ASIAN ACADEMY *of*
MANAGEMENT JOURNAL
of ACCOUNTING
and FINANCE

AAMJAF Vol. 13, No. 1, 83–111, 2017

INSTRUMENTAL-VARIABLE ESTIMATION OF BANGKOK-WEATHER EFFECTS IN THE STOCK EXCHANGE OF THAILAND

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ABSTRACT

The incorrect fixed-effect assumption, missing-data problem, omitted-variable problem, and errors-in-variables (EIV) problem are estimation problems that are generally found in studies on weather effects on asset returns. This study proposes an approach that can address these problems simultaneously. The approach is demonstrated by revisiting the effects on the Stock Exchange of Thailand. The sample shows daily data from 2 January 1991 to 30 December 2015. Artificial Hausman instrumental-variable regressions successfully improve the quality of the analyses for ordinary least squares regressions when significant EIV problems are identified and the regression results in a conflict. The study finds significant air pressure and rainfall effects and empirically shows that the temperature effects reported by previous studies were induced by the fixed-effect assumption and are therefore incorrect.

Keywords: instrumental-variable estimation, artificial Hausman regression, weather effects, model misspecification, Thai stock returns

INTRODUCTION

Good or bad weather in the regions in which investors trade can affect their moods (e.g., Howarth & Hoffman, 1984), which, in turn, influences economic decision-making (e.g., Lucey & Dowling, 2005). Prices and returns may increase or decrease

Publication date: 30 August 2017

To cite this article: Khanthavit, A. (2017). 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. https://doi.org/10.21315/aamjaf2017.13.1.4

To link to this article: https://doi.org/10.21315/aamjaf2017.13.1.4

according to the weather conditions due to changing risk preferences, which leads marginal investors to increase or decrease the discount rates (Mehra & Sah, 2002), or attitude misattribution, which causes marginal investors to incorrectly associate good or bad weather and attitudes regarding good or bad prospects for the assets (e.g., Hirshleifer & Shumway, 2003). Recently, Brahmana, Hooy and Ahmad (2012) explained that the changing prices and returns could result from herd behaviour of investors. These incidents constitute weather effects. However, because these weather conditions do not affect the fundamentals of firms, their values remain unchanged. In an efficient market, rational investors trade against and profit from these weather-sensitive investors. Weather effects should not exist or should disappear within a short time.

It is important to test for weather effects because significant effects imply market inefficiency. Furthermore, they imply that economic and behavioural factors determine asset prices and returns. Tests for weather effects have been conducted extensively using national and international market data. Reviews of early studies are presented, for example, by Cao and Wei (2005), as well as in recent studies by Furhwirth and Sogner (2015). The test results were mixed depending on the sample periods, countries, markets, assets, weather variables, and econometric models.

Despite the various choices for econometric models for weather effects, the ordinary least squares (OLS) regression model — in which returns are related linearly to interesting weather variables — is the most popular model and can be found in recent studies (e.g., Goetzman, Kim, Kumar, & Wang, 2015). I argue that the OLS regression model suffers from at least four estimation problems.

First, the model assumes that weather effects are fixed over the sample period. This assumption is inconsistent with the empirical findings in previous studies. For example, Yoon and Kang (2009) found significant temperature effects in the Korean stock market for the full sample period of 15 January 1990, to 13 December 2006. However, when the researchers divided the sample into two sub-samples — from 15 January 1990, to 30 September 1997, and from 1 October 1997, to 13 December 2006 — they found significant effects in the first but not the second sub-period.

Second, weather variables may be missing due to faulty equipment or missed observations. When variables are missing, researchers may choose an imputation approach and impute proxies for the missing data. Alternatively, they may choose a listwise-deletion approach in which they remove the missing observations and consider only complete observations in the analyses. Worthington (2009) chose the former approach; Khanthavit (2016a) chose the latter. If researchers choose the imputation approach, the OLS estimates are necessarily biased and inconsistent because the proxies have errors and induce an errors-in-variables (EIV) problem in regressions (Durbin, 1954). However, if they choose the listwise-deletion approach, the analyses omit useful information that would have been drawn from the discarded observations (Little, 1992).

Third, even when weather variables are complete, the variables can be observed erroneously. The samples are observed at a weather station near the market; however, the relevant weather variables that induce moods and potentially affect prices are in areas where investors trade. Although the literature argued that most investors were in the same city as the market, the weather station may not be located near the market or investors. For example, in Saunders (1993), the LaGuardia weather station is approximately 13 kilometers from the New York Stock Exchange and Wall Street; it is well known that New York City is large, covering an area of 789 square kilometers. For this reason, the observed weather variables are mere proxies; the OLS estimates are biased and inconsistent (Durbin, 1954).

Fourth, investors can be sensitive to various weather conditions such as temperature, cloud cover, and rainfall (Watson, 2000). If the model omits one or more influential weather variables, the OLS results are necessarily biased and inconsistent (Ramsey, 1969). Studies such as those by Saunders (1993) and Cao and Wei (2005), which considered single-weather variables, were vulnerable to this omitted-variable problem. Other studies, such as that by Worthington (2009), who considered large sets of weather variables, risked introducing biases and inconsistencies. Despite their large sizes, the sets may still be incomplete.

In this study, I propose an approach to resolve the four estimation problems and apply it to test for the weather effects in the Stock Exchange of Thailand (SET). The approach is the main contribution of the study. Some of these estimation problems were addressed separately in the literature, but the outcomes were neither satisfactory nor successful. The remaining problems have not yet been addressed. In this study, the four problems are resolved simultaneously.

Choosing the SET as the sample market allows me to demonstrate the features of the proposed approach. The SET is Thailand's only stock market. It 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, the Bangkok weather affects most investors.

The SET was established on 30 April 1975, whereas the Bangkok weather began being recorded on 1 January 1991. The sample period necessarily begins on 1 January 1991, and covers 25 years. If weather effects exist, it is unlikely that the effects remain fixed over such a long period.

The weather conditions under consideration are drawn from the meteorological station at Bangkok's Don Muang Airport. Bangkok is much larger than New York City; it covers an area of 1,569 km^2. The airport is 25 km from the stock market's former location and is 22 km from its current location. Due to the size of Bangkok and the distance from the weather station to the market's location, the observed weather variables are proxies for the true variables that affect investors' moods. Below, Table 1, panel 1.1 indicates that on average, 2.66% of the weather data are missing. The proposed approach employs the imputation approach to fill in the missing data. Together, the weather proxies and imputed data induce the EIV problem in estimation.

Seven Bangkok-weather variables, i.e., air pressure, cloud cover, ground visibility, rainfall, relative humidity, temperature, and wind speed, are studied. Despite these many variables, some variables that were included in previous studies are omitted. For example, the geomagnetic storms in Dowling and Lucey (2008) are omitted because the storm data are not available. The wind direction in Worthington (2009) is omitted because the direction cannot be averaged to represent the daily direction data and because it is not a significant variable in that study. If the omitted variables are important, the OLS estimates are biased and inconsistent.

Second, from a practical perspective, the SET is an interesting and important market for study. Thailand is among the world's top emerging economies. Bloomberg Markets (2013) ranked Thailand third only after China and South Korea. From the World Federation of Exchanges database, in May 2016, the SET's market capitalisation was 387.86 billion U.S. dollars, accounted for 1.79% of the aggregate capitalisation of 23 stock markets in the Asia-Pacific region, and ranked eleventh in size after the Singapore market. In terms of trading value, the SET ranked first for three consecutive years among ASEAN stock markets (Stock Exchange of Thailand, 2016).

Third, in the past, weather effects were studied for the SET, including in works by Nirojsil (2009) and Sriboonchitta, Chaitip, Sriwichailamphan, and Chaiboonsri (2014). Significant temperature effects were reported. For those studies, the effects were assumed to be fixed; the number of weather variables was small; and the missing-variable, EIV, and omitted-variable problems were never raised. My results can be compared and contrasted with the results of the above-mentioned studies, and new findings for the SET can be discussed.

METHODOLOGY

The Model, Estimation and Hypothesis Tests

In this study, I follow the procedure of previous studies (e.g., Dowling & Lucey, 2005; Worthington, 2009) to relate the stock return linearly to *M* weather variables on day *t* as in Equation (1).

$$r_t = \beta_0 + \rho r_{t-1} + \beta_1 W_t^1 + ... + \beta_M W_t^M + e_t \tag{1}$$

where r_t and r_{t-1} are the stock returns on days *t* and *t*-1, respectively. Day $t = 1, 2, \ldots, T$, where *T* is the number of observations. W_t^m is the weather variable *m* on day *t*. $m = 1, \ldots, M$. β_0 is the intercept. β_m is the slope coefficient for W_t^m. I add the lagged return $r_{t\text{-}1}$ to the model to capture the possible return's autocorrelation (e.g., Saunders, 1993; Yoon & Kang, 2009). ρ is the autocorrelation coefficient. Finally, e_t is the regression error. The model in Equation (1) can be estimated by the OLS technique. If all OLS assumptions are satisfied, OLS coefficients are the most efficient, unbiased, and consistent.

Previous studies, e.g., Yoon and Kang (2009), considered various weather variables but estimated the effect for each variable one at a time. I do not follow this approach because weather variables tend to be correlated (Worthington, 2009). A significant effect may be observed not directly from the regressing variable but rather indirectly from its correlated companions; the model in Equation (1) allows me to identify the unique and direct effect of each variable on returns (Stock & Watson, 2003).

If the weather variable m is significant, the coefficient β_m must be different from zero. Under the null hypothesis, if no weather effects are present, i.e., $\beta_1 = \cdots = \beta_M = 0$, the Wald statistic is distributed as a chi-square variable of *M* degrees of freedom. All hypothesis tests are based on Newey and West's (1987) heteroscedasticity- and autocorrelation-consistent covariance matrix. The Newey-West lag is chosen by the integer part of $\sqrt[4]{\mathrm{T}}$ (Baum, 2006).

Estimation Problems and Corrections

Fixed-effect assumptions

In previous studies, the fixed-effect assumption was addressed by dividing a long full sample into several short sub-samples (e.g., Saunders, 1993; Yoon & Kang, 2009). However, these studies still had to use a fixed-effect assumption for the sub-samples. The sub-samples were able to cover a long period of time; thus, the fixed-effect assumption was inappropriate or incorrect. For example, in Yoon and Kang (2009), the sub-samples covered eight years. Akhtari (2011) offered an alternative model to address the fixed-effect assumption, in which the effect was allowed to change linearly with time. This specification was very restrictive. If the relationship of the effect with time was not monotonic, such as that in Saunders (1993), the model failed.

I follow Doyle and Chen (2009) to address the fixed-effect assumption by separating the full sample into one-year sub-samples, estimating the model for each sub-sample, and examining the way in which the effects change annually over the course of the full sample. The one-year sub-samples should be short enough to accommodate possible changes for the effects. The model in Equation (1) in year τ is:

$$r_{\tau t} = \beta_{\tau 0} + \rho_{\tau} r_{\tau,t-1} + \beta_{\tau,1} W^{1}_{\tau,t} + ... + \beta_{\tau M} W^{M}_{\tau,t} + e_{\tau,t} \tag{2}$$

where subscript τ indicates that the variables and coefficients are used for the year τ sub-sample.

In their study, Doyle and Chen (2009) also proposed a comprehensive model in which the full-sample data were considered and in which individual coefficients were assigned to measure the effects of the one-year sub-samples. The comprehensive model allowed the researchers to test for significant weather effects jointly using Wald tests or *F*-tests; however, I do not adopt the comprehensive model. In this study, the full sample period is 25 years, and there are seven weather variables present. Moreover, seven projection errors are added to the artificial Hausman regression to correct possible EIV and omitted-variable problems. The comprehensive model will be too large to be managed adequately. However, a joint test is possible by using the summed chi-square Wald statistics of individual sub-samples.

Missing-variable problems

Some weather records are missing. To fix this problem, I impute the unconditional means of the variables into the missing cases (Afifi & Ekashoff, 1967). The unconditional means are chosen over the means that are conditioned on stock returns (Dagenais, 1973) and over the observed variables from a nearby weather station (Worthington, 2009) because the unconditional means are convenient and readily available. Moreover, the records from the nearby City Hall station — which is the other weather station in Bangkok — are also missing; under the null hypothesis under which the stock returns and weather variables are uncorrelated, the conditional and unconditional means are the same.

Errors-in-variables and omitted-variable problems

When the estimation is free of EIV and omitted-variable problems, the OLS estimates are optimal. Otherwise, the estimates are biased and inconsistent. I discussed why OLS estimation of weather effects generally had problems. For the same reasons, it is likely that the problems are present in this study. Instrumental-variable (IV) regressions help resolve these problems. IV estimates are consistent, regardless of whether the two problems are present.

In this study, I use the artificial Hausman (AH) regression (Dagenais & Dagenais, 1997) to estimate the models in Equations (1) and (2). The AH regression is a form of IV regression and is preferred to alternative IV regressions, e.g., the two-stage least squares regression, because the test for the EIV problem can be performed before the analyses begin (Racicot & Theoret, 2008; 2010). In my study, if the EIV problem is significant, I use the AH estimates for the analyses. However, if the problem is not significant, I use the OLS estimates.

Artificial Hausman Regression

The modified model

I modify the model in Equation (1) for the AH regression as follows.

$$r_t = \beta_0 + \rho r_{t-1} + \beta_1 W_t^1 + ... + \beta_M W_t^M + \theta_1 \hat{u}_t^1 + ... + \theta_M \hat{u}_t^M + e_t \qquad (3)$$

where $\hat{u}_t^m$ is defined by the projection regression, $W_t^m = \gamma_0 + \gamma_1 Z_t^1 + ... + \gamma_K Z_t^K + \hat{u}_t^m$, of W_t^m onto a set $(Z_t^1, ..., Z_t^k)$ of K IVs. The AH estimates $(\beta_0, \rho, \beta_1, ...\beta_M)$ from Equation (3) are identical to the two-stage least squares estimates (Racicot & Theoret, 2008). The model in Equation (2) can be modified for the AH regression in the same way. Once the models are modified, they can be estimated by the OLS. If the problems are not present, $\theta_1 = ... = \theta_M = 0$. The Wald statistic is a chi-square variable of *M* degrees of freedom. Racicot and Theoret (2008, 2010) used the conventional OLS covariance matrix for hypothesis tests, while Coen and Hubner (2009) used White's (1980) heteroscedasticity-consistent matrix. In this study, however, I use Newey and West's (1987) heteroscedasticity- and autocorrelation-consistent matrix because e_t can be heteroscedastic as well as autocorrelated.

Choices for instrumental variables

IVs must be informative, in that they must explain the movement of W_t^m well, and must be valid, in that they are not correlated with e_t in Equations (1) and (2). It is difficult to choose IVs satisfactorily for a weather variable. The first choice is its lag or other weather variables. These variables are informative. As seen in Table 1, Panel 1, the weather variables have significant AR(1) coefficients, whereas Panel 2 and Worthington (2009) reported strong correlations among weather variables. In this study, the current variables cannot be IVs because they will all appear as regressors in the model. Their lags may not be possible because some observations are missing.

The second choice is cumulant IVs, as proposed by Dagenais and Dagenais (1997). The cumulant IVs are convenient because they can be computed from the stock returns and weather variables. For the models in Equations (1) and (2), the IVs are a unit vector ι_T of size *T*,

$$
\begin{aligned}
z_1^m &= w^{m*}w^m,\\
z_2^m &= w^{m*}r,\\
z_3^m &= r^*r,\\
z_4^m &= w^{m*}w^{m*}w^m - 3w^m\left[E\left(\frac{w^{m'}w^m}{T}\right)*I_T\right],\\
z_5^m &= w^{m*}w^{m*}r - 2^m\left[E\left(\frac{w^{m'}r}{T}\right)*I_T\right] - r\left\{\iota_T'\left[E\left(\frac{w^{m'}w^m}{T}\right)*I_T\right]\right\},\\
z_6^m &= w^{m*}r^*r - w^m\left[E\left(\frac{r'r}{T}\right)\right] - 2r\left[E\left(\frac{r'w^m}{T}\right)\right],\\
z_7^m &= r^*r^*r - 3r\left[E\left(\frac{r'r}{T}\right)\right],
\end{aligned}
$$

where w^m and r are the vectors of deviation of weather variable W^m and stock return r from their means. I_T is the identity matrix of size *T*, and * denotes the Hadamard element-by-element matrix multiplication operator. Note that z_1^m is Durbin's

(1954) IV and z_4^m is Pal's (1980) IV. Dagenais and Dagenais (1997) acknowledged that the results improved when they only considered $\{\iota_T, z_1^m, z_4^m\}$.

The third choice is two-step IVs in Racicot and Theoret (2010). These IVs are extremely informative and strongly valid. In the first step, a set of IVs is chosen and regressed on the weather variable W^m. In the second step, the regression errors are treated as IVs for computing the projection errors $\hat{u}_t^m$. Racicot and Theoret (2010) showed empirically that the adjusted R^2 of erroneous dependent variables for the two-step IVs, based on the $\{\iota_T, z_1^m, z_4^m\}$. set, could reach 80%, whereas the correlation of OLS errors with the IVs was almost zero.

Due to their informativeness and validity, in this study, I use Racicot and Theoret's (2010) two-step IVs in the estimation. Four sets of IVs are considered in the first step Durbin's (1954) $\{\iota_T, z_1^m\}$, Pal's (1980) $\{\iota_T, z_4^m\}$, Racicot and Theoret's (2010) $\{\iota_T, z_1^m, z_4^m\}$, and Dagenais and Dagenais's (1997) $\{\iota_T, z_1^m, ..., z_7\}$. Their informativeness performances are compared, and the set with the highest average R^2 will be chosen for the analyses.

The data

The data are daily. The stock returns are computed from log index differences. The stock indexes to be studied are the closing SET, SET 50, and MAI indexes. The SET index is a broad-based, value-weighted index of all stocks on the Stock Exchange of Thailand; the SET 50 index is the value-weighted index of the 50 largest and most actively trading stocks; and the MAI index is the value-weighted index of all stocks on the Market for Alternative Investment (MAI). The SET index, SET 50 index, and MAI index began on 28 December 1990, 16 August 1995, and 2 September 2002, respectively. All indexes ended on 30 December 2015. The indexes were retrieved from the Stock Exchange of Thailand's database.

Approximately 58% and 96% of the trading volumes of SET and MAI stocks are from small, individual investors, and the remainder is from local institutes, proprietary traders, and foreign investors (Khanthavit & Chaowalerd, 2016). It is likely that the percentage share from small, individual 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 the parts of the market that are dominated by large investors and individuals, respectively.

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). These variables are a collection of weather variables that have also been considered in previous studies (e.g., Dowling & Lucey, 2008); they are the most comprehensive set of variables among all weather studies for Thailand (e.g., Hirshleifer & Shumway, 2003; Dowling & Lucey, 2005; Nirojsil, 2009).

The weather variables affect stock returns via investors' moods. Goldstein (1972) and Keller et al. (2005) reported a link between high air pressure and positive mood. Low cloud cover was related to good moods, while high cloud cover was related to bad moods and depression (Eagles, 1994). As for ground visibility, Lu and Chou (2012) explained that people were more prone to melancholy feelings and a decline in their general spirit due to insufficient light levels. In Schwarz and Clore (1983), people rated their life satisfactions much higher on sunny days than on cloudy or rainy days; in Sanders and Brizzolara (1982), low levels of humidity were associated with good moods. The relationship of temperature with moods was mixed. While Cunningham (1979) and Howarth and Hoffman (1984) reported a positive relationship, Griffitt and Veitch (1971) and Goldstein (1972) reported a negative one. Finally, Troros, Deniz, Saylan, Sen and Baloglu (2005) and Denissen, Butalid, Penke, and van Aken (2008) found that wind deteriorated moods.

Recently, Brahmana, Hooy and Ahmad (2015) pointed out that weather conditions in tropical countries varied much less relatively to those in colder countries, e.g. the U.S., for which most weather studies were conducted. The researchers challenged whether or not weather conditions could influence return behaviours in tropical countries in ways similar to those in colder countries. I argue that the ways weather conditions affect moods are contingent on how good or bad the weather conditions were prior to the time the relationship between moods and current weather is measured (Keller et al., 2005). For this reason, weather effects can exist in Thailand too, although it is a country in the tropical zone. Moreover, significant weather effects were found for tropical countries. For example, in national studies, Brahmana, Hooy and Ahmad (2015) found cloud-cover effects for Indonesia, and Nirojsil (2009) found temperature effects for Thailand. In international studies, Hirshleifer and Shumway (2003) and Dowling and Lucey (2008) found the effects for Brazil, Indonesia, Malaysia, Mexico and Singapore.

Table 1
Descriptive statistics

Panel 1: Index Returns and Untreated Weather Variables

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

Note: *** = significance at the 99% confidence level. N.A. = not applicable, [1] and [2] = statistics are computed from the observed data on trading days and calendar days, respectively, Gr. Visibility = Ground Visibility; Re. Humidity = Relative Humidity

Panel 2: Correlations[1] and Variance-Inflation Factors[2] of Imputed, De-seasonalised Weather Variables

Weather Variables	Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed
Air Pressure	1.0000						
Cloud Cover	–0.1044***	1.0000					
Ground Visibility	–0.0047	–0.1206***	1.0000				
Rainfall	0.0034	0.1821***	–0.1620***	1.0000			
Relative Humidity	–0.1073***	0.5014***	–0.2253***	0.2681***	1.0000		
Temperature	–0.3420***	–0.3286***	0.1414***	–0.2628***	–0.2899***	1.0000	
Wind Speed	–0.1029***	–0.0443***	0.1875***	–0.0813***	–0.1319***	0.0872***	1.0000
VIF	1.2434	1.4438	1.1023	1.1376	1.4861	1.4351	1.0602

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

The weather data are for Bangkok weather and are measured by the Thai Meteorological Department's weather station at Don Muang Airport. The data coverage began on 1 January 1991, and ended on 31 December 2015. I retrieved the data from the Thai Meteorological Department's database.

During the sample period, the SET had four regimes of trading hours:

1. From 9.00 to 12.00 for the 1 January 1991–30 June 1992 period
2. From 10.00 to 12.30 and from 14.30 to 16.00 for the 1 July 1992–3 November 1994 period
3. From 10.00 to 12.30 and from 14.30 to 16.30 for the 4 November 1995–5 September 1999 period
4. From a random morning beginning time (between 9.55 and 10.00 to 12.30) and from a random afternoon beginning time (between 14.25 and 14.30) to a random closing time (between 16.35 and 16.40) for the 6 September 1999–31 December 2015 period

Following Hirshleifer and Shumway (2003), I calculate the daily weather variables by their average levels from 6.00 to 16.00. I am aware that in regime (1), the weather conditions in the afternoon are not able to affect morning prices and returns. However, the averages can serve as samples for the days because the weather variables were autocorrelated, they served as proxies, and the induced EIV problem was readily addressed by the proposed approach.

Significant weather effects may be spurious due to weather and return seasonality (Hirshleifer & Shumway, 2003). To avoid possible spuriousness, I de-seasonalised the weather variables, as in Hirshleifer and Shumway (2003), with their averages for each week of the year over the 1991–2015 sample period. Zero is imputed in the missing cases because it is the unconditional means of de-seasonalized variables.

Table 1, Panel 1 reports the descriptive statistics of the index returns and untreated weather variables. The daily mean returns are small, relative to their standard deviations. The return skewnesses are almost zero, whereas the excess kurtoses are very large. The return autocorrelations are significant, thus supporting the use of Newey and West's (1987) covariance matrix for hypothesis tests. Although the Jarque-Bera (JB) tests reject the normality hypothesis for the three indexes, the OLS regressions are valid even for the one-year sub-periods. The number of observations for each sub-period is large, ranging from 242 to 245 trading days.

Temperature, cloud cover, humidity, and ground visibility are negatively skewed; rainfall, wind speed, and air pressure are positively skewed. All variables, except for cloud cover, have fat-tailed distributions. The normality hypothesis is rejected for the seven weather variables. The AR(1) coefficients are significant, which suggests that weather's lagged values are informative and can be candidates for IVs. It is important to note, nevertheless, that the number of weather observations is not equal for either calendar or trading days. The significant AR(1) coefficients are indicative, and the lagged values may not be very useful.

Table 1, Panel 2 reports the correlations among the de-seasonalised variables. The weather samples are those for non-missing calendar days. All correlations, except those for air pressure-ground visibility and air pressure-rainfall pairs, are highly significant. The significant correlations support the models in Equations (1) and (2), which show a direct and unique effect for each variable. In placing correlated variables together in a regression risk multicollinearity, I check for multicollinearity using the variance inflation factors (VIFs) in the last row of the panel. The statistics are computed from the imputation series for trading days because these series will be used in the estimation. The largest VIF is 1.4861 and is much smaller than the 10-level threshold. The VIFs do not suggest multicollinearity.

Table 2 reports the informativeness and validity performance of the two-step IV sets. 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. For all seven weather variables and three index returns, the two-step IVs based on Pal's (1980) set perform the best. The average informativeness R^2s are highest at more than 0.85, and the validity R^2s are practically zero. With respect to their performance, the Pal (1980)-based, two-step IVs are used in the estimation.

Table 2
Informativeness and validity of two-step instrumental variables

IV Choice	Index Return	Informativeness R^2								Validity R^2
		Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	Average	
Durbin (1954)	SET	0.9595	0.9353	0.7929	0.2693	0.8960	0.8000	0.8200	0.7819	2.78E-06
	SET 50	0.9647	0.9377	0.6943	0.2703	0.9532	0.7958	0.8653	0.7831	3.43E-05
	MAI	0.9464	0.9457	0.7270	0.2455	0.9202	0.7684	0.9668	0.7886	8.13E-07
Pal (1980)	SET^C	0.9613	0.9724	0.8801	0.5121	0.8734	0.9228	0.9103	0.8618	3.04E-06
	SET 50^C	0.9573	0.9711	0.8563	0.5240	0.9814	0.8875	0.9176	0.8707	5.21E-05
	MAI^C	0.9306	0.9666	0.8403	0.4727	0.9755	0.8966	0.9564	0.8627	2.89E-05
Racicot-Theoret (2010)	SET	0.9352	0.8988	0.7740	0.0990	0.8206	0.7477	0.8096	0.7264	4.00E-06
	SET 50	0.9343	0.9107	0.6775	0.0978	0.9152	0.7390	0.8502	0.7321	6.26E-05
	MAI	0.9164	0.9204	0.7145	0.0861	0.8793	0.7398	0.9280	0.7406	2.65E-05
Dagenais-Dagenais (1997)	SET	0.9300	0.8926	0.7681	0.0986	0.8145	0.7383	0.8037	0.7208	1.81E-07
	SET 50	0.9259	0.9039	0.6719	0.0973	0.9038	0.7298	0.8430	0.7251	1.67E-05
	MAI	0.8964	0.8714	0.6986	0.0853	0.8453	0.7132	0.8802	0.7129	3.31E-06

Note: ^{C} = instrumental variables chosen for the analysis.

EMPIRICAL RESULTS

Tests for Errors-in-Variable (EIV) Problems and Weather Effects

I test for the EIV problems first. If the problems are significant, the tests for significant individual-weather coefficients and weather effects are based on AH regressions. However, if they are not, the tests are based on OLS regressions. Table 3, Panel 1 reports the results for the SET index return. For the full period from 1991 to 2015, the test cannot detect the EIV problem. The OLS coefficient for ground visibility is significant but weak at the 90% confidence level. The Wald test cannot identify the weather effects. The inability to detect the weather effects may result from the incorrect assumption of fixed weather effects over the full period. When I repeat the procedure for the one-year sub-periods, the results are quite different.

The joint test, based on the summed $\chi^2(7)$ statistics for EIV problems over the 25-year period, rejects the no-EIV hypothesis at a 99% confidence level. For individual sub-periods, the EIV problems are significant in 1991, 1996, 1998, 2002, 2004, 2005, 2006, 2007, 2008, 2013, 2014, and 2015. As opposed to the full-period regression test, the summed -$\chi^2(7)$ joint test is able to identify significant weather effects. The confidence is very high at the 99% level. The effects for individual sub-periods are found in 1991, 1992, 1995, 1999, 2002, 2003, 2008, 2011, and 2013. To further identify the weather variables that contribute to the significant effects, I add the 25 $\chi^2(1)$ statistics for individual weather variables over the 25 one-year sub-samples. The summed statistics are significant for air pressure and rainfall. This finding leads me to conclude that the significant weather effects for the SET index return are air pressure and rainfall effects.

Table 3, Panel 2 reports the results for the SET 50 index return. The full period is 21 years from 1995 to 2015. The results are similar to those for the SET index return. The full-sample regression tests cannot detect either EIV problems or weather effects. However, when the full period is broken into 21 one-year sub-periods, the summed chi square statistics suggest significant EIV problems and weather effects. Air pressure and rainfall are the contributing variables to the significant weather effects.

The results for the MAI index return are reported in Table 3, Panel 3. The 14-year full-period regression detects the EIV problem at the 90% confidence level; the joint tests from individual sub-sample regressions also find significant EIV problems. The weather effects are not significant in the full-period regression test. Although the sub-sample tests for 2008 and 2014 find significant weather effects, based on the joint test, the effects are not significant for the full period. Because the effects are weak or nonexistent in the full period and sub-periods, I conclude that weather does not influence the MAI index returns.

Table 3
Test results for errors-in-variables problems and weather effects

Panel 1: SET Index Returns

Period	Joint EIV Problems $\chi^2(7)$	Individual Regression Coefficients $\chi^2(1)$								Joint Weather Effects $\chi^2(7)$
		Lagged Return	Weather Variables							
			Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	
1991-2015	11.1611	16.0137***	2.0422	0.9597	2.9155*	0.5333	0.1066	2.3966	0.1510	7.7263
1991	21.4992***	0.0039	0.1173	1.9959	0.1089	2.1054	0.0020	2.5329	4.1593**	18.8048***
1992	1.8380	0.1112	0.9880	0.6086	0.0483	4.2269**	0.7330	0.7805	0.1895	12.9761*
1993	5.4128	5.8212**	2.1591	0.2481	0.3722	1.3637	0.1801	0.9295	0.4641	8.8417
1994	10.8720	0.1818	0.4676	1.2496	1.5643	0.0797	1.9500	2.8453*	0.0005	7.8758
1995	5.8836	4.4570	2.7801*	0.9116	7.2904***	0.0526	0.0171	0.2860	1.2665	12.8647*
1996	20.2902***	2.6881	0.0656	0.1530	3.5558*	0.8058	1.0248	0.0160	1.8659	9.3154
1997	11.2448	7.7710***	1.2002	4.1569**	0.0320	0.0216	0.0104	2.8247*	0.0341	8.9169
1998	18.5791***	2.6889	1.0644	4.6411**	0.0006	4.7449**	1.5486	0.0616	0.2874	11.4691
1999	2.9577	3.8762**	2.0390	2.7050	0.1251	2.7983*	0.1062	2.8749*	0.0743	13.6880*
2000	1.0434	0.2531	1.0536	0.4368	0.1073	1.9379	0.8410	0.8910	0.1671	5.0422
2001	8.9603	0.4252	1.5488	0.0458	0.0002	0.0402	0.3289	2.8030*	0.0039	4.7817
2002	26.0256***	2.5744	1.8324	2.3428	0.0315	17.4375***	0.4962	0.1485	1.3056	26.7597***
2003	9.4662	4.1825**	5.6235**	0.6125	0.2318	4.3067**	0.4709	0.3561	0.3032	19.8781*
2004	29.5476***	0.0042	0.5720	0.0969	0.5728	0.0079	0.0335	0.0145	0.2798	2.1754
2005	25.6466***	3.6331*	3.1481*	0.0216	0.4454	1.6001	0.2623	2.5071	2.5399	8.5241
2006	14.2256**	2.8726*	0.1932	2.60E-5	0.0971	2.0475	0.0564	0.0412	1.7086	7.9538
2007	64.1189***	2.6707	0.0143	1.5086	0.0140	1.1890	1.2174	0.8963	0.0970	5.3124
2008	28.3844***	0.4515	5.3053**	1.1748	4.1674**	3.7328*	1.2236	0.5370	1.5055	20.0672***
2009	7.6383	0.9005	1.2310	0.0069	2.3948	0.9463	0.2950	0.0200	0.1548	8.5274
2010	8.0449	0.1116	0.0330	0.2858	1.2015	0.3847	1.8525	0.2502	1.3324	10.6605
2011	6.9352	0.6594	2.0334	0.0167	0.2004	0.0703	3.4824*	1.9141	3.6174*	12.7987*
2012	7.2667	0.0946	0.0650	6.5844**	3.1954*	0.3921	2.7496*	0.0943	0.3189	11.4803
2013	15.8180**	0.0452	3.4837*	0.7602	0.4645	0.6769	1.3596	2.4337	1.0498	14.0294*
2014	13.5893*	1.8738	2.4654	0.4271	1.0810	0.0411	0.0822	0.0019	0.8894	9.4056
2015	30.3922***	0.0550	0.1565	1.2496	0.3318	0.0239	0.6914	1.0190	0.0219	6.9359
Joint Ho. χ^2 (d.f.)	395.6806*** (175)	48.4068*** (25)	39.6405** (25)	32.2400 (25)	27.6346 (25)	51.0337*** (25)	21.0151 (25)	27.0793 (25)	23.6367 (25)	279.0849*** (175)

(*continued on next page*)

Table 3: (*continued*)

Panel 2: SET 50 Index Return

Period	Joint EIV Problems $\chi^2(7)$	Individual Regression Coefficients $\chi^2(1)$								Joint Weather Effects $\chi^2(7)$
		Lagged Return	Weather Variables							
			Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	
1995-2015	8.8996	10.9749***	3.6016**	0.5397	0.4184	0.3361	0.1076	2.3172	0.0197	7.1809
1995	5.0252	0.4235	0.1022	0.0516	1.5035	0.0667	0.2168	0.0846	2.1656	7.2301
1996	25.4553***	2.2913	0.0025	0.1595	4.1782*	1.2454	1.2091	0.0389	2.5739	10.7780
1997	8.3435	8.1335***	1.1698	4.0766	8.59E-04	0.0137	0.0043	2.4156	0.0139	8.0863
1998	15.8826**	2.5608	0.8202	5.3947**	0.0024	4.3627**	1.8623	0.1097	0.1671	11.7195
1999	3.3853	3.8759**	2.4791	2.7985*	0.1606	2.2137	0.3002	3.2144*	0.2775	15.0331**
2000	1.1338	0.4717	1.2260	0.3840	0.0415	1.0880	0.9985	0.8752	0.1788	4.0575
2001	8.3910	0.2971	1.9173	2.73E-06	0.0346	0.0810	0.7380	3.3307*	0.0106	6.7658
2002	22.7391***	3.1530*	1.3467	2.0092	0.0191	18.3017***	0.5939	0.0691	2.0486	25.9243***
2003	10.7521	6.9559***	5.7508**	1.3437	0.0495	2.4070	0.0397	0.0270	0.0502	15.5127**
2004	28.3276***	0.1108	0.5178	0.6498	0.4980	0.1184	0.5545	0.0498	0.4446	2.9174
2005	24.8223***	2.4485	3.0333*	0.0590	0.3247	1.0859	0.3772	2.1441	2.5472	7.6225
2006	16.1366**	2.6831	0.0797	0.0014	0.0435	2.3281	0.0863	0.0408	1.4246	8.7377
2007	61.6746***	2.1180	0.0220	1.5082	0.0603	1.4910	1.6071	0.8669	0.1745	6.7304
2008	28.7694***	0.1492	4.2015**	1.2973	1.4552	3.5658**	0.3265	0.3092	1.2095	15.3666**
2009	7.8143	1.3668	1.4589	0.0113	2.1868	0.9707	0.2191	0.0209	0.2092	8.8685
2010	9.1244	0.0963	0.0700	0.3260	1.0861	0.3393	1.9387	0.4746	0.8543	9.5850
2011	8.6512	0.3020	2.2533	0.0183	0.3325	0.0578	3.3846*	1.9359	3.1277*	12.2582*
2012	9.6098	0.2904	0.0316	7.3967***	3.0912*	0.5393	3.6614*	0.2754	0.3687	12.8014*
2013	19.8580*	0.2410	3.6838*	0.5156	0.5173	0.3606	0.9803	1.9837	1.3901	12.0008
2014	15.4010**	1.4388	2.7586*	0.2921	1.2854	0.0539	0.0415	0.0129	0.7488	10.3139
2015	21.4061***	0.0213	0.1130	1.0024	0.6926	0.0017	0.0711	0.2503	0.0055	4.3716
Joint Ho. χ^2(d.f.)	352.7030*** (147)	39.4289*** (21)	33.0381** (21)	29.2960 (21)	17.5639 (21)	40.6924*** (21)	19.2112 (21)	18.5297 (21)	19.9909 (21)	216.6815*** (147)

(*continued on next page*)

Table 3: (*continued*)

Panel 3: MAI Index Return

Period	Joint EIV Problems $\chi^2(7)$	Individual Regression Coefficients $\chi^2(1)$								Joint Weather Effects $\chi^2(7)$
		Lagged Return	Weather Variables							
			Air Pressure	Cloud Cover	Ground Visibility	Rainfall	Relative Humidity	Temperature	Wind Speed	
2002-2015	12.5102*	0.4393	0.2720	0.0005	0.8597	2.3125	0.9802	0.2672	0.5772	6.0490
2002	20.1022***	2.4105	6.6000**	2.4687	2.1253	0.7406	1.0045	3.4212*	0.3263	7.3761
2003	6.1235	0.8187	0.6177	2.5634	0.7532	5.5392**	1.6312	0.1000	0.2302	10.7521
2004	40.9875***	0.7816	0.3237	0.0090	3.10E-4	0.1344	0.0062	0.1555	0.2341	1.9196
2005	7.5942	3.0708*	0.0313	0.4965	0.2514	0.0082	0.9539	0.4743	1.9278	3.1415
2006	3.8403	2.7419*	0.7770	0.0850	2.9195	0.0082	1.3029	1.3664	2.1308	6.1711
2007	7.8029	9.1828***	0.6014	2.8127*	3.48E-04	1.1915	0.2581	0.3009	2.3456	9.9397
2008	7.1613	5.1891**	4.5967**	0.3500	0.2366	7.9097***	0.1163	0.4080	0.0149	14.3343**
2009	10.9464	0.1752	0.0075	0.0060	1.1825	0.5334	0.0196	0.3439	0.0011	3.1193
2010	2.7323	3.3785*	0.0319	1.5119	4.3584**	0.7183	1.5751	0.0075	2.1857	11.0308
2011	7.1032	4.2680**	0.6430	0.0147	0.0971	0.0056	2.4390	0.0429	3.8920**	11.4595
2012	6.3406	3.2385	0.4733	0.4268	1.3134	0.0403	0.0537	0.5213	0.1023	2.8607
2013	15.2938	0.1005	1.5618	1.8983	0.2229	0.4142	0.1741	3.2673*	0.9861	10.3045
2014	10.2514	1.6044	1.1948	2.1545	0.8226	0.7767	0.0844	0.0186	0.1267	15.0025**
2015	23.8521***	7.0503***	0.3745	0.7465	0.2293	0.1452	1.5991	0.1732	2.3015	5.4304
Joint Ho. χ^2(d.f.)	170.1316*** (98)	44.0110*** (14)	17.8346 (14)	15.5440 (14)	14.5130 (14)	18.1655 (14)	11.2180 (14)	10.6011 (14)	16.8053 (14)	112.8422 (98)

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. d.f. = degrees of freedom; Joint Ho. = Joint Hypothesis.

DISCUSSION

Usefulness of Artificial Hausman Regressions

Although the EIV problems are present, OLS and AH regressions may yield similar results. If the results for the two regressions are generally similar, the AH regression is not useful; this regression should be avoided because it is more complicated and more difficult to estimate.

To demonstrate that AH regression warrants the effort, I check for the sub-periods in which EIV problems are significant and then compare the weather-test results for the AH regression against the OLS regression. The fact that the two regressions give the same weather-test results implies a zero probability of conflict. I test the no-conflict hypothesis using Pearson's chi square test. The test fails if the probability is zero. Thus, I assume small probabilities of 1% and 5% under the null hypothesis. The results are shown in Table 4.

From the table, the hypothesis is rejected for the three index returns when the probability is 1%. At a 5% probability of conflict, the hypothesis is rejected for the SET and SET 50 index returns. Based on this finding, the AH regression is useful. The analyses begin with the OLS results. However, when the EIV and missing-variable problems are present, the OLS coefficients are both biased and inconsistent. The AH coefficients remain consistent. The quality improves if the analyses switch from using OLS results to AH results.

Table 4
Tests for the Usefulness of artificial hausman regressions

Statistics		SET Index Return	SET 50 Index Return	MAI Index Return
Number of Significant EIV Cases		12	11	5
Number of Conflicting Weather Results		2	3	1
$\chi^2(1)$	Pb = 1%	29.4533***	75.9282***	18.0500***
	Pb = 5%	3.2667*	10.9136***	2.2500

Note: * and *** = significance at 90% and 99% confidence levels, respectively. *Pb* = Probability of conflicting results for the OLS regression with the artificial Hausman regression, given that the EIV problem is significant.

IV Regressions in Furhwirth and Sogner (2015)

Furhwirth and Sogner (2015) noted that the weather effects on asset prices were indirect and resulted from changes in investor's mood. In the indirect-effects specification, weather and control variables can be correlated with regression errors. Hence, an IV two-stage least squares estimation was used to provide consistent estimates. The researchers reported that the IV results differed from the OLS results, implying that the IV regressions were important and useful. My approach is able to manage the misspecification from the weather's indirect effects as well. The AH regressions produce exactly the same estimates as the two-stage least squares regressions (Racicot & Theoret, 2008).

Time-Varying Weather Effects and Market Efficiency

If the market is efficient, weather effects cannot exist or must disappear quickly. The fact that the effects exist is evidence against market efficiency. Although the market is not fully efficient, efficiency should improve over time due to factors such as adaptive investors, strong competition, communication networks and financial innovation (Lo, 2004). For Thailand, Khanthavit (2016b) found improving efficiency for the SET and SET 50 index returns but not for the MAI index return.

Researchers, e.g., Yoon and Kang (2009), argued that existing weather effects in early sub-samples and disappearing effects in later sub-samples supported the improving-efficiency hypothesis. In essence, the researchers linked improving efficiency to a negative relationship between weather effects and time.

In this study, the results in Table 3 allow me to examine this important improving-efficiency hypothesis. I follow the procedure in Doyle and Chen (2009) by using the sizes of chi-square statistics in the last columns of Panels 1 to 3 to measure the significance of the weather effects and relate them to time. Before I continue with the test, I note in Table 3 that the weather effects appeared in early sub-periods, disappeared, re-appeared, and then disappeared again. This is known as wandering behaviour. Although market efficiency improves over time, it may also wander. The results in Table 3 allow me to relate the weather effects to the efficiency levels. In equation (2), the size and significance of the return's autocorrelation coefficient ρ_τ indicate the efficiency levels (Lo, 2004). The chi square statistics for the significance of ρ_τ are readily available in Column 3 of Panels 1 to 3. Table 5 shows the regression coefficients of the chi square statistics for weather effects with those of ρ_τ's significance and time. This test is new and is the first to explicitly relate the weather effects with the efficiency levels. If the weather effects disappear over time, the time coefficient must be negative and significant. If the effects wander with the efficiency level, the market-efficiency coefficient must be positive and significant. However, in Table 5, none of the time coefficients are significant; therefore, I conclude that the weather effects in the SET exist and wander over time. It is interesting and important to find for the SET 50 index that the market-efficiency coefficient is positive and significant at the

95% confidence level. The results support the covariation of weather effects with market-efficiency levels.

Table 5
Relationships of Bangkok-weather effects with time and market efficiency

Index Return	Time	Market-Efficiency
SET^{OLS}	–0.0583	0.1050
$SET\ 50^{AH(Pal)}$	0.1615	1.4656^{**}
MAI^{OLS}	0.2259	0.2170

Note: ** = significance at the 95%, confidence level, ^{OLS} = results from the OLS regression, and $^{AH(Pal)}$ = results from the artificial Hausman regression using the two-step, Pal (1980)-based IVs.

Who are Weather-Sensitive Investors?

Forgas (1995) proposed that investors with limited knowledge tended to allow mood to interfere with decision-making. In Thailand, these investors are small, local, individual investors (Dowling & Lucey, 2008). Comparing the results of the SET 50 index returns, in which large investors are dominant, against the MAI index returns, in which small individuals are dominant, sheds light on Forgas' (1995) proposal.

In Table 3, Column 3 of Panels 2 and 3, the no return autocorrelation-based market-efficiency hypothesis was rejected for both the SET 50 and MAI index returns. Thus, if the weather effects were present, the dominant investors should have been the contributors. The fact that weather effects existed for the SET 50 index return but not for the MAI index return negates the Forgas (1995) hypothesis. It is likely that large investors were weather-sensitive and caused weather effects in the Stock Exchange of Thailand. This finding is counter-intuitive. So, how can it be explained?

Consider the Kyle (1985) model. If it is modified to incorporate weather effects, the value known to informed investor can be the sum of the true stock value and weather part, while the random trade quantity of noise trader is due to noise plus the weather part. Moreover, if the volatility of the noise is large, the weather part in the random trade quantity is effectively zero. In equilibrium, the price reflects the true value, the weather part, and the noise-trader's volume.

Small, individual investors were considered noise traders in the literature (e.g., De Bondt, 1998). For MAI stocks, they were the majority, whose trading constituted 96% of the aggregate volume (Khanthavit & Chaowalerd, 2016). The noise-trader's volume was large and dominant vis-à-vis the weather part, so that weather effects were not significant.

Comparison with Previous Studies on the Stock Exchange of Thailand

Weather effects were studied for the Stock Exchange of Thailand, for example, by Nirojsil (2009) and Sriboonchitta et al. (2014). Although their methodologies and sample periods differed, their results corresponded to one another. The temperature effects were significant. In Table 3, I could not find significant temperature effects in the summed chi square tests or full sample tests. By examining the results in Table 3, Panel 1 for the same sample periods as theirs, i.e., from 1992 to 2008 for Nirojsil (2009) and from 1996 to 2010 for Sriboonchitta et al. (2014), I find significant but weak temperature effects at the 90% confidence level in 1994, 1997, 1999, and 2001. An important and interesting question is why our results differ. Three possible explanations are as follows.

First, their models were mis-specified due to measurement errors in the temperature variable. To check this theory, I re-estimate Equation (1) for their sample periods and with the lagged return and only using the temperature variable. I check for the EIV problem and test for the temperature effect using the OLS estimates when the EIV problem is not present. If it is present, I use the AH estimates. The results are in Columns 2 and 3 of Table 6. Using the approach I proposed, the temperature effects are found. Thus, the EIV problem cannot be the explanation.

Second, from Table 1, Panel 2, the temperature was significantly correlated with air pressure and rainfall. Thus, the significant temperature effects could, in fact, have been the air pressure and rainfall effects. I check for this explanation by estimating Equation (1) in their sample periods. The results are in Table 6, Columns 4 to 6. In Column 5, the temperature effects are still significant, but they are at a 90% confidence level and are much weaker than the effects shown in Column 3. The significant temperature effect is partly explained by the significant air pressure and rainfall effects.

Third, the fixed-effect hypothesis implicitly made by Nirojsil (2009) and Sriboonchitta et al. (2014) was incorrect. If the incorrect hypothesis is the explanation, the temperature effect should disappear in the regression of Equation (2) for the one-year sub-periods in their full samples. I use the chi square statistics in Table 3, Panel 1 to check for this explanation. The results are in Table 6, Columns 7 to 9. The summed chi square statistics in column 8 for significant temperature coefficients are small and not significant for the two studies. However, the joint tests in Table 6, Column 9 find significant weather effects. To link the main contributors of the significant effects with air pressure and rainfall, I compute the summed chi square statistics for significant air pressure and rainfall effects for Nirojsil (2009) and Sriboonchitta et al.'s (2014) sample periods. I find that the air pressure statistics for Nirojsil (2009) and Sriboonchitta et al. (2014) are significant at the 95% and 90% confidence levels, respectively. The rainfall statistics for both studies are significant at the 99% confidence level. These findings, together with that for the second explanation, lead me to conclude that the significant temperature results in the previous studies were incorrect. They were driven by the incorrect fixed-effect assumption. In fact, the significant weather effects were the air pressure and rainfall effects I found in this study.

Further Investigation of Air Pressure and Rainfall Effects on Stock Returns

Boker, Leibenluft, Deboeck, Virk, and Postolache (2008) explained that air pressure affected moods due to its effect on neurotransmitters implicated in mood regulation. With respect to Wurtman and Wurtman (1989), sunlight associated with rainy days caused falling serotonin levels to fall, which led to bad moods. Studies, e.g., Goldstein (1972), have reported that good moods were associated with high air pressure levels, but others, e.g., Schwarz and Clore (1983), reported that bad moods were associated with rainfall. Based on these findings, the air pressure and rainfall effects on stock returns should be unidirectional. In this study, however, I find that the significant air pressure and rainfall coefficients can change signs from one sub-period to another (Khanthavit, 2016c). For example, for the SET index return, the air pressure coefficients were significant and positive in 1995, 2003, 2011, and 2013 but were significant and negative in 2005 and 2008. The rainfall coefficients were significant and positive in 1998 and 2002; they were significant and negative in 1992, 1998, 2003, and 2008. Sign changes are also possible. Denissen et al. (2008) and Keller et al. (2005) noted that mood reactions to day-to-day weather fluctuations might not be generalised to reactions to seasonal fluctuations. Although seasonality was removed from among the sample weather variables (Hirshleifer & Shumway, 2003), the issue of whether the good or bad weather was temporary or prolonged was important to both investors and their moods (Watson, 2000).

Table 6
Comparison with previous studies

Sample Periods	Full-Period Regressions					Sub-Period Regressions on Seven Weather Variables		
	Temperature Only		Seven Weather Variables					
	EIV Problems[1]	Temperature Effects[1]	EIV Problems[2]	Temperature Effects[1]	Joint Weather Effects[2]	EIV Problems[3]	Temperature Effects[4]	Joint Weather Effects[3]
Nirojsil (2009)	4.4999**	5.6582**	9.7270	3.7792*	0.1820	284.4968***	18.8132	276.1736***
Sriboonchitta et al. (2014)	2.2414	4.1466**	10.0305	2.8939*	0.2451	186.4423***	14.2421	163.0719***

Note: *, **, and *** = significance at the 90%, 95%, and 99% confidence levels, respectively. [1] and [2] = $\chi^2(1)$ and $\chi^2(7)$ statistics. [3] = $\chi^2(119)$ statistics for Nirojsil (2009) and $\chi^2(105)$ statistics for Sriboonchitta et al. (2014). [4] = $\chi^2(17)$ statistic for Nirojsil (2009) and $\chi^2(15)$ statistic for Sriboonchitta et al. (2014).

CONCLUSION

Tests for weather effects generally have at least four estimation problems: incorrect fixed-effect assumptions, missing-data problems, errors-in-variables (EIV) problems, and omitted-variable problems. The incorrect assumptions, missing-data problems, and omitted-variable problems were addressed in previous studies. However, the results were not satisfactory or the approaches were not successful. Moreover, the EIV problem had never been raised. In this study, I proposed an approach to resolve the four estimation problems simultaneously. The incorrect fixed-effect assumption was fixed by breaking a long full-sample period into short one-year sub-periods. The missing-data problem was resolved by imputing unconditional means of weather variables into the missing cases. I mitigated the omitted-variable problem by considering a comprehensive set of weather variables. Finally, I corrected the EIV and omitted-variable problems by using OLS regressions together with artificial Hausman (AH) regressions and choosing consistent AH results when the problem was present. Otherwise, the efficient, unbiased, and consistent OLS results were chosen for the analyses.

I revisited the Bangkok weather effects to demonstrate the advantages of the proposed approach. Bangkok was chosen because it featured conditions that led to the four estimation problems, and the Stock Exchange of Thailand is an important emerging market. The study found conflicting results in OLS and AH regressions in some sub-periods when the EIV problem was present. In the conflict cases, the study chose consistent AH results over biased and inconsistent OLS results. As opposed to previous studies, this study did not find significant temperature effects but instead identified significant air pressure and rainfall effects. The study showed that the temperature effects were due to the incorrect fixed-effect assumption. The temperature effects were, in fact, the air pressure and rainfall effects.

It is important to note that the approach did not completely resolve the incorrect fixed-effect assumption; the assumption was still made for the one-year sub-periods. It is more realistic to allow the effects to vary daily over the sample period. The study can be extended into time-varying weather effects, but I leave this extension for future research.

ACKNOWLEDGEMENTS

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

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