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RESEARCH ARTICLE

Time-Varying Weather Effects on Thai Government Bond Returns

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Abstract: This study proposed a state-space model that allows time-varying weather effects on asset returns. It resolves the model misspecification of the unrealistic, fixed effect assumption commonly made by previous weather studies. The model was applied to examine the weather effects on Thai government bond returns from July 2, 2001, to December 30, 2015. Kalman filtering was used in the estimation. The study found that the weather effects were time-varying. They were wandering in the early sample period but disappearing in the later period. The effects were not co-integrated with the market's inefficiency levels.

Keywords: model misspecification, weather effects

JEL Classifications: C13, G10, G14

Weather effects are defined as incidents in which weather conditions influence asset returns indirectly via the trading activity of weather-sensitive, marginal investors in inefficient markets. Weather can affect the moods (e.g., Howarth & Hoffman, 1984) and risk preferences of these investors (Mehra & Sah, 2002) so that they raise or lower asset prices, although the fundamentals of the assets remain unchanged. Tests for these effects are important. Weather effects are behavioral. Significant effects suggest that prices and returns are driven by both behavioral and fundamental factors; behavioral asset pricing models are preferred (Saunders, 1993). These effects are evidence against market efficiency, suggesting that traders should trade against weather-sensitive investors for abnormal profits (Hirshleifer & Shumway, 2003).

Weather effects have been studied extensively using national and international market data. Cao and Wei (2005) reviewed early studies, while Furhwirth and Sogner (2015)have made recent contributions. Previous studies assumed that the effects were fixed over sample periods. However, the fixed-effect assumption was neither realistic nor supported by empirical findings. For example, when using a full sample from January 15, 1990, to December 13, 2006, Yoon and Kang (2009) found significant temperature effects for the

Korean stock market. After the researchers broke the sample into two sub-periods, they found significant effects only for the first sub-period, but not for the second sub-period. When the fixed-effect assumption is incorrect, the model is misspecified. Significant or insignificant findings can also be incorrect.

Khanthavit (2016a) noted that breaking a longer full-sample period into shorter sub-sample periods mitigated the misspecification problem. Nevertheless, in most studies,the sub-periods were still too long—long enough to allow the effects to change. For example, the sub-periods in Yoon and Kang (2009) were eight years long. Khanthavit (2016a) followed Doyle and Chen (2009) to break the full period into one-year sub-periods, arguing that the changing effects should be gradual and that a fixed effect sufficiently described the return behavior for the year.

The fixed-effect assumption was still made in Khanthvait (2016a) for each of the one-year sub-periods. It is likely that the misspecification problem was lessened. However, it is not clear that the remainder could induce incorrect results. For example, a sample country such as Thailand has its winter from mid-October to mid-February. If the temperature effect were to change, the test might not be able to detect it for that winter because the significant effect was split and averaged away in either year.

In this study, weather effects are not assumed to be fixed but rather are allowed to change stochastically over time. I apply a state-space model in which asset returns are related to weather conditions in the measurement equation. The unobserved weather effects are considered state variables, whose stochastic behaviors are described by the transition equations. The state-space model is estimated by Kalman filtering.

Methodology

The State-Space Model

I relate day t's asset return r_t linearly with its lag r_{t-1} and weather variable W_t^m, where m = 1, ... , M and t = 1, ... ,T, as in the measurement equation (1).

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

The error term $\tilde{e}_t$ is a normal variable, with a zero mean and σ standard deviation. $\tilde{\rho}_t$ is the return's autocorrelation coefficient. $\tilde{\beta}_t^m$ is the stochastic effect of weather variable W_t^m on the return. I imposed a zero intercept because daily data are used in the empirical part, and the daily returns are not significantly different from zero.

The model in equation (1) differs from the models used in previous studies (e.g., Dowling & Lucey, 2005; Worthington, 2009). Its coefficients are not fixed but rather change stochastically over time. The stochastic-coefficient specification removes the fixed-effect misspecification. I treat these stochastic coefficients as state variables, whose behaviors are described by the transition equation (2).

$$\begin{bmatrix} \tilde{\rho}_t \\ \tilde{\beta}_t^1 \\ \vdots \\ \tilde{\beta}_t^M \end{bmatrix} = \begin{bmatrix} \rho_{t-1} \\ \beta_{t-1}^1 \\ \vdots \\ \beta_{t-1}^M \end{bmatrix} + \begin{bmatrix} \tilde{u}_t \\ \tilde{v}_t^1 \\ \vdots \\ \tilde{v}_t^M \end{bmatrix}. \quad (2)$$

The stochastic vector $[\tilde{u}_t \quad \tilde{v}_t^1 \quad \ldots \quad \tilde{v}_t^M]'$ of normal variables has a zero mean vector and covariance matrix Q. I assumed a random walk behavior for the coefficients because the effects should change gradually from one day to the next, and their best predictors are their current levels (Rockinger & Urga, 2000). The random walk assumption is not theoretically correct because the effects range from plus to minus infinity. As shown empirically below, extreme coefficients are unlikely.

The Estimation

The model is estimated by Kalman filtering. It is a recursive procedure for computing the optimal estimators of time t's unobserved state variables, based on observed information available up to and including time t. This recursive procedure consists of predicting and updating phases. In the predicting phase, the state variables and prediction error variances are estimated using the observed information from the previous period. Once the new information is available, the estimated state variables are updated in the updating phase. In addition to parameter estimates, Kalman filtering returns the estimates and standard errors of the stochastic coefficients. The time-varying weather effects can be examined using their t statistics computed daily over the full sample period.

Estimation Problems

Missing weather variables. Weather variables may be missing due to faulty equipment or missed observations, while W_t^m must appear in equation (1) on each and every day. Weather proxies need to be imputed in the missing cases. Worthington (2009) chose imputation variables from a nearby weather station. However, in many cases, as in Thailand, variables from a nearby station are not available or are also missing. In this study, the unconditional means of the missing variables are chosen because they are readily available (Afifi & Ekashoff, 1967). I did not choose the means conditioned on asset returns (Dagenais, 1973) because, under the null hypothesis, the weather variables and returns are uncorrelated.

Endogeneity. Equation (1) suffers from endogeneity problems due to the weather variables being correlated with the error term (Stock & Watson, 2003). The problems resulted primarily from three sources and caused biased and inconsistent estimates.

The first source is errors in variables. The imputation means are proxies for missing observations. They necessarily contain errors. The errors exist even if the variables are not missing and imputation is not needed. The areas where investors trade can be close to or far from the weather station. So, the observed variables at the station are also proxies; they contain errors.

The second source is omitted variables. Investors' moods are driven by various weather variables such as temperature, relative humidity, and so forth(Watson, 2000). Although the number of M variables is large, some influential variables may be omitted, most likely due to data unavailability. For example, geomagnetic storms in Dowling and Lucey (2008) are not measured by the Thai Meteorological Department.

The third source was recently identified. Weather effects are indirect effects of weather on asset returns via weather-influenced mood. Treating the indirect effects as though they are direct ones induces an endogeneity problem similar to the one that stems from errors in variables (Furhwirth & Sogner, 2015).

The Instrumental-Variable(IV) Method

Explanation. In conventional regressions, an IV method can correct endogeneity problems (Stock & Watson, 2003). It can do the same in a state-space model (Dooley & Mathieson, 2007). In equation (1), the method substitutes IVs for the weather variables; the IV-modified, state-space model is estimated by Kalman filtering.

The choice of IVs.IVs must be informative, meaning that they are highly correlated with the weather variable W_t^m. IVs must also be valid, meaning they are uncorrelated with the error $\tilde{e}_t$. In this study, I chose Racicot and Theoret's (2010) two-step IVs. The researchers showed empirically that the adjusted R^2's with the dependent variables could reach 80% and the correlation with the error was almost zero. First, a set of IVs is chosen and regressed on W_t^m. Second, the regression residual is treated as the IV for W_t^m.

I followed Racicot and Theoret (2010) to consider the set $\{\boldsymbol{\iota}_T, \mathbf{z}_D^1, \mathbf{z}_P^1, \cdots, \mathbf{z}_D^M, \mathbf{z}_P^M\}$ in the first step. $\boldsymbol{\iota}_T$ 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 as follows.

$$\mathbf{z}_D^m = \mathbf{w}^m * \mathbf{w}^m, \tag{3}$$

$$\mathbf{z}_P^m = \mathbf{w}^m * \mathbf{w}^m * \mathbf{w}^m - 3\mathbf{w}^m \left[\mathrm{E}\left(\frac{\mathbf{w}^m\prime\mathbf{w}^m}{T}\right) * \mathbf{I}_T\right] \tag{4}$$

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. Dagenais and Dagenais (1997) proved that cumulant IVs were orthogonal to the error term. Moreover, their Monte Carlo simulation results supported the set of $\mathbf{z}_D^m$ and $\mathbf{z}_P^m$ over a larger set of alternative cumulant IVs.

The Data

The Sample Market

The sample market is the Thai government bond market. Thailand is one of the world's most important emerging markets. The 2015 market capitalization of its government bonds was 208 billion U.S. dollars. Among the sample countries of the *Asia Bond Monitor* (Asian Development Bank, 2016), the Thai market ranked fourth in terms of market capitalization after Japan, China, and Korea.

The Thai government bond market data enabled me to ensure that weather effects, if they exist, are driven by behavioral and not fundamental factors.

The investors are large investors, including dealers, local and foreign institutional investors, and high net-worth individual investors. Almost all of these investors, with the exception of foreign investors, are in the Bangkok metropolitan area. The influential weather is, therefore, the weather of Bangkok. Although government bond returns can be driven fundamentally by weather-related incidents such as extensive drought and flooding, it is unlikely that the fundamental impacts of Bangkok weather would reach those scales.

According to Forgas (1995), it is more likely that investors with limited knowledge allow mood to interfere with their decision making. In Thailand, these investors would be small, local individual investors (Dowling & Lucey, 2008). Using this data set, I can check for the Forgas (1995) hypothesis. If it is correct, the weather effects cannot exist in the Thai bond market.

Finally, there are few studies of weather effects on bond returns and interest rates (Keef & Roush, 2005; Furhwirth & Sogner, 2015; Khanthavit, 2016b). This study adds to the short list of bond return and interest rate studies.

Data Sources and Construction

The bond return data are daily, running from July 2, 2001 to December 30, 2015. They are computed by the relationship $r_t^i = -i \times \left(s_t^i - s_{t-1}^i\right)$, where and are the government-spot rates for the i-year tenor on days t and t-1. The spot-curve data are constructed by the Thai Bond Market Association (Thai BMA).This study considers Thailand's benchmark tenors of 3, 5, 7, 10, and 15 years.

As suggested by previous studies (e.g., Dowling & Lucey, 2008; Lu & Chou, 2012), the weather variables are air pressure (hectopascal), cloud cover (decile), ground visibility (km.), rainfall (mm.), relative humidity (%), temperature (°C), and wind speed (knots per hour). Although the set is comprehensive, some variables, for example, geomagnetic storms in Dowling and Lucey (2008) and wind direction in Worthington (2009), are not included because of their unavailability or insignificance. The weather variables are Bangkok variables, measured by the Thai Meteorological Department's weather station at Don Muang Airport. The data ran from January 1, 1991 to December 31, 2015.

Thai bonds trade over the counter, and dealers report execution and bid yields to the Thai BMA each day at 4.00 p.m. I followed Hirshleifer and Shumway (2003) to calculate the daily weather variables using their average levels from 6.00 a.m. to 4.00 p.m. Then, I de-seasonalized the variables using their averages for each week of the year over the 1991–2015 period to avoid possible spuriousness from weather and return seasonality.

Some weather observations were missing. I imputed zero—the unconditional mean of de-seasonalized variables—into the missing cases to obtain complete weather series. In the analysis, all the return and weather series were normalized by their averages and standard deviations.

Descriptive Statistics

Bond returns and weather variables. Table 1, Panel A shows the descriptive statistics of the bond returns. By construction, the averages and standard deviations rise with the tenors. The returns are negatively skewed, fat-tailed, and auto-correlated. Normality is rejected by the Jarque-Bera tests for all the bonds. The insignificant average returns but significant autocorrelations support the zero-intercept and autoregressive specifications in equation (1). The statistics of the untreated weather variables are shown in Panel B. All the weather variables, except for cloud cover, have fat-tailed distributions. The normality hypothesis is rejected for all the weather variables. Despite the non-normality of the observed variables, Kalman filtering is usable. Given the linear relationship of the observed variables and the dynamics of the state variables in the state-space equations (1) and (2), the Kalman filter is optimal; it returns minimum mean square linear estimates (Kellerhals, 2001). The numbers of observations are not equal and are less than 9,131 calendar days from 1991 to 2015. This finding suggests missing weather observations, making imputation necessary to complete the weather series.

The weather variables are highly correlated (Worthington, 2009); putting all the weather variables simultaneously in equation (1) may cause multicollinearity. I report the variance inflation factors of weather variables in Panel B. The largest one is 1.5429, which is much smaller than the threshold of 10; multicollinearity is not present in the analysis.

Table 1
Descriptive Statistics

***Panel A** Bond returns*

Statistics[1]	Tenor				
	3-Year	5-Year	7-Year	10-Year	15-Year
Average	2.34E-05	3.98E-05	6.40E-05	1.13E-04	1.79E-04
S.D.	1.12E-03	2.43E-03	3.59E-03	5.43E-03	6.75E-03
Skewness	-0.8992	-0.4288	-0.5508	-0.8133	-0.1768
Excess Kurtosis	19.8945	8.4475	10.1849	11.2923	19.8655
Minimum	-0.0148	-0.0168	-0.0323	-0.0605	-0.0711
Maximum	0.0114	0.0196	0.0274	0.0372	0.0855
Jarque-Bera Stat.	101,868***	18,405***	26,792***	33,229***	100,780***
AR(1) Coefficient	0.3613***	0.2983***	0.2999***	0.2734***	0.2929***
Observations	6,127	6,127	6,127	6,127	6,127

Note: *** = significance at the 99%-confidence level.[1] = computed from the bond-return data on trading days.

***Panel B** Weather variables*

Statistics[2]	Air Pressure (hectopascal)	Cloud Cover (decile)	Ground Visibility (k.m.)	Rainfall (mm.)	Relative Humidity (%)	Temperature (°C)	Wind Speed (knots per hour)
Average	96.8359	5.4684	8.8597	0.3415	65.9481	29.9739	5.6941
S.D.	29.7429	1.4240	1.4502	1.5404	10.5586	2.1562	2.3735
Skewness	0.3750	-0.5623	-1.1244	7.9375	-0.4709	-0.8150	1.0708
Excess Kurtosis	0.0041	-0.2794	1.2496	84.6261	2.9606	2.8484	1.8259
Minimum	0.0000	0.0909	2.5091	0.0000	4.0909	8.1000	0.2727
Maximum	250.5455	8.0000	14.2727	27.5500	97.3636	36.3455	18.8182
Jarque-Bera Stat.	209***	494***	2,443***	2,746,116***	3,588***	4,004***	2,927***
AR(1) Coefficient	0.9095***	0.7099***	0.6667***	0.1031***	0.8066***	0.7993***	0.7335***
Observations	8,920	8,835	8,859	8,890	8,922	8,922	8,869
Variance Inflation Factors[3]	1.2579	1.4460	1.1487	1.1057	1.5249	1.3874	1.1117
Informativeness R^2	0.9170	0.7971	0.9055	0.7658	0.8914	0.7019	0.6012

Note: *** = significance at the 99%-confidence level. [2] = computed from the untreated weather data on non-missing calendar days. [3] = computed from the imputation data on bond-trading days.

Table 2
Parameter Estimates

Parameters[1]	Tenor				
	3Y	5Y	7Y	10Y	15Y
σ	0.8275***	0.8924***	0.8835***	0.9034***	0.8718***
q_r	0.0169***	0.0030***	0.0056***	0.0068***	0.0071***
q_1^W	0.0015	0.0022	0.0074***	0.0057***	0.0005
q_2^W	0.0196***	0.0100***	0.0129***	0.0127***	0.0201***
q_3^W	0.0046***	0.0017	0.0043***	0.0003	0.0119***
q_4^W	0.0066***	0.0009	0.0018	0.0034	0.0026
q_5^W	0.0132***	0.0028*	0.0132***	0.0143***	0.0328***
q_6^W	0.0072***	0.0017	0.0074***	0.0044**	0.0082***
q_7^W	0.0107***	0.0023	0.0077***	0.0073***	0.0113***
$q_{r,1}$	-0.9998*	0.2772*	-0.4774*	-0.9801***	0.7469
$q_{r,2}$	-0.2548	0.5347	-0.1185	0.8132***	0.8392***
$q_{r,3}$	0.9972***	0.4313	-0.3341	0.1660	0.9032***
$q_{r,4}$	0.0163	0.4255	-0.6339	-0.9941***	0.5338
$q_{r,5}$	0.2408	-0.5518	-0.1878	-0.8958***	-0.9462***
$q_{r,6}$	-0.7528***	-0.1652	-0.1747	-0.9502***	-0.6988***
$q_{r,7}$	0.2793	-0.4775	-0.1610	-0.9005	-0.8332***
$q_{1,2}$	0.2633	0.9597***	-0.8076***	-0.9060***	0.9509
$q_{1,3}$	-0.9957*	0.8987	-0.6674***	-0.0506	0.9334
$q_{1,4}$	-0.0239	0.9850	0.9802	0.9656***	-0.0557
$q_{1,5}$	-0.2488	-0.9517*	0.9523***	0.9639***	-0.8970
$q_{1,6}$	0.7492	-0.9850	0.9431***	0.9873***	-0.8997
$q_{1,7}$	-0.2874	-0.9760	0.9429***	0.9661***	-0.9324
$q_{2,3}$	-0.1928	0.9262**	0.9722***	-0.0207	0.9913***
$q_{2,4}$	-0.9688***	0.9878	-0.6750	-0.7652**	-0.0053
$q_{2,5}$	-0.9995***	-0.9954***	-0.9475***	-0.9855***	-0.9699***
$q_{2,6}$	-0.4333	-0.9175	-0.9267***	-0.9023***	-0.9682***
$q_{2,7}$	-0.9995***	-0.9978**	-0.9573***	-0.9845***	-0.9982***
$q_{3,4}$	-0.0442	0.8884	-0.5108	-0.1093	0.1260
$q_{3,5}$	0.1798	-0.8860	-0.8628***	0.0164	-0.9933***
$q_{3,6}$	-0.7866***	-0.9158	-0.8569***	0.1088	-0.9309***
$q_{3,7}$	0.2184	-0.9304*	-0.8765***	0.0017	-0.9878***
$q_{4,5}$	0.9737***	-0.9895	0.8742	0.8616***	-0.2343
$q_{4,6}$	0.6409	-0.9434	0.8718	0.9454	0.2317
$q_{4,7}$	0.9635***	-0.9934	0.8589	0.8659**	0.0219
$q_{5,6}$	0.4495	0.8951	0.9901***	0.9603**	0.8894***
$q_{5,7}$	0.9991***	0.9914	0.9994***	0.9999***	0.9667***
$q_{6,7}$	0.4126	0.9413	0.9869***	0.9602***	0.9763***

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively.[1] σ is the standard deviation of the error $\tilde{e}_t$. q_r and q_m^W are the standard deviations of the errors $\tilde{u}_t$ and $\tilde{v}_t^m$. Finally, $q_{i,j}$ is the correlation in the covariance matrix . Subscripts r = lagged return, 1 = air pressure,…, 7 = wind speed.

Informativeness and validity of IVs. Informativeness is measured by a high R^2 of the regression of weather variables on IVs; validity is measured by a low R^2 of the regression of the error term in equation (1) on IVs. The last row of Table 1, Panel B reports the R^2's of the regressions of weather variables on their two-step IVs. The R^2's are high, ranging from 0.6012 to 0.9170. 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

The study is motivated by the incorrect, fixed-effect assumption. Therefore, before I proceeded with the estimation, I conducted cumulative-sum (CUSUM) and CUSUM-square tests of recursive residuals for parameter stability of the model in equation (1) across bond tenors. At the 95% confidence level, the CUSUM tests rejected the stability hypothesis for the 3-year tenor, while the CUSUM-square tests rejected the hypothesis for all the tenors. The results support the use of Kalman-filtering estimation technique in weather studies. The CUSUM and CUSUM-square charts are not shown, but available upon request.

Parameter Estimates

In Table 2, the standard deviations are significant, suggesting that the parameters are estimated precisely. It is interesting to find that the correlations between some error pairs in the transition equations are high and significant. In many cases, they are almost one.

Time-Varying Weather Effects

Kalman filtering returns filtered and smoothed estimates of the unobserved . In this study, I chose to consider the smoothed estimates because they are conditioned on all the T observations in the sample period. The estimates should be more precise than the filtered estimates, which are conditioned on the part of the observed variables from day one to day t. The direction and significance of the effect of on day t can be examined from the sign and size of its t statistic.

Figure 1, Panels A to G show the t statistics for the effects of the seven weather variables. They exhibited time-varying behavior. Some effects showed similar patterns for all the sample bonds, for example, the cloud-cover effect in Panel B and relative-humidity effect in Panel E. Others showed different patterns, for example, the air-pressure effect in Panel A and ground-visibility effect in Panel C. The weather could induce either positive or negative effects; the significant effects did not last very long (from less than a year up to two years); and the movement did not show annual patterns.

Discussion

Implications for Previous Weather Studies

Because the fixed-effect assumptions are not realistic, previous studies that made such assumptions may have reported incorrect results. Even if the full sample period was broken into shorter sub-periods (e.g., Yoon & Kang, 2009; Khanthavit, 2016b) or the shortest one-year sub-periods (e.g., Khanthavit, 2016a), the sample-breaking approach might not be very effective. Significant effects could be short-lived; they did not exhibit annual patterns. The effects were averaged out and became insignificant. The insignificant results driven by the fixed-effects assumption were evidenced by Khanthavit (2016b). That study examined the same set of weather variables for Thai bond returns. The author could not find any effects for the full sample from July 2, 2001, to December 2015. For the three five-year sub-periods, rainfall and temperature effects were found. In contrast, I found significant effects many times for all seven weather variables and sample bonds during the full sample period.

Weather-Sensitive Investors

Because almost all the investors were large and well-informed investors, the fact that weather effects existed in the Thai bond market provides evidence against Forgas (1995) who argued that small investors tended to be weather sensitive. Large and well-informed investors could be weather sensitive as well. This finding aligns with Khanthavit (2016a) who found that large institutional and foreign investors in the Stock Exchange of Thailand were weather sensitive.

Wandering or Disappearing Weather Effects

In Figure 1, the effects exhibit clear wandering patterns from 2001 to 2010. The t statistics were positive or negative and moved upward or downward

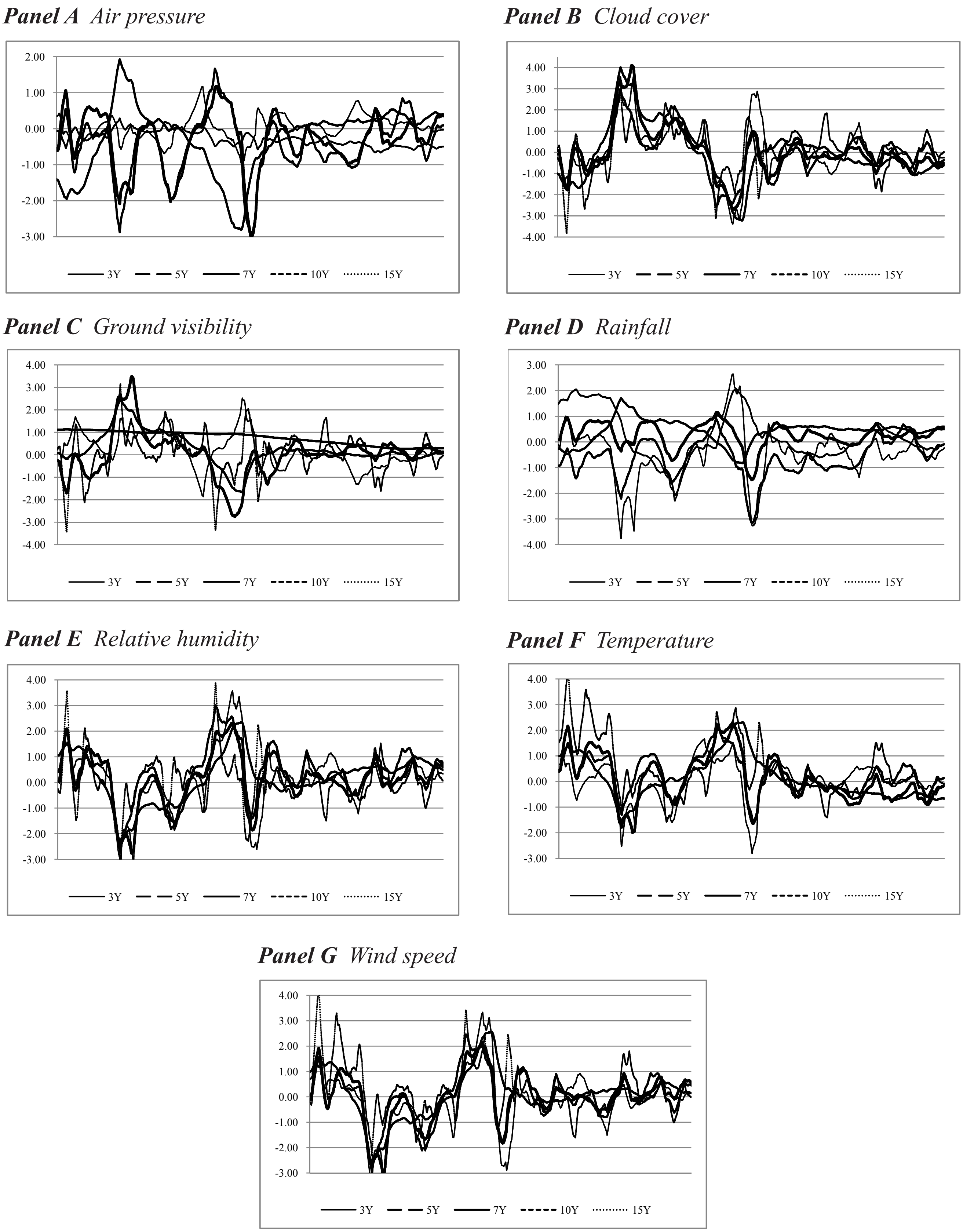

Figure 1. T-statistics for time-varying weather effects.

until they reached their peaks or troughs. Those surrounding peaks and troughs were significant. Then, they changed directions. These wandering patterns repeated themselves. After 2010, however, the statistics were less volatile. They varied around zero in 2014 and 2015. These findings lead me to conclude that the effects were significant and wandering in the early period and then disappeared in the later period.

Weather Effects and market Efficiency

Researchers (e.g., Hirshleifer & Shumway, 2003) considered weather effects as 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 evidence of improving market efficiency.

I tested whether weather effects moved with the market's inefficiency level. In equation (2), the autocorrelation and weather coefficients are I(1) variables. If the variables moved together, they had to be co-integrated. The co-integration tests are Engle and Granger's (1987) two-step tests. The Engle-Granger statistics are reported in Table 3.

For the 3-year, 5-year, and 7-year bonds, the weather effects and inefficiency levels were not co-integrated. The inefficiency of a 10-year bond was co-integrated with the air-pressure, relative-humidity, and wind-speed effects; the inefficiency of a 15-year bond was co-integrated with the ground-visibility and relative-humidity effects.

Why were a few weather effects co-integrated with market inefficiency? A possible explanation is that the market remained inefficient throughout the sample period. This explanation is supported by the t statistics for market inefficiency in Figure 2. The statistics were significant for the whole sample period and showed no sign of moving toward zero in the later period.

In Table 2, the correlations of certain pairs were high, significant, and almost one—for example, the 0.9972 correlation of the (lagged return, ground visibility) pair in the 3-year bond case. So, why were the coefficients in those high-correlation cases not co-integrated?

If their absolute correlations were one, the coefficients were the same variables and they were necessarily co-integrated. Because the estimates were not exactly one, the coefficients were different variables. Co-integration had to be driven by a common driving force (Gonzalo & Granger, 1995). Market efficiency was informational efficiency. The significance of inefficiency levels depended on the speed of dissemination of all information in the market, while the significance of weather effects depended on the speed of weather information alone. Weather information was a subset of market information. No co-integration implied that the common driving force did not exist. The force that drove the speed of weather information was not powerful enough to drive the speed of market information.

Table 3

Engle-Granger Co-integration Test Statistics for Autocorrelation Coefficient With Weather Coefficients

Weather Variable	Tenor				
	3Y	5Y	7Y	10Y	15Y
Air Pressure	-0.5179	5.2671	0.1508	-2.6968***	-1.2820
Cloud Cover	-0.9766	7.5780	0.9747	-1.2113	-1.4899
Ground Visibility	-0.6119	12.1833	0.5698	-0.4667	-1.6597*
Rainfall	-0.9872	12.2614	0.0109	3.7783	-0.9900
Relative Humidity	-0.9912	6.3374	0.6101	-1.8997*	-2.6581***
Temperature	-0.5820	3.4367	0.3128	-0.6753	-1.3485
Wind Speed	-0.9832	14.0666	0.6513	-2.0143**	-1.5631

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

Finally, the inefficiency and weather coefficients were I(1) variables. In theory, they could take on extreme values. I examined all the smoothed estimates. The (maximum, minimum) values of inefficiency and weather coefficients were (0.5502, 0.0713) and (0.5308, -0.4497), respectively. In Table 2, the standard deviations were very small. Hence, extreme-value incidents were unlikely.

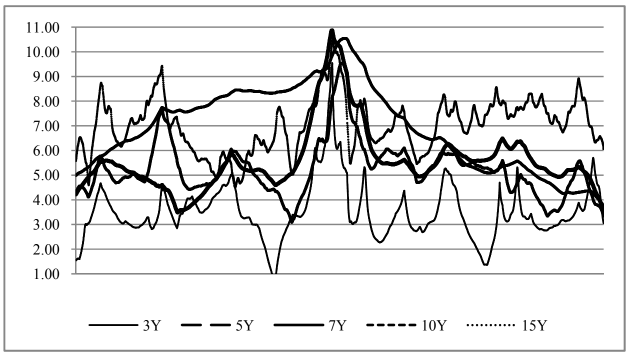

Figure 2. T-statistics for market inefficiency.

Conclusion

The fixed-effect assumption made by previous weather studies was unrealistic and potentially incorrect, therefore resulting in model misspecification and questionable results. I proposed a state-space model for this weather study, which allowed the effects to vary daily. I applied the model to estimate the effects for the Thai government bond market. Using daily bond returns from July 2, 2001, to December 30, 2015, I found that the weather effects were time-varying. They exhibited wandering behavior in the early sample period up to 2010; they were less volatile in the later period, and they fluctuated around zero in the ending period. The significant effects were short-lived—of less than one year to about two years—and their movements did not show annual patterns. These findings are important. Together, they imply that breaking a full sample into short sub-samples might not suffice to prevent significant effects from being averaged out. And the significant effects might not describe returns in the sample period very well.

In this study, the effects were direct from weather to asset returns. Theoretically, they had to be indirect via investors' mood (Furhwirth & Sogner, 2015). If the effect of mood on asset return is fixed, but the weather effects on mood are time-varying, the indirect-effect model and this study's direct-effect model are equivalent. To demonstrate this, referring to Furhwirth and Sogner's (2015) equation (2), substitute the mood equation in the return equation and re-arrange terms. This is the measurement equation. Then, treat the weather coefficients as state variables, whose dynamics are described by the transition equation.

The mood effect needs not be fixed. If this is the case, my model is misspecified. I leave the task of addressing this possible misspecification to future research.

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