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A Kalman Filtering Approach to Event Study Analysis when Performance Variables are Nonstationary

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Abstract

A Kalman filtering regression model is proposed to resolve nonstationarity problems commonly found in certain performance variables, e.g., trading volume, of event study analyses. Resolution is possible when the expected performance variables are allowed to move according to random walk processes. The model can be used for cases in which performance variables have deterministic or stochastic trends. The model is applied to examine the trading turnover behavior in the Thai stock and bond markets in the time around the military coups of 2006 and 2014. The model is successful; it passes validity tests, namely, the nonstationarity and parameter constancy tests. The findings suggest that the results reported by previous studies that failed to treat the stationarity problems are misleading.

Keywords: Abnormal behavior, regression model, stochastic trend.

1. Introduction

Introduced by Fama et al. (1969), event study analysis has been one of the most important tools in economics and finance. By examining the behavior of abnormal performance variables−the deviation of realized variables from their expected or normal values in the time surrounding the events, event studies enable researchers to assess whether abnormal firm performance is associated with the specific firm events, such as earnings announcements, mergers and acquisitions, and inclusion in important indexes. Additionally, these studies help researchers to assess whether and how the market responds to some well-specified events, such as military coups and regulatory changes (Peterson 1989).

1.1. The event-study method

1) Identification of abnormal performance variables

Let y_t be the performance variable in period t. In most studies, the performance variable is asset returns (e.g., Fama et al. 1969, Brown and Warner 1985, Eryigit 2019). Other performance variables are return volatility and trading volume, as in Yadav (1992). Kim and Verrecchia (1991) linked abnormal returns with the change in traders' beliefs due to information pertaining to the events; the researchers linked return volatility and trading volume with traders' idiosyncratic reactions to the information. More recently, in the studies for emerging markets (e.g., Khanthavit 2019), gross and net foreign trading volume have been considered as performance variables to address how certain investor groups react to information.

The performance variable $\tilde{y}_t$ is the sum of the expected or normal value μ_t and the unexpected or abnormal variable $\tilde{e}_t$, as in Equation (1) (Fama et al. 1969),

$$\tilde{y}_t = \mu_t + \tilde{e}_t. \tag{1}$$

The value μ_t is given by a particular model for the expected value (Kothari and Warner 2007). If the event is significant, with respect to Bowman (1983), the researchers must find the following:

$$E\left(\tilde{e}_t \mid \mu_t, \text{event}\right) \neq E\left(\tilde{e}_t \mid \mu_t\right) = 0, \tag{2}$$

where $E\left(\tilde{e}_t \mid \mu_t, \text{event}\right)$ is the expected abnormal variable in period t surrounding the event. The variable $\left(\tilde{e}_t \mid \mu_t, \text{event}\right)$ can be estimated by the following

$$\left(\tilde{e}_t \mid \mu_t, \text{event}\right) = \tilde{y}_t - \mu_t. \tag{3}$$

The expected value μ_t is unobserved and must be estimated using samples that are not influenced by the event.

Izan (1978) modified Fama et al.'s (1969) methodology in (1) to measure the abnormal variables by parameterizing the variables in the regression model in (4),

$$\tilde{y}_t = \mu_t + \sum_{a=-A_{\mathrm{Pre}}}^{-1} \delta_a D_t^a + \delta_0 D_t^0 + \sum_{b=+1}^{+B_{Post}} \delta_b D_t^b + \tilde{e}_t, \tag{4}$$

where $t = -N, ..., -A_{\mathrm{Pre}}, ..., -1, 0, +1, ..., +B_{Post}$. With respect to Fama et al. (1969), the period from $t = -N$ to $t = -A_{\mathrm{Pre}} - 1$ is the estimation window, the period from $t = -A_{\mathrm{Pre}}$ to $t = +B_{Post}$ is the event window, and the period $t = 0$ is the event period.

The dummy variable $D_t^{\tau=a,0,b}$ is 1.00 if the period t is τ. Otherwise, it is 0.00. The regression coefficient δ_τ measures the abnormal variable in period τ. This method is the conditional regression method used in Thompson (1985), the event-parameter regression method in Malatesta (1986), and the extended regression method in De Jung et al. (1992).

The coefficient δ_τ and $\left(\tilde{e}_\tau \mid \mu_\tau, \text{event}\right)$ in (3) are equivalent when the event periods do not affect μ_τ. When μ_τ follows a market model, the market return and beta may change with the event. δ_τ is biased due to the structural change.

Although the noneffect condition is restrictive, the analysis based on Fama et al.'s (1969) approach requires much more restrictive assumptions (Thompson 1985). For this reason, the focus of this study will be on the model in (4) in the discussion that follows.

2) Alternative models for expected performance variables

The researchers must assume a model for the expected performance variable μ_τ. Cable and Holland (1999) offered a model for μ_τ in (5),

$$\mu_t = \alpha + \beta_1 X_{1,t} + \beta_2 X_{2,t} + ... + \beta_K X_{K,t}, \tag{5}$$

where $X_{i,t}$ is the explanatory variable. α and β_i are the intercept and slope coefficients, $i = 1, 2, ..., K$. The model is general. By appropriately defining the explanatory variables and restricting the coefficients, researchers can modify the model to a desired, common model in event studies, such as the constant-mean model and the market-adjusted variable model. That is, researchers can fix

$\beta_1 = \beta_2 = ... = \beta_K = 0$ to obtain the constant-mean model. They can consider $X_{i,t}$ as the market variable and disregard the remaining explanatory variables to obtain the market-adjusted variable model. If the performance variable y_t is the stock return, the model is the capital asset pricing model if the researchers set $\alpha = 0$ and consider only the risk-free and market returns as the explanatory variables.

1.2. Methodological issues

When conducting event studies, researchers encounter several options at different points in the process. Therefore, the research on event study methodology is extensive. A review of the literature is provided by, among others, Bowman (1983), Peterson (1989), Binder (1998), Kothari and Warner (2007), and Corrado (2011). Methodological improvement and extension continue still today. For example, Andreou et al. (2016) proposed a smooth transition autoregressive model that takes into account the probability of contaminated events. Recently, Khanthavit (2019) chose the estimation window based on the cumulative sum control chart (CUSUM) test to ensure constancy of the model's parameters.

1) Nonstationary performance variables

Regression models in Equations (1) and (4) are valid and the event study results are usable only when the performance variables y_t are stationary. Nevertheless, few studies, e.g., Cable and Holland (1999), checked for the stationarity property of the variable.

Stationarity checks are not critical if the performance variables are asset returns (Conrad and Kaul 1988). For return volatility and trading volume, however, stationarity checks are very important. There is evidence to suggest that return volatility follows an integrated process (e.g., Choudhry 1995). Moreover, trading volume has been found to exhibit a deterministic trend (e.g., Lee and Rui 2002) and stochastic trends (e.g., Lo and Wang 2000).

Nonstationary performance variables can be detrended to obtain stationarity. The stationarity property is satisfied. However, it is important for the researchers to note that detrending methods have a substantial impact on the time-series properties of detrended variables. Lo and Wang (2000) employed six methods to detrend weekly volume turnovers of stocks on the New York Stock Exchange and the American Stock Exchange from July 1962 to December 1996. The researchers found that different methods gave different results; therefore, they continued to use the raw rather than detrended series in their analysis.

2) The research question

Because different detrending methods give inconsistent time-series properties of detrended variables and as some methods are unable to remove the trends, researchers may follow Lo and Wang (2000) in using the nonstationary, raw performance variables. However, a method to resolve the nonstationarity problem is needed. Despite extensive methodological designs, such a method has never been proposed.

In this study, a Kalman filtering method is proposed to work with nonstationary performance variables. In (5), the coefficients α and β_i are not constant but follow random walk processes, leading to a nonstationary expected variable μ_t (Conrad and Kaul 1988). In a state-space representation setting, the nonstationary variable is related to the random coefficients and explanatory variables in the measurement equation, while the unobserved random coefficients are considered state variables whose stochastic behaviors are described by the transition equation. The model is estimated by Kalman filtering.

2. A Kalman Filtering Regression Model for Nonstationary Performance Variables

2.1. The design

Kalman filtering has been considered in previous event studies. However, the objective is not to resolve the nonstationarity problems in performance variables. Researchers, e.g., Brockett et al. (1994) and Mazouz and Saadouni (2007), have acknowledged that the coefficients in equation (5) were time-varying and modeled them by random walk processes. Recently, Andreou et al. (2016) noticed that confounding events could contaminate the samples in estimation windows. These researchers mitigated the contamination effect by random coefficients in Equation (5). The aforementioned studies estimated the models by Kalman filtering regressions.

In this study, the expected variable μ_t is nonstationary so that it is consistent with the nonstationary, raw performance variable $\tilde{y}_t$. For simplicity, a mean-adjusted model for μ_t is assumed. The model performs as well as the alternatives (Brown and Warner 1985). It is assumed the mean is random. Equations (4) and (5) constitute the measurement equation in (6),

$$\tilde{y}_t = \tilde{\alpha}_t + \sum_{a=-A_{\text{Pre}}}^{-1} \delta_a D_t^a + \delta_0 D_t^0 + \sum_{b=+1}^{+B_{\text{Post}}} \delta_b D_t^b + \tilde{e}_t, \tag{6}$$

where $\tilde{\alpha}_t$ is the random expected value of y_t in period t. The expected value and variance of $\tilde{e}_t$ are 0.00 and σ_e^2, respectively.

The movement of $\tilde{\alpha}_t$ is described by the transition equation (7),

$$\tilde{\alpha}_t = \alpha_{t\text{-}1} + \tilde{v}_t. \tag{7}$$

The expected value and variance of $\tilde{v}_t$ are 0.00 and σ_v^2, respectively, while the covariance of $\tilde{e}_t$ with $\tilde{v}_t$ is 0.00.

A random walk without drift for $\tilde{\alpha}_t$ is assumed because the specification is simple and popular (Coutts et al. 1997), the movement reflects the random arrival of information to the market (Ross 1989), and it is supported by data from previous studies (Buckland and Fraser 2000, Mazouz and Saadouni 2007). The specification tends to produce an $\tilde{\alpha}_t$ that wanders erratically but within acceptable limits (Coutts et al. 1997).

A random walk with drift is not chosen to describe $\tilde{\alpha}_t$'s movement because the period t is a short interval of one day or one week in most studies. The change should be gradual and $\tilde{\alpha}_t$ should be approximately the same as $\alpha_{t\text{-}1}$ (Rockinger and Urga 2000).

When applying Kalman filtering in their event studies, Brockett et al. (1994) and Buckland and Fraser (2000) used different approaches to recover abnormal variables. Brockett et al. (1994) estimated (6) and (7) by constraining the abnormal-variable coefficients δ_τ to 0.00. The researchers then measured abnormal variables by the prediction error for $\tilde{y}_t$ from the Kalman filtering regression. Buckland and Fraser (2000) followed Brockett et al. (1994) to constrain the abnormal-variable coefficients δ_τ to 0.00. The researchers then regressed the filtered α_t on event dummy variables to obtain the abnormal performance variables. Those studies are not followed. The prediction error in Brockett et al. (1994) and filtered $\alpha_{t\text{-}1}$ are influenced by the information on the event in the updating algorithm of a Kalman filter. Their results are biased for nonsignificant events. The filtered $\alpha_{t\text{-}1}$ in Buckland and Fraser (2000) is nonstationary. Regressions of the filtered α_t on the event dummies is not valid.

2.2. Model estimation

The model in (6) and (7) is estimated using Kalman filtering. Kalman filtering is a recursive procedure for computing the optimal estimators of period t's unobserved $\tilde{\alpha}_t$ based on the observed performance variable $\tilde{y}_t$ available up to and including period t. This recursive procedure consists of predicting and updating phases. In the predicting phase, $\tilde{\alpha}_t$ and prediction error variances are estimated using the observed $\alpha_{t\text{-}1}$ from the previous period. Once the new information α_t is available, the estimated α_t is updated in the updating phase. Harvey (1989) explained the steps of model estimation in details.

2.3. Hypothesis tests

If the event is significant and the information pertaining to it reaches the market in period τ, the abnormal performance variable in the period must be different from 0.00. Hence, the null hypothesis of no information in period τ is $\delta_\tau = 0.00.$ Moreover, if the event is not significant, there should not be any new information in any period; therefore, the joint hypothesis test for a nonsignificant event is $\delta_{-A_{\text{Pre}}} = \delta_{-A_{\text{Pre}}+1} = \ldots = \delta_{+B_{\text{Post}}} = 0.00.$ The hypothesis is tested by the Wald statistic. Under the null hypothesis, the statistic is a chi-squared variable with $A_{\text{Pre}} + B_{\text{Post}} + 1$ degrees of freedom.

Researchers are interested in the movement of abnormal performance variables over the event window. The movement in n periods onward from the first period $-A_{\text{Pre}}$ is measured by the cumulative abnormal performance variable $(CAPV_n)$ in Equation (8)

$$CAPV_n = \begin{cases} \sum\limits_{a=-A_{\text{Pre}}}^{-A_{\text{Pre}}+n\text{-}1} \delta_a, & \text{if } n \le A_{\text{Pre}} + 1, \\ \sum\limits_{a=-A_{\text{Pre}}}^{0} \delta_a + \sum\limits_{b=1}^{n-A_{\text{Pre}}-1} \delta_b, & \text{if } A_{\text{Pre}} + 1 < n \le B_{Post} + A_{\text{Pre}} + 1. \end{cases} \tag{8}$$

If the movement is significant, the cumulative abnormal variable $CAPV_n$ must be different from zero, so that the null hypothesis is $CAPV_n = 0.00.$

2.4. Validity tests

1) The stationarity test

The model in (6) and (7) is proposed to resolve the nonstationarity problems in performance variables. If the model is successful, the error term $\tilde{e}_t$ in (6) must be stationary. Stationarity of the error term $\tilde{e}_t$ will be checked for using the augmented Dickey-Fuller (ADF) test. The optimum lag number for the test is the one that gives the minimum Bayesian information criterion. An information criterion measures the distance of the model being considered from the true but unobserved model. The error term $\tilde{e}_t$ to be tested is the fitted error term from the Kalman filtering regression.

2) The parameter constancy test

The full window may cover a long period of time. A long full window due to a long estimation window improves the accuracy of parameter estimates, but it risks model parameter nonconstancy due to confounding events and structural changes (Peterson 1989, Andreou et al. 2016). Parameter nonconstancy renders the results unusable. To ensure parameter constancy, the CUSUM test will be conducted based on the fitted error term from the Kalman filtering regression.

3. An Application to Thailand's 2006 and 2014 Military Coups

To demonstrate how and how well the proposed method works, the method is applied to revisit the trading volume performance of Thailand's stock and government bond markets in the time surrounding the military coups of September 19, 2006 and May 22, 2014.

Thailand is one of the world's leading emerging markets. In April 2019, the market capitalization of the Stock Exchange of Thailand (SET) was 544 billion U.S. dollars. According to the World Federation of Exchanges (2019), the SET ranked eleventh among markets in the Asia-Pacific region and was the twenty-fourth largest market in the world.

Thailand's government-bond market is also very large. In the third quarter of 2018, the market capitalization was 240 billion U.S. dollars. In the sample countries in the Asia Bond Monitor (Asian Development Bank 2018), Thailand ranked fourth in terms of market capitalization after Japan, China, and Korea.

The two recent coups are interesting. From an economic perspective, the two recent coups instituted "Thai-style democracy", as opposed to previous coups where the motivation was to deter the political influence of the left, under which the military bloodlessly seized power from purportedly corrupt elected governments, ended the prolonged, widespread, and violent anti-government protests, and promised to return the country to democracy (Maisrikrod 2007). The financial markets should have reacted significantly to these Thai-style democratic military coups (Duggan 2004).

From a statistical perspective, all the trading volume series are nonstationary. Below, the tests reveal that the sample series follow deterministic trends with the exception of stock volume around the 2014 coup. The 2014 stock series is interesting. It shows mixed test results. While the trend test indicates that the series is trend stationary, the first autoregressive coefficient is high and close to 1.00. The ADF test of the raw series suggests that it has a unit root. Although the samples possess different time-series properties, the proposed model should be able to perform satisfactorily for all the samples as it is designed.

3.1. The methodology

1) Identification of the event dates

Statements announcing the two coups were made on September 19, 2006 and May 22, 2014. Therefore, these two days are the occurrence dates. It is important to note that the announcements were made after the market's trading hours at 11.00 p.m. and 4.30 p.m., respectively. The occurrence dates cannot be the event dates; the investors could not trade on the information about the coups.

In the study, the approach by Ahmed (2017) will be used to identify the event dates as the subsequent trading days, Thursday, September 21, 2006 and Friday, May 23, 2014, so that the event day $t = 0$ is the first day investors can react to the coups.

2) Length of the pre-event window

It is difficult to predict exactly when coups will happen. The pre-event period need not be very long. Nazir et al. (2014) recommend against long pre-event windows to avoid possible confounding events. A window that is too short is not recommended either. Researchers are unable to analyze impacts if the window is too short. A 20-day pre-event window is chosen because it is the shortest length for a window of those typically chosen in event studies (Peterson 1989). As a result, the pre-event window covers days -20 to -1. The postevent window is also 20 days long. This window runs from days +1 to +20. Altogether, the event window is 41 days including the event date.

3) Length of the estimation window

For accuracy of the parameter estimates, long estimation windows are preferred to short ones (Salinger 1992). However, if the windows are too long, it is likely that the estimation suffers from structural changes and confounding events. Typical lengths of the estimation window range from 100 to 300 days (Peterson 1989). Three hundred days are chosen for an improved prediction model. The first day of the estimation sample is $-N=-320$. It is important to note that choosing a long estimation window risks model parameter instability. Previous studies, e.g., Mazouz and Saadouni (2007) and Andreou et al. (2016), reported that the random-parameter model was able to mitigate parameter instability problems. CUSUM tests of the model will be conducted to ensure parameter constancy before the results are analyzed.

4) The empirical model

Kalman filtering is a highly nonlinear regression model. When the model has many parameters to be estimated, the estimation routine barely converges and resulting estimates are not very accurate. In this study, the full sample is 341 days, and the event window is 41 days. If the abnormal performance variables are measured for 41 days, there will be 43 parameters to be estimated. It is likely the estimation problems will be severe.

To lessen these problems, the approach in Khanthavit (2019) is followed to measure the abnormal performance variables for nine intervals; these intervals consist of days $[-20,-16]$, $[-15,-11]$, $[-10,-6]$, $[-5,-1]$, $[0]$, $[+1,+5]$, $[+6,+10]$, $[+11,+15]$ and $[+16,+20]$. Intervals 1 to 4 and 6 to 9 examine the behavior of the abnormal variable in the 4 weeks before and after the event date, while day $[0]$ reveals how the variable reacts to the information on the event date. Under this setting, the number of parameters reduces from 43 to 11 parameters. With respect to (6), the empirical model becomes as follows

$$\tilde{y}_t=\tilde{\alpha}_t+\sum_{a=-4}^{-1}\delta_a D_t^a+\delta_0 D_t^0+\sum_{b=+1}^{+4}\delta_b D_t^b+\tilde{e}_t, \tag{9}$$

where δ_j measures the average abnormal performance variable of interval j, and the dummy variable D_t^j is the dummy variable for the interval $j=-4,\ldots,0,\ldots,+4.$ $D_t^{j=-4}$ is 1.00 if t falls into interval j for days $[-20,-16]$. Otherwise, it is 0.00. The dummy variables $D_t^{-4<j\leq+4}$ are defined in a similar way.

3.2. The data

The samples are the trading volumes in the stock and bond markets surrounding the 2006 and 2014 coups. The event dates are September 21, 2006 and May 23, 2014. These are the trading days following the occurrence dates of September 19, 2006 and May 22, 2014. The sample periods are from June 2, 2005 to October 19, 2005 (January 28, 2013 to June 19, 2014) for the 2006 (2014) coup.

The volume variables are daily volume turnovers. The stock volume turnover is the ratio of the trading value over the market capitalization at the market value, while the bond volume turnover is the ratio of the outright trading value over the market capitalization at the par value. Although the volume variables can be constructed based on various definitions, the volume turnover definition was chosen because it is a natural measure of trading activity when viewed in the context of standard portfolio theory (Lo and Wang 2000). The data for the stock and bond markets were retrieved from the SET and Thai Bond Market Association (Thai BMA) databases, respectively.

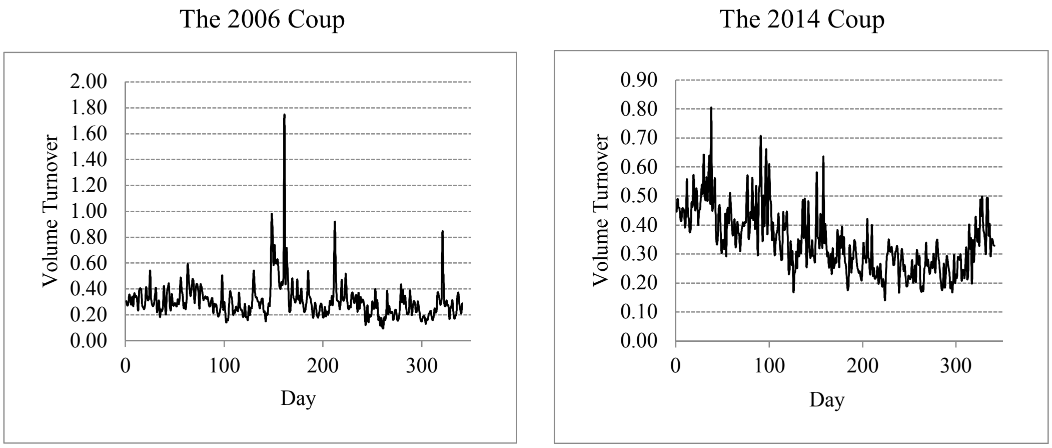

Figure 1 Raw stock volume turnovers

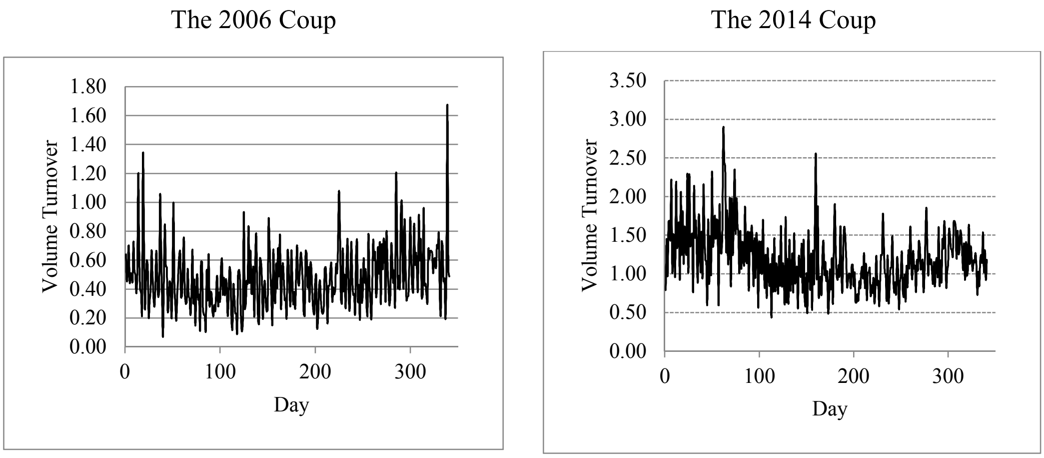

Figure 2 Raw bond volume turnovers

Figures 1 and 2 plot the raw stock and bond volume turnovers for the full windows. For the 2006 (2014) coup, Day 1 is June 2, 2005 (January 28, 2013) and Day 341 is October 19, 2005 (June 19, 2014). The descriptive statistics for the estimation and full widows for the two coups are reported in Table 1. All the variables are positively skewed and have fat-tailed distributions. The Jarque-Bera test rejects the normality property at the 99% confidence level. The variables are serially correlated at the first orders.

Despite the nonnormality of the performance variables, Kalman filtering is usable. Given the linear relationship of the variables and the dynamics of the state variables in (6) and (7), the Kalman filter is optimal; it returns minimum mean square linear estimates (Kellerhals 2001).

The trend test reports significant time-trend coefficients for all series except for the 2006 bond series for the estimation window. The augmented Dickey-Fuller test rejects the nonstationarity hypothesis for all the detrended series. This evidence suggests that the volumes are nonstationary; they follow deterministic trends.

The first-order autoregressive coefficients of the stock volume for 2014 are significant, large, and close to 1.00. They are 0.7172 for the estimation window and 0.7028 for the full window. Moreover, for the raw series, the ADF test cannot reject the nonstationarity hypothesis for the estimation window, but it marginally rejects the hypothesis at the 90% confidence level for the full window. Therefore, it is not clear whether the series follows a deterministic or stochastic trend.

Finally, the CUSUM test for structural changes and parameter constancy is conducted for the raw and detrended volumes. At the 95% confidence level, the test rejects the constancy hypothesis for the raw stock series for 2014 and for the raw bond series for both 2006 and 2014. The test rejects the hypothesis for all the detrended series for both 2006 and 2014 with the exception of the bond series for the 2014 estimation window.

Table 1 Descriptive Statistics

Statistics		Stock Market			
		The 2006 Coup		The 2014 Coup	
		Estimation Window[a]	Full Window[b]	Estimation Window[a]	Full Window[b]
Average		0.3133	0.3072	0.3440	0.3426
Standard Deviation		0.1460	0.1438	0.1125	0.1092
Skewness		4.1900	4.0929	0.7875	0.7903
Excess Kurtosis		33.0329	31.8966	0.5833	0.6751
First-Order Autoregressive Coefficient		0.5101***	0.5159***	0.7172***	0.7028***
Time Trend Coefficient		-2.42E-04**	-2.55E-04***	-9.47E-04***	-6.59E-04***
Jarque-Bera Test for Normality (χ^2_2)		1.45E+04***	1.54E+04***	35.2607***	41.9762***
Augmented Dickey-Fuller t Statistic (Lag Number)	Raw Series	-7.0466*** (1)	-7.6901*** (1)	-2.4349 (4)	-2.8028* (4)
	Detrended Series	-7.1929*** (1)	-7.8938*** (1)	-11.3431*** (0)	-3.6451*** (4)
Cumulative Sum Control Chart Test for the No Structural Change Hypothesis	Raw Series	Cannot Reject	Cannot Reject	Reject	Reject
	Detrended Series	Reject	Reject	Reject	Reject

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

The 2006 stock series follows a deterministic trend; the inability of the CUSUM test to reject the no-change hypothesis suggests its low power. The fact that significant parameter nonconstancy is present in the samples requires that the proposed model must be able to resolve the parameter nonconstancy problems as well as the nonstationarity problems.

3.3. The empirical results

1) The conventional event-parameter regression model

Before the results for the Kalman filtering regression model are reported, the conventional event-parameter regression model will be estimated to obtain the baseline results for comparison. All the models are estimated using the EViews 9.5 statistical package (IHS Global 2017).

Table 1 Descriptive Statistics (cont.)

Statistics		Bond Market: The 2006 Coup, Estimation Window[a]	Bond Market: The 2006 Coup, Full Window[b]	Bond Market: The 2014 Coup, Estimation Window[a]	Bond Market: The 2014 Coup, Full Window[b]
Average		0.4596	0.4745	1.1883	1.1964
Standard Deviation		0.2045	0.2136	0.4134	0.3967
Skewness		0.9565	1.1982	0.9334	0.8930
Excess Kurtosis		1.5807	3.4129	1.1438	1.2447
First-Order Autoregressive Coefficient		0.1899***	0.1846***	0.1527*	0.1566**
Time Trend Coefficient		2.13E-04	3.80E-04***	-1.75E-03***	-0.0011***
Jarque-Bera Test for Normality (χ^2_2)		76.9769***	247.0973***	59.9120***	67.3321***
Augmented Dickey-Fuller t Statistic (Lag Number)	Raw Series	-4.7464*** (4)	-4.5427*** (4)	-4.1463*** (4)	-4.4116*** (4)
	Detrended Series	-4.9163*** (4)	-5.1532*** (4)	-5.1486*** (4)	-4.8748*** (4)
Cumulative Sum Control Chart Test for the No Structural Change Hypothesis	Raw Series	Reject	Reject	Reject	Reject
	Detrended Series	Reject	Reject	Cannot Reject	Reject

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

The conventional model is the model in (6) with a constant expected performance variable $\tilde{\alpha}_t = \alpha$ restriction. Parameter significance and hypothesis tests are based on Newey and West's (1987) heteroscedasticity and autocorrelation-consistent covariance matrix.

Panel 2.1 of Table 2 reports the results for the raw series. The results are similar to those in Lumjiak et al. (2018) and Khanthavit (2019). This finding is expected. Their data and those in this study are similar, and the methodologies are equivalent.

The model does not pass the CUSUM test for structural changes. In Table 1, the series have deterministic trends. However, the series are not detrended in estimation. Additionally, the model does not add a time trend as an explanatory variable. Therefore, the model is mis-specified. The results are biased.

The results for the detrended series are reported in Panel 2.2 of Table 2. Although the series are detrended to obtain stationarity with respect to Table 1, the model does not pass the CUSUM test for structural changes. The model fails. The results are biased and not usable.

2) The Kalman filtering regression model

Panel 3.1, Table 3 reports the results of the proposed Kalman filtering regression model. The ADF test rejects the nonstationarity hypothesis for the fitted errors of all the series at the 99% confidence level. This finding is the evidence for the successful performance of the proposed model to resolve nonstationarity problems in event studies. The model passes the CUSUM test for all the series. The results can be used for the analysis. Parameter significance and hypothesis tests are performed based on White's (1981) consistent covariance matrix for nonlinear models.

The Wald statistics reveal that the 2006 and 2014 coups had significant impacts on the stock and bond markets. For the 2006 stock market, the abnormal volume is significant for days $[-5,-1]$ and $[0]$. In 2014, it is significant on days $[0]$, $[+1,+5]$, and $[+6,+10]$. For the bond market, the abnormal volume is significant only on day $[0]$ in 2006, while it is significant on days $[-20,-16]$, $[-15,-11]$, $[-10,-6]$ and $[0]$ in 2014.

Table 2 The Conventional event-parameter regression model

Panel 2.1 Raw Series

Abnormal Variable	Stock Market: The 2006 Coup	Stock Market: The 2014 Coup	Bond Market: The 2006 Coup	Bond Market: The 2014 Coup
Days −20 to −16	0.3133***	−0.0696***	0.1065***	0.1982***
Days −15 to −11	−0.1440***	−0.1087***	0.1584***	0.3535***
Days −10 to −6	−0.1142***	-0.0476**	0.1062**	0.1834***
Days −5 to −1	−0.1052***	-0.0445***	0.0167	−0.0372
Day 0 (Event Date)	0.0159	0.0846***	0.2062***	−0.1303***
Days +1 to +5	0.5323***	0.0384**	0.1507***	0.0836
Days +6 to +10	0.0097	0.0651***	0.1555***	−0.1050
Days +11 to +15	−0.0611***	0.0679***	0.0555	−0.1025*
Days +16 to +20	−0.0868***	−0.0133	0.2308**	0.0045
Test for the No Coup Effect Hypothesis (χ_9^2)	3.74E+04***	3.81E+03***	314.8326***	348.5034***
Augmented Dickey-Fuller t Statistic (Lag Number)	−7.7079*** (1)	−2.8688* (4)	−5.2841*** (4)	−4.4764*** (4)
Cumulative Sum Control Chart Test for the No Structural Change Hypothesis	Cannot Reject	Reject	Reject	Reject

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

Panel 2.2 Detrended Series

Abnormal Variable	Stock Market: The 2006 Coup	Stock Market: The 2014 Coup	Bond Market: The 2006 Coup	Bond Market: The 2014 Coup
Days −20 to −16	−0.1052***	0.0309**	0.0485	0.3638***
Days −15 to −11	−0.0741***	−0.0048	0.0986***	0.5244***
Days −10 to −6	−0.0638***	0.0595***	0.0444	0.3598***
Days −5 to −1	0.0585***	0.0659***	−0.0470	0.1447***
Day 0 (Event Date)	0.5757***	0.1970***	0.1414***	0.0548***
Days +1 to +5	0.0539*	0.1527***	0.0847***	0.2719***
Days +6 to +10	-0.0156	0.1828***	0.0876**	0.0888
Days +11 to +15	-0.0400*	0.1889***	−0.0142	0.0967*
Days +16 to +20	0.0138	0.1110***	0.1591	0.2092***
Test for the No Coup Effect Hypothesis (χ_9^2)	3.75E+04***	4.34E+03***	186.3391***	318.7708***
Augmented Dickey-Fuller t Statistic (Lag Number)	−7.8938*** (1)	−3.6451*** (4)	−5.1532*** (4)	−4.8748*** (4)
Cumulative Sum Control Chart Test for the No Structural Change Hypothesis	Reject	Reject	Reject	Reject

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

It is important to note that the results in Panel 3.1 of Table 3 are very different from those of the conventional model in Panel 2.1 of Table 2. Incorrect results lead to incorrect interpretation. For example, the significant abnormal volume on the days prior to the event date in Panel 2.1 of Table 2 is interpreted as suggesting leaked information about the coup attempts (Dube et al. 2011). The information then disseminated into the stock and bond market at least a month before the coups. The results in Panel 3.1 of Table 3 suggest otherwise. With the exception of the bond market in 2014, the evidence to support information leakage is weak.

Panel 3.2 of Table 3 reports the cumulative abnormal volume for the nine intervals in the event windows. In calculating the statistics, the abnormal volume is scaled for all intervals except for day 0 by a factor of 5 because those intervals are 5 days. Only the statistics for the bond market in 2014 are significant and rising. The statistics for the remaining three cases are not significant. The tests are not powerful. The significance bands increase with the number of days the abnormal volumes are accumulated (Khanthavit 2019).

Table 3 The Kalman filtering regression model

Panel 3.1 Abnormal Volume

Abnormal Variable	Stock Market		Bond Market	
	The 2006 Coup	The 2014 Coup	The 2006 Coup	The 2014 Coup
Days −20 to −16	−0.0188	0.0422	0.0050	0.2264***
Days −15 to −11	0.0092	−0.0045	0.0563	0.3869***
Days −10 to −6	0.0045	0.0490	0.0038	0.2177***
Days −5 to −1	0.1293*	0.0448	−0.0864	−0.0029
Day 0 (Event Date)	0.6540***	0.1713***	0.1024***	−0.0954*
Days +1 to +5	0.1600	0.1189**	0.0471	0.1223
Days +6 to +10	0.0979	0.1448**	0.0520	−0.0606
Days +11 to +15	0.0469	0.1526	−0.0479	−0.0567
Days +16 to +20	0.0964	0.0690	0.1262	0.0515
Standard Deviation of the Measurement Equation Error	0.0989***	0.0604***	0.2015***	0.3410***
Standard Deviation of the Transition Equation Error	0.0401	0.0183***	0.0091***	0.0271***
Test for the No Coup Effect Hypothesis (χ^2_9)	5.42E+04***	1.79E+03***	564.0596***	2.15E+06***
Augmented Dickey-Fuller t Statistic (Lag Number)	−16.3087*** (0)	−16.8092*** (0)	−6.5172*** (4)	−7.7361*** (4)
Cumulative Sum Control Chart Test for the No Structural Change Hypothesis	Cannot Reject	Cannot Reject	Cannot Reject	Cannot Reject

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

Panel 3.2 Cumulative Abnormal Volume

Abnormal Variable	Stock Market		Bond Market	
	The 2006 Coup	The 2014 Coup	The 2006 Coup	The 2014 Coup
Days −20 to −16	−0.0940	0.2112	0.0249	1.1322***
Days −15 to −11	−0.0482	0.1888	0.3064	3.0666***
Days −10 to −6	−0.0257	0.4341	0.3256	4.1549***
Days −5 to −1	0.6207	0.6581	−0.1063	4.1401***
Day 0 (Event Date)	1.2747	0.8294	−0.0039	4.0448***
Days +1 to +5	2.0749	1.4238	0.2314	4.6562***
Days +6 to +10	2.5645	2.1481	0.4916	4.3531**
Days +11 to +15	2.7990	2.9111	0.2522	4.0698*
Days +16 to +20	3.2811	3.2562	0.8831	4.3274

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

4. Discussion

4.1. Stochastic trend vs. deterministic trend

The specification in (7) implies that the expected performance variable $\tilde{\alpha}_t$ follows a stochastic trend, while the performance variable $\tilde{y}_t$ may follow stochastic or deterministic trend. Although the trend test such as the one in Table 1 supports a deterministic trend in the series, Harvey (1997) argued that the trend could not be adequately captured by a straight line. Equation (7) follows Harvey's (1997) suggestion that a slowly evolving, stochastic trend is used, even though the test suggests a deterministic trend. The results in Table 3 indicate that specification (7) is able to describe the trends in the sample series. The model passes both the stationarity and parameter constancy tests.

4.2. Stationary performance variables

The model is designed to resolve nonstationarity problems in performance variables. However, some performance variables in event studies, such as stock and bond returns, are stationary. The question is whether the model can be used for the stationarity case.

The model can be used due to two reasons. First, the sample may be contaminated by confounding events or structural changes. The random expected variable $\tilde{\alpha}_t$ absorbs the contamination impacts (e.g., Andreou et al. 2016). Second, if the series is not contaminated, the expected variable $\tilde{\alpha}_t = \alpha$ is a constant. While the estimate $\hat{\alpha}_t$ moves randomly in the model, its variance σ_v^2 is not different from zero or is very small (Coutts et al. 1997). Effectively, the estimate $\hat{\alpha}_t$ is constant.

To ensure that the proposed model works as well for stationary performance variables, the model for stock and bond returns is estimated for the 2006 and 2014 coups. The stock and bond returns are the logged return computed from the closing SET indexes and the closing Thai BMA government-bond clean price indexes, respectively. The indexes are retrieved from the SET and Thai BMA databases.

For the raw sample series, only the bond return for the 2006 coup has a trend and cannot pass the CUSUM test. All the returns are stationary. The proposed model is successful. The fitted errors for the stock and bond returns from the Kalman filtering regressions for the two coups can pass the stationarity and CUSUM tests. Interested readers may obtain the detailed results upon request.

4.3. Alternative specifications for expected performance variables

It is possible that researchers may prefer an alternative model to the mean-adjusted model in (7). For example, Lumjiak et al. (2018) chose a market-adjusted model. The model for expected performance variable is $\tilde{\mu}_t = \tilde{\alpha}_t + \tilde{\beta}_t X_t^m$, where $\tilde{\beta}_t$ is the random slope coefficient and X_t^m is the exogenous market variable. The specification (7) is modified to $\begin{bmatrix} \tilde{\alpha}_t \\ \tilde{\beta}_t \end{bmatrix} = \begin{bmatrix} \alpha_{t-1} \\ \beta_{t-1} \end{bmatrix} + \begin{bmatrix} \tilde{v}_t^{\alpha} \\ \tilde{v}_t^{\beta} \end{bmatrix}$. The error vector $\begin{bmatrix} \tilde{v}_t^{\alpha} \\ \tilde{v}_t^{\beta} \end{bmatrix}$ has a zero mean vector and a (2×2) covariance matrix $\Omega_{(2\times 2)}$. This model is similar to the model in Buckland and Fraser (2000) and Mazouz and Saadouni (2007). The random walk $\begin{bmatrix} \hat{\alpha}_t \\ \tilde{\beta}_t \end{bmatrix}$ resolves the nonstationarity problems; it also helps to mitigate contamination impacts if they are present in the samples (e.g., Andreou et al. 2016).

4.4. A system of equations

Researchers may study a group of S performance variables for a specific event. In this case, the researchers can estimate the model for each variable individually. Tests based on the cross-equation average of abnormal variable are not very powerful, especially when the abnormal variables have different signs (Binder 1998). It is recommended that researchers estimate a system of equations, where the system for (6) becomes

$$\begin{bmatrix} \tilde{y}_t^1 \\ \vdots \\ \tilde{y}_t^s \end{bmatrix} = \begin{bmatrix} \tilde{\alpha}_t^1 \\ \vdots \\ \tilde{\alpha}_t^s \end{bmatrix} + \begin{bmatrix} \sum_{a=-A_{\text{Pre}}}^{-1} \delta_a^1 D_t^a + \delta_0^1 D_t^0 + \sum_{b=+1}^{+B_{Post}} \delta_b^1 D_t^b \\ \vdots \\ \sum_{a=-A_{\text{Pre}}}^{-1} \delta_a^S D_t^a + \delta_0^S D_t^0 + \sum_{b=+1}^{+B_{Post}} \delta_b^S D_t^b \end{bmatrix} + \begin{bmatrix} \tilde{e}_t^1 \\ \vdots \\ \tilde{e}_t^s \end{bmatrix}$$ and Equation (7) becomes

$$\begin{bmatrix} \tilde{\alpha}_t^1 \\ \vdots \\ \tilde{\alpha}_t^s \end{bmatrix} = \begin{bmatrix} \tilde{\alpha}_{t-1}^1 \\ \vdots \\ \tilde{\alpha}_{t-1}^s \end{bmatrix} + \begin{bmatrix} \tilde{v}_t^1 \\ \vdots \\ \tilde{v}_t^s \end{bmatrix}$$. The error vectors $\begin{bmatrix} \tilde{e}_t^1 \\ \vdots \\ \tilde{e}_t^s \end{bmatrix}$ and $\begin{bmatrix} \tilde{v}_t^1 \\ \vdots \\ \tilde{v}_t^s \end{bmatrix}$ have a zero expected value vector. Their covariance matrices are $\Sigma_{(S\times S)}$ and $\Omega_{(S\times S)}$ of size $(S\times S)$, respectively. Their cross covariance is zero.

The joint hypothesis test for zero abnormal variables in period τ is $\delta_\tau^1 = ... = \delta_\tau^S$. The Wald statistic under the null hypothesis is a chi-squared variable with S degrees of freedom. If the event is significant, some δ_τ^s for variable S in period τ must be nonzero. The joint hypothesis of a nonsignificant event is $\delta_{-A_{\text{Pre}}}^1 = ... = \delta_{+B_{\text{Post}}}^S$. Under the null hypothesis, the Wald statistic is distributed as a chi-squared variable with $\left\{S\times\left(A_{\text{Pre}} + B_{\text{Post}} + 1\right)\right\}$.

It should be noted that the system of equations has limitations. Because Kalman filtering regressions are highly nonlinear, the system cannot be very large. For a large system, researchers may follow Andreou et al. (2016) by estimating the model for each equation and use Boehmer et al.'s (1991) statistics for hypothesis tests.

4.5. The differenced stock volume turnover for the 2014 coup

In Table 1, it is not clear whether the 2014 stock volume turnover is trend stationary or difference stationary. In Panel 2.2 of Table 2, the series were treated as being trend stationary. The model fails. In this section, therefore, the series are treated as being difference stationary and are used to test for the significance of the military coup in 2014.

The ADF statistic is −15.6938. It rejects the nonstationarity hypothesis for the differenced series at the 99% confidence level. At the 95% confidence level, the CUSUM test indicates parameter constancy and no structural changes.

The conventional event-parameter regression passes the stationarity and parameter constancy tests. The results for the abnormal volume are similar to the results from the Kalman filtering regression in Panel 3.1 of Table 3. This is because once the detrending is successful and structural change or parameter nonconstancy is not present in the detrended series, the conventional event-parameter regression model is well specified. The results are usable. The detailed results are available upon request.

5. Conclusions

In event study analyses, if performance variables such as trading volume and variance are nonstationary, the variables can be detrended for stationarity. The detrended variables are stationary and the analyses can proceed in the usual ways with Fama et al.'s (1969) conventional method or Izan's (1978) event-parameter regression method. Lo and Wang (2000) reported that different detrending methods gave different time series properties of the detrended series. Researchers would rather work with the raw variables.

In this study, a Kalman filtering regression model is proposed for event study analyses. It allows researchers to employ raw performance variables even when the variables are nonstationary. The nonstationarity problems are resolved because the method allows the expected performance variables to move randomly, following random walk processes.

The model is applied to study the behavior of volume turnover in the stock and bond markets in the time surrounding the military coups in 2006 and 2014. The model is successful. The fitted errors from the regression can pass the stationarity and parameter constancy tests at high confidence levels. The results in this study contradict those of Lumjiak et al. (2018) and Khanthavit (2019). While those two studies support the information leakage hypothesis, this study suggests that the evidence is weak. As the two studies failed to treat the nonstationary variables, it is likely their results are biased and misleading.

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