. In Table 4, attentive investors are associated with negative autocorrelation. These results are predicted by the limited-attention models (e.g. Bogousslavsky, 2016).

Conclusion

If investors' attention, memory, and capacity to process information are influenced by moods, then moods must contribute to significant autocorrelation of stock returns. In this study, I measured good and bad moods based on Bangkok's weather variables and tested whether and how good and bad moods contributed to autocorrelation of returns on the Stock Exchange of Thailand index portfolio. Using daily data from January 2, 1991, to December 29, 2017, I found that good moods contributed significantly to positive autocorrelation.

In the limited-attention model by Hendershott et al. (2018), there can be many groups of inattentive investors. Some are faster to respond, and some are slower. If these investors trade different stocks, the cross-correlation of stock returns should vary with their trades. Moreover, if their attention is influenced to different degrees by weather-induced moods, the cross-correlation must be explained by weather conditions. This issue is an interesting topic for future research.

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