MOVING TOWARD EFFICIENCY: THE STUDY OF TIME-VARYING INFORMATIONAL EFFICIENCY IN THE STOCK EXCHANGE OF THAILAND

Sophana Buraprathep
Faculty of Commerce and Accountancy
Thammasat University
Bangkok, Thailand

ABSTRACT

The application of random walk or general auto-regressive model to investigate time-varying degree of informational efficiency in the previous literatures has some drawbacks. To make improvements on model specification, this study proposes the stochastic AR(p) coefficient model that relates the dynamic behavior of degree of efficiency with time in three functional forms. Using daily returns from Thailand's stock market from April 30th, 1975 to September 19th, 2014, this study finds the statistically relationship between degree of efficiency and time, which is well described either by the linear or the logistic function. Furthermore, the results suggest that degree of informational efficiency in the stock market improves through time as indicated by the decreasing numbers of day to disseminate particular amount of information.

Keywords: Time-varying market efficiency, informational efficiency, stochastic AR(p) coefficient model, Kalman filter

1. Introduction

Market efficiency is one of the most important foundations of finance theories. Although the hypothesis of efficiency has been extensively studied for financial markets in developed and emerging countries, the literature in this area is still growing. New sample markets as well as new techniques or improvements are introduced in order to achieve correct and insightful understanding. In the early period of the study, Fama (1970) concentrated his interest on informational efficiency, classifying efficiency into three separate forms, namely, weak-, semi-strong- and strong-form. Among these three forms, the test for weak form efficiency is the most popular because it employs market price data which are readily available to investigators. Examples of such studies include Fama (1965), Lo and Mackinlay (1988), Worthinton and Higgs (2006), Kim and Shamsuddin (2008), etc. Most of the tests for weak-form efficiency are restrictive in that they focus on whether the markets are or are not efficient during a sample period. Nevertheless, Grossman and Stiglitz (1980) argued that the market could not be fully efficient so that it was worth the effort of informed investors to gather the necessary information.

It should be noted that market efficiency is informational. The market is considered fully efficient if all information is known instantaneously to all investors and is reflected in prices. Based on this definition, the market should be interpreted as being more efficient, or less inefficient, if it takes less time for information to flow to investors and to be fully reflected in the relevant asset prices. So, even though the market is inefficient for a period in time, it is interesting to ask whether the market is less inefficient or more efficient in the following period. From a theoretical perspective, Lo (2004) proposed the Adaptive Market Hypothesis (AMH) to show that market efficiency is an evolutionary process and can be improved through time. Briefly, AMH asserts that individuals have their own interest and can make mistakes. However, they will learn from their mistakes and adapt themselves to the changing environments. Competition as well as innovation also leads to the evolution of the market, which, in turn, improves the degree of efficiency. His study found that degree of efficiency in US market varied over time as indicated by AR(1) coefficient from rolling regression. These findings point to the fact that, despite inefficiency, the degree may be time-varying.

The question as to whether the degree of market efficiency is time varying has been addressed in the literatures. Emerson et al. (1997) found evidence of changing auto-regression (AR) coefficients from a regression of stock returns in Bulgarian stock market. This study is the pioneer in support of time-varying degree of efficiency. Their framework has been broadly accepted and extended by subsequent studies. For example, Zelewska-Mitura and Hall (2000) employed this approach to investigate whether stocks listed in different periods have different degrees of efficiency, Li (2003a) applied it to study time-varying efficiency of two stock exchanges in China, Li (2003b) extended the scope of study using data from A-share and B-share markets of each stock exchange, while Arouri et al. (2010) employed it to investigate degrees of efficiency in emerging markets before and after liberalization. Apart from Emerson et al (1970)'s framework, Khantavit et al. (2012) recently applied time-varying smoothed transition autoregressive model (time-varying STAR) to the study of evolving market efficiency in Thailand's stock market.

The approaches used by the abovementioned studies have drawbacks at least in three respects. Firstly, the rolling regression model applied by Lo (2004) is inappropriate because AR coefficient of the model is fixed in each estimation window. Thus, the series of constant coefficients shall not be able to represent the correct dynamic process of degree of efficiency. Secondly, the time-varying AR(p) model suggested by Emerson et al. (1997) imposes random walk specification to AR(p) coefficient. With normally distributed disturbance of the random walk process, the coefficient is allowed to be any value between minus and plus infinity as well as to revert to the high level even if it has a falling trend. The theoretical and empirical evidences suggest otherwise. Once the market becomes more efficient, as indicated by a decreasing in magnitude of AR(p) coefficient, it is less likely to become less efficient in the future. Lastly, the time-varying STAR model applied by Khanthavit et al. (2012) imposes deterministic specification to AR(p) coefficient. It is, therefore, unable to capture stochastic behavior of the coefficient, if it indeed exists.

This study proposes the stochastic AR(p) coefficient model to examine time-varying degree of informational efficiency in Thailand's stock market. The degree of efficiency is measured by tracking the amount of time, as implied by the size of AR(p) coefficient from the regression of market return, the market needs to disseminate information. Besides, this model makes important improvements on what has been applied in the past. Firstly, this stochastic model is more suitable to investigate the time-varying degree of efficiency than the constant parameter model applied by Lo (2004). Secondly, the proposed specification is in a general form, which capable of accommodating the specification of AR(p) coefficient even if it is a random walk, as proposed by Emerson et al. (1997), or deterministic, as proposed by Khanthavit et al. (2012), or even a constant. Finally, and most importantly, the model imposes functional relationship of AR(p) coefficient with time in order to align with the theoretical perspective that the AR(p) coefficient has a negative relationship with time and should move towards a long-run value, not necessarily zero, as time goes to infinity. The key contribution of this study is to propose some improvements on the model as well as to provide an insightful analysis of how Thailand's market efficiency improves over time based on correct specification of the degree of efficiency that the market must have as time passes.

The scope of this study is limited to informational efficiency in weak form. That is, all the information should be reflected in the current market price so that past prices cannot predict future prices and abnormal returns cannot be made consistently. The author uses daily data of logarithm returns on SET Index from April 30th, 1975, the establishment of the Stock Exchange of Thailand (SET), to September 19th, 2014, totally 9,682 observations. Kalman filtering technique is applied to estimate the unobserved stochastic AR(p) coefficient based on the regression of the market returns. The remaining of this paper is organized as follows; Section 2 discusses the time-varying coefficient models applied in the previous literatures and the model proposed by this study. Section 3 briefly discusses the methodology for model estimation.

Section 4 presents data and descriptive statistics. Next, the empirical results are reported and discussed in Section 5. Finally, Section 6 provides conclusions of the study.

2. Time-Varying Coefficient Models for Investigating Evolving Market Efficiency

2.1 The Existing Models

There are at least three specifications of time-varying coefficient models applied in previous studies to investigate changes in the degree of efficiency. The first one is rolling regression applied by Lo (2004), yet this specification assumes that AR coefficient is constant in each estimation window (the reader may refer to Lo (2004) for more details on model specification). The second one is a time-varying AR(p) model proposed by Emerson et al. (1997). The model is expressed as follows:

$$r_t = \beta_{0t} + \sum_{i=1}^{p} \beta_{it} r_{t-i} + \nu_t,\ \nu_t \sim N(0, \sigma_\nu^2) \quad (1)$$

$$\beta_{it} = \beta_{it-1} + \omega_t,\ \omega_t \sim N(0, \sigma_\omega^2) \quad (2)$$

where r_t denotes return at time *t*,
β_{0t} denotes arbitrary time-varying drift parameter,
β_{it} denotes time-varying auto-regression coefficient of i^{th} lag order of returns for i = 1,…,*p*,
ν_t denotes white noise disturbance of return, $\nu_t \sim N(0, \sigma_\nu^2)$, and
ω_t denotes white noise disturbance of auto-regression coefficient, $\omega_t \sim N(0, \sigma_\omega^2)$,

AR coefficient, β_{it}, in this model is stochastic and its behavior is described by random walk process in eq. (2). β_{it} plays a key role in determining the degree of market efficiency because it implies how fast information is reflected in the asset prices. Especially when AR(1) specification is imposed, the coefficient β_{1t} can be applied with half-life (HL) measurement to estimate the numbers of days for information dissemination. Basically, HL is computed by dividing minus logarithm 2 by the logarithm of AR(1) coefficient, i.e. $h = \frac{-\log 2}{\log \beta_1}$. The lower AR(1) coefficient, the faster a half of a particular amount of information is relayed to the market.

Some studies provide arguments on using random walk process to describe dynamic behavior of β_{it}. For example, Rockinger and Urga (2000) suggested that the best predictor of the future value of a parameter is its present value. Hence, the random walk process seemed to be the most appropriate choice. In addition, Li (2003a) mentioned that the random walk process was flexible enough to nest two possibilities of β_{it} to be both constant and time-varying in one specification. He also argued that the coefficient will be forced to change, even if it is constant when assuming other processes rather than random walk.

However, the author argues that random walk specification of AR coefficient is inaccurate. This is mainly due to the assumption of Gaussian white noise disturbance term, ω_t. It is obvious that β_{it} will have no directional trend and is likely to have any value. Without any mechanism to relate β_{it} with time, it is allowed to bounce back to a higher level once it is close to the long-run value. In such a case, it would say that once the market becomes more efficient or less inefficient, the degree of efficiency could be deteriorated at any point of time in the future. Intuitively, when a market has achieved a certain level of efficiency, it shall not turn back to being less efficient.

Apart from random walk, Li (2003b) assumed that β_{it} followed general auto-regression of order one process (GAR(1)). He claimed that the specification of GAR(1) was parsimonious to either constant or time-varying degree of efficiency. Nevertheless, the author considers that this specification still has some flaws. This is because it does not incorporate a mechanism to impose a functional relationship between the coefficient and time, and again, it is allowed a reversion to a higher value.

The third specification is a time-varying STAR model proposed by Khanthavit et al. (2012). The model is expressed as follows;

$$\begin{aligned} r_t = &\left\{\rho_0^1 + \textstyle\sum_{i=1}^{p} \rho_i^1 r_{t-i}\right\} \\ &+\left\{(\rho_0^2 - \rho_0^1) + \textstyle\sum_{i=1}^{p} (\rho_i^2 - \rho_i^1) r_{t-i}\right\} G(s_t; \theta_1, c_1) \\ &+\ldots+\left\{(\rho_0^m - \rho_0^{m-1}) + \textstyle\sum_{i=1}^{p} (\rho_i^m - \rho_i^{m-1}) r_{t-i}\right\} G(s_t; \theta_{m-1}, c_{m-1}) + \varepsilon_t \end{aligned} \quad (3)$$

where r_t denotes return at time t,
ρ_i^k denotes coefficient of return at lag order i^{th} of the k^{th} autoregressive process, for i = 1,…,p and k = 1,…,m,
ρ_0^k denotes intercept of the k^{th} autoregressive process,
$G(s_t; \theta_k, c_k)$ denotes the logistic function, where s_t denotes time variable, $\theta_k \geq 0$, and c_k is parameter of the logistic function, and
ε_t denotes random disturbance, $\varepsilon_t \sim N(0, \sigma^2)$

This model explains market returns via a combination of autoregressive processes. They are related by a monotonic function of time, $G(s_t; \theta_k, c_k)$, to accommodate a smooth transition between each AR(p) process. Their study allowed lag order p to be greater than one and applied π-Absorption Time (AT) measurement to measure improvement in the degree of efficiency. AT measures the period of time a market requires to disseminate (1-π%) of information. If π is set at 50%, AT measurement will yield the same result as HL measurement.

This approach facilitates the investigation of time-varying degree of efficiency, especially when returns processes are described by AR(p) where p > 1. The aggregate size of all AR(p) coefficients are taken into consideration via the general impulse response function of AT measurement in order to make an inference on the improvement of degree of efficiency. Nevertheless, specification of autoregressive process of this model is deterministic. Therefore, with a particular set of parameters, market return at each period can be specified with certainty.

2.2 The Proposed Stochastic AR(p) Coefficient Model

This study proposes the stochastic AR(p) coefficient model that improves drawbacks of the existing models discussed above. The model is formulated as follows:

$$r_t = \beta_0 + \sum_{i=1}^{p} \tilde{\beta}_{it} r_{t-i} + \nu_t \quad (4)$$

$$\tilde{\beta}_{it} = \alpha_0^i + \alpha_1^i f(t) + \sum_{j=1}^{m} \sum_{k=j+1}^{m+1} \alpha_k^i \beta_{it-j} + \omega_t^i \quad (5)$$

where r_t denotes logarithm return at time t,
β_0 denotes longterm mean rate of return,
$\tilde{\beta}_{it}$ denotes stochastic AR coefficient of the i^{th} lag order of returns for i = 1,…,p,
ν_t denotes white noise disturbance, $\nu_t \sim N(0, \sigma_\nu^2)$,
α_0^i denotes drift term or long-term mean of $\tilde{\beta}_{it}$,
α_1^i denotes time coefficient,
α_k^i denotes coefficient of the j^{th} lag order of $\tilde{\beta}_{it}$ for j = 1,…,m,
$f(t)$ denotes a functional relationship of $\tilde{\beta}_{it}$ with time, and
ω_t^i denotes white noise disturbance, $\omega_t^i \sim N(0, \sigma_\omega^2)$.

Similar to the previous studies, $\tilde{\beta}_{it}$ is related to the degree of market efficiency as its magnitude reflects how much time the market takes to relay information. In case AR(1) specification is imposed, such as in Rockinger and Urga (2000) and Arouri et al. (2012), the HL measurement can be applied. And in case lag order p is greater than one, such as in Khanthavit et al. (2012), AT measurement can be applied. Though, this model is opposite to Emerson et al. (1997) in several respects.

Firstly, mean rate of market returns, β_0, in this model is assumed to be constant. The author considers that the assumption of time-varying long term mean rate of return is not only unnecessary, but also inaccurate. It is unreasonable to say that mean rate of return changes over time when economic conditions in the long run remain unchanged. Moreover, if β_0 follows random walk, when the model is restricted so that all AR(p) coefficients, $\tilde{\beta}_{it}$, are dropped to zero, r_t will also collapse to random walk, which is inconsistent with theory of time series model in which returns are stationary.

Secondly, eq. (5) nests the specification of $\tilde{\beta}_{it}$ to be a constant, or random walk process, or auto-regressive process into one. For example, if parameters restrictions are imposed such that α_0^i and α_1^i equal zero, m and α_k^i equals to one, the reduced-form specification will facilitate a random walk process. Again, if α_0^i and α_1^i are restricted to zero, but the absolute value of α_k^i is less than one, the reduced-form will accommodate auto-regressive specification. In addition, if $\alpha_1^i$and α_k^i are simultaneously restricted to zero and σ_ω^2 is very small, the reduced-form specification will facilitate a constant degree of market efficiency.

Thirdly, a functional relationship with time, $f(t)$, is imposed to describe dynamic behavior of $\tilde{\beta}_{it}$. With a particular set of parameter values, $\tilde{\beta}_{it}$ shall be decreased through time, as suggested by the hypothesis of improving efficiency. As the true relationship of $\tilde{\beta}_{it}$ with time is unknown, $f(t)$ in eq. (5) can be a constant, increasing function or decreasing function. This study, however, proposes three functional forms as follows;

$$f_1(t) = t \tag{6}$$

$$f_2(t) = \frac{1}{t} \tag{7}$$

$$f_3(t) = 1 - \frac{1}{1+e^{-\theta(t-\tau)}} \tag{8}$$

The function of time in the eq. (6) linearly relates the stochastic AR(p) coefficient with time variable t. In case degree of efficiency has relationship with time in this manner, parameter α_1^i should be significant and negative. On the other hand, eq. (7) relates AR coefficient with time in a non-linear manner. This function accommodates the possibility of rapid improvement in the degree of market efficiency. In case the relationship between degree of efficiency and time can be explained by this non-linear function, parameter α_1^i should be significant and positive. In addition, $\tilde{\beta}_{it}$ will dramatically drop to an insignificant value within a few sample periods.

In eq. (8), the author applies the logistic function proposed by Khanthavit et al. (2012) to relate $\tilde{\beta}_{it}$ with time. In opposite to the specification in eq. (7), this specification facilitates either gradual or rapid improvement of degree of efficiency, as indicated by the size of parameter θ that could be estimated from the regression of market returns. From casual observation, like that of the development of communication network trading systems, as well as empirical evidences, such as Li (2003a and 2003b) and Khanthavit et al. (2012), it is more likely that the degree of efficiency slowly improves through time.

Lastly, the specification in eq. (5) is general in that the number of lag order m is not specified. However, this study proposes lag order m equals to one to estimate the model. With this specification, the proposed process for $\tilde{\beta}_{it}$ can be absolutely compared with random walk or GAR(1) specification applied in the previous studies. If the estimated parameters in eq. (5) are statistically significant, they will be the evidences to support the argument that neither random walk nor GAR(1) is correctly specified.

3. Model Estimation

3.1 Kalman Filter

This study will apply Kalman filter technique to estimate the stochastic, unobserved parameter $\tilde{\beta}_{it}$. Briefly, Kalman filter is a recursive procedure for computing the optimal estimator of state, e.g. the unobserved variable, at time *t*, based on the measurement, e.g. the observed information, available up to and including time *t.* This recursive procedure consists of predicting and updating phases. In the predicting phase, the state and prediction error variance are estimated using the observed information from the previous period. Once the new information at time *t* is available, the estimated state is updated. New observation plays an important role to update the state in such the way that the lower the variance of new observation (relative to the variance of prediction error), the greater impact of new observation it has on the estimated state at the next period, and vice versa (the reader can refer to Harvey (1991) for more details).

To apply Kalman filter, a time series model is put in a state space form, consisting of measurement equation and transition equation. The stochastic AR(p) coefficient model in equation (4) and (5) can be put in state space form as follows:

$$r_t = \boldsymbol{R_t B_t} + \beta_0 + v_t \quad (9)$$
$$\boldsymbol{B_t} = \boldsymbol{A B_{t-1}} + \boldsymbol{D_t} + \boldsymbol{\omega_t} \quad (10)$$

where $\boldsymbol{R_t}$ denotes observation vector, e.g. $[r_{t-1} \quad \cdots \quad r_{t-p}]$

$\boldsymbol{B_t}$ denotes state vector or vector of stochastic AR(p) coefficient, e.g. $[\tilde{\beta}_{1t} \quad \cdots \quad \tilde{\beta}_{pt}]'$

$\boldsymbol{A}$ denotes transition matrix. This is a diagonal matrix which contains α_k^i on its main diagonal, and

$\boldsymbol{D_t}$ denotes a vector of drift term, α_0^i, and function of time, $\alpha_1^i f(t)$.

The estimation of unobserved state vector $\boldsymbol{B_t} = [\tilde{\beta}_{1t} \quad \cdots \quad \tilde{\beta}_{pt}]'$ depends on a set of unknown parameters of the model, $\psi = \{\beta_0, \alpha_0^i, \alpha_1^i, \alpha_k^i, \theta, \tau, \sigma_v^2, \sigma_\omega^2\}$. This calls for a maximum likelihood estimation to estimate these parameters. With assumptions of normally distributed error terms, and independence between the error terms and initial state vector, the likelihood function can be written in prediction error decomposition form as follows:

$$Log\ L = -\frac{1}{2} T log 2\pi - \frac{1}{2}\sum_{t=1}^{T} log|F_t| - \frac{1}{2}\sum_{t=1}^{T} v_t' F_t^{-1} v_t \quad (11)$$

Denote v_t as prediction error and denote F_t as prediction error covariance. Maximum likelihood estimation finds the value of unknown parameters in ψ so that log likelihood function in eq. (11) is maximized.

3.2 Lag Order Identification

As the number of lag order p of the stochastic AR(p) coefficient model is unknown, it is crucial to specify lag order properly since it has important implications on the correctness of model specification as well as the interpretation of the degree of efficiency. This study applies information criteria to identify the appropriate order of p in eq. (4) because it provides a measurement of goodness-of-fit of the statistical model given a set of observations. Two particular information criteria tests are going to be estimated; Akike information criterion (AIC) and Schwatz Bayesian criterion (SBIC). These tests are also applied in Khanthavit et al. (2012) to identify lag order of time-varying STAR model.

Based on the auto-regressive process with constant parameter, AIC and SBIC can be calculated as follows:

$$AIC = T \times ln(\sum_{t=1}^{T} v_t^2) + 2(p+1) \tag{12}$$

$$SBIC = T \times \ln(\sum_{t=1}^{T} v_t^2) + (p+1) \times ln(T) \tag{13}$$

where T denotes total number of observations and v_t denotes disturbance term of the auto-regressive process and p is numbers of lag orders. The model with the most appropriate lag order is the one that gives the lowest AIC or SBIC. In case estimations of AIC and SBIC lead to an inconsistent conclusion, the higher order of lag term will be chosen in order to be more conservative and avoidance of model misspecification. It should be noted that these tests are preliminary because the AR(p) coefficients are assumed to be constant under testing procedures, whereas they are stochastic in the proposed model.

3.3 Model Comparison

This study proposes three functional forms in eqs. (6) to (8) to relate the degree of market efficiency with time. Though, these three specifications of the stochastic AR(p) coefficient model are nested with the constant and random walk specifications, neither of them are nested to each other. Thus, traditional tests for parameter restriction and model comparison cannot be performed. This calls for an alternative statistical test to compare the proposed specifications with one another. In this study, the author will follow the test for model comparison suggested by Voung (1989) because it is able to provide directional information for choosing between non-nested models.

Briefly, Voung (1989)'s test for model comparison is based on Kullback-Leibler Information Criterion (KLIC), which measures the distance between the true unknown distribution and hypothesized model. The test can be applied to any given pair of competing models, whether or not they are nested, non-nested, or overlapping, and both, only one or neither of them are correctly specified. KLIC is computed from the expected value of the difference between log likelihood values of the true unknown model and the competing model. Given this expression, KLIC will always be positive. However, when comparing KLIC of two competing models; namely the null model and the alternative model, by subtracting one from another, it can be either positive or negative. Therefore, in order to make conclusion, Voung (1989) suggested the following test statistic:

$$V = \frac{\sqrt{n}\left(\frac{1}{n}\sum_{i=1}^{n} m_i\right)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i-\bar{m})^2}} = \sqrt{n}(\bar{m}/s_m), \quad m_i = \ln L_{i,0} - Ln\ L_{i,1} \tag{14}$$

where $\ln L_{i,0}$ denotes log likelihood value at the i^{th} observation, for i = 1,…, n, of the null model and $\ln L_{i,1}$ denotes the same for the alternative model. V statistic is compared with critical value at a conventional significant level from a standard normal distribution. If V is greater than the positive critical value, we reject the null hypothesis that both models are equivalent in favor of the null model. On the other hand, if V is lower than the negative critical value, we reject the null hypothesis that both models are equivalent in favor of the alternative model. If the absolute value of V is between minus and plus critical value, neither model is distinguished. In this study, the test statistic V will be compared with critical values at 99%, 95% and 90% for hypothesis testing.

4. Data and Descriptive Statistics

This study employs the daily closing price index of the Stock Exchange of Thailand (SET Index) obtained from the SETSMART database to represent the overall market returns. In fact, the Exchange provides SET Total Return Index (SET TRI) which can be used as a proper measurement of market performance as it is adjusted for changes in number of stocks resulting from corporate actions, e.g. right issuance, public offering, exercise of warrants, etc. However, the author proposes to use the SET Index to investigate evolving efficiency in Thailand's stock market based on the following two reasons. Firstly, the SET TRI series is available since January 2nd, 2002, while the SET Index series is available since April 30th, 1975, (the opening of the Exchange). The longer series of data, the more insightful it should provide on the changing degree of efficiency with respect to evolution of the stock market. Secondly, the SET Index and SET TRI are highly correlated, as evidenced by their correlation coefficient of 0.9906[1]. Therefore, estimated results using data from SET Index shall not be biased.

The samples cover the first official trading day from April 30th, 1975 to September 19th, 2014. Then, logarithm returns on SET Index is computed using $\ln(\frac{p_t}{p_{t-1}})$, where p_t denotes the daily closing index at time t. This logarithm returns, in total of 9,681 observations, is used for model estimation. The descriptive statistics of logarithm returns are summarized in Table 1.

[1] Sample period to estimate correlation is from January 2nd, 2002 to September 19th, 2014.

Table 1
Summary of Descriptive Statistics

Statistics	Mean	Standard deviation	Skewness	Kurtosis	JB (p-value)
SET Index	0.0003	0.0146	-0.1066	11.7664	1,547.60 (0.0000)

Table 2
Identification of Optimal Number of Lags Using AIC and SBIC

Numbers of lags	1	2	3	4	5
AIC	-54575.191	-54572.982	-54566.080	-54560.779	-54553.314
SBIC	-54560.835	-54551.448	-54537.368	-54524.891	-54510.248

Following the information reported in Table 1, logarithm returns is characterized as negative skewness and leptokurtosis, with a skewness of -0.10664 and kurtosis of 11.76642. These evidences of non-normality are affirmed by the Jarque-Bera (JB) normality test statistic, showing that the null hypothesis of normally distributed return series is rejected with 99% confidence interval. However, it should be noted that the application of Kalman filter shall not be affected by the non-normality of returns series. This is because Kalman filter is based on orthogonal projection theory so the classical assumption of Gaussian distribution is not required.

The results of AIC and SBIC tests are demonstrated in Table 2. They indicate that the model with only one lag order has the minimum AIC and SBIC. Although the results of these tests are derived from the estimation of classical time-invariant coefficient AR(p) model, the author proposes that it is applicable to the stochastic AR(p) coefficient model because the constant AR coefficient shall be considered as the average value of all stochastic AR(p) coefficients. Moreover, previous researchers such as Rockinger and Urga (2000), Arouri et al. (2012) also applied time-varying AR(1) coefficient model to describe return process in their studies. Therefore, this study specifies the stochastic AR(1) coefficient model to investigate time-varying degree of efficiency in Thailand's stock market.

5. Empirical Evidences

5.1 Estimation Results of the Stochastic AR(1) Coefficient Model

According to the indicative results from AIC and SBIC tests, the stochastic AR(1) coefficient model can be expressed as follows;

$$r_t = \beta_0 + \tilde{\beta}_{1t} r_{t-1} + \nu_t \tag{15}$$

$$\tilde{\beta}_{1t} = \alpha_0^1 + \alpha_1^1 f(t) + \alpha_2^1 \beta_{1t-1} + \omega_t \tag{16}$$

The proposed functions of time in eqs. (6) to (8) are substituted in $f(t)$ in eq. (16). Next, $\tilde{\beta}_{1t}$ is the smoothed estimate from the Kalman filter and other unknown parameters of the model are then derived from maximum likelihood estimation. Besides, when restriction is imposed such that α_0^i and α_1^i equal to zero, and α_2^i equals to one, the restricted model represents random walk specification applied in the previous studies. For purpose of comparison, this study estimates both restricted and unrestricted forms of the stochastic AR(1) coefficient model. The results are summarized in the following table.

Table 3
Estimation Results of Random Walk and Stochastic AR(1) Coefficient Model

Parameters	**Random walk model**	**Stochastic AR(1) coefficient model with**		
		linear function of time (eq. (6))	**inverse function of time (eq. (7))**	**logistic function of time (eq. (8))**
Panel A				
$\hat{\beta}_0$	0.0240	0.0191	0.0195	0.01806
	(1.6402)	(1.5047)	(1.5415)	(1.4155)
$\hat{\alpha}_0^1$	-	0.3980***	0.1837***	0.0643
		(12.4538)	(12.3323)	(1.4436)
$\hat{\alpha}_1^1$	-	-0.3756***	4.3810***	0.2813***
		(-7.4787)	(3.3986)	(3.3700)
$\hat{\alpha}_2^1$	-	0.0285	0.0369**	0.0285
		(1.5886)	2.0582	(1.0809)
$\hat{\theta}$	-	-	-	9.5281*
				(1.6798)
$\hat{\tau}$	-	-	-	0.5246***
				(7.9467)
$\hat{\sigma}_\nu$	1.4318***	1.0842***	1.0848***	1.0838***
	(137.2620)	(40.3541)	(40.4225)	(223.2911)
$\hat{\sigma}_\omega$	0.0095***	0.6937***	0.6983***	0.6942***
	(3.4769)	(24.6888)	(24.7853)	(65.39538)
Panel B				
LRT	-	1,854.7193***	1,815.0010***	1,856.6937***
df		3	3	5

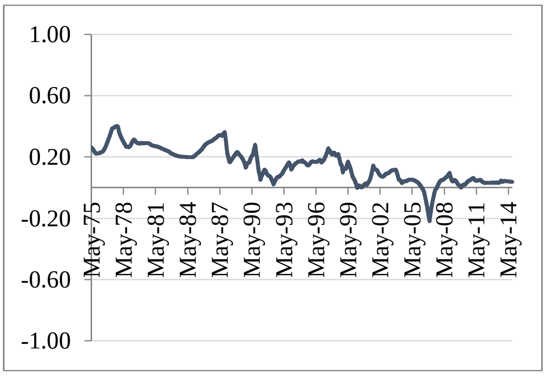
Note. Figure in parentless is t-statistic. *, ** and *** denote the estimated parameters are significant at 10%, 5% and 1% level, respectively. LRT denotes likelihood ratio test in which the random walk model is the restricted model and the stochastic AR(1) coefficient model is the unrestricted model. And df = $df_U - df_R$; where df_U and df_R represent numbers of free parameters of the unrestricted and restricted models, respectively.

Table 3 is separated into 2 Panels; Panel A presents the estimated coefficients together with the t-statistics, while Panel B presents likelihood ratio test (LRT) statistics. Several messages are presented in Panel A. Considering parameters in eq. (16); the results show that drift parameters, $\hat{\alpha}_0^1$, from two models are statistically significant. The estimated drift term in the model with linear function of time is equal to 0.3985, while it is 0.1837 in the model with inverse function of time. These figures represent a long-term mean value of the stochastic AR(1) coefficients, $\hat{\beta}_{1t}$. Suppose the dynamic process of $\hat{\beta}_{1t}$ is truly described by these two models, $\hat{\alpha}_0^1$ of each model will reflect the average number of day in which the information is disseminated to the stock market. However, this expression is subject to the test for model comparison, which will be discussed later in subsequent section.

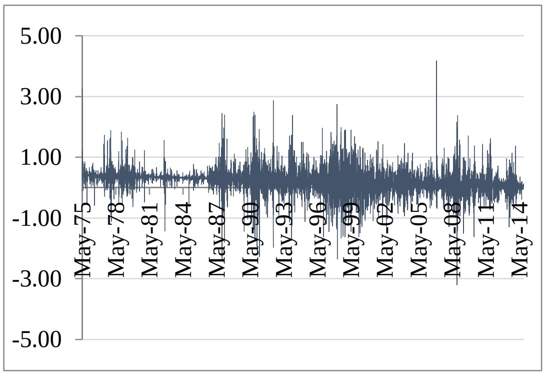
Besides, coefficients of trend element, $\hat{\alpha}_1^1$, are statistically significantly different from zero in all three specifications. These evidences are very important because they indicate that the degree of market efficiency has a statistical relationship with time, which is consistent with the hypothesis of this study. The sign of $\hat{\alpha}_1^1$ is negative in the model with the linear function of time, while it is positive in the model with inverse and logistic functions of time. These results indicate that, in the long run, $\hat{\beta}_{1t}$ will behave in at least three manners; linearly decreasing, abruptly decreasing within a very short period of time, or S-shape decreasing. At the same time, they also imply how degree of efficiency in the stock market improves. In addition, parameter $\hat{\theta}$ in the model with logistic function of time is also important to explain how fast the degree of efficiency improves. A big positive value of $\hat{\theta}$ suggests a rapid improvement, while a small positive value suggests otherwise. In this study, $\hat{\theta}$ is equal to 9.5281 and is significantly different from zero. Nevertheless, its effect on $\hat{\beta}_{1t}$ is deprived by a small value of $\hat{\alpha}_1^1$, which equals to 0.2813. As a result, the magnitude of $\hat{\beta}_{1t}$ in the model with logistic function of time will gradually decrease throughout the sample period.

The estimated volatility $\hat{\sigma}_\omega$ is large vis-à-vis $\hat{\sigma}_v$ and is statistically significant. This indicates that $\hat{\beta}_{1t}$ is not constant, but rather time-varying and has a relationship with time as mentioned earlier. Nevertheless, except in the model with inverse function of time, this study finds no evidence of relationship between $\hat{\beta}_{1t}$ and its one-period lagged value. Lastly, LRT statistics are highly significant at 1% level, with the values of 1,854.7193, 1,815.0010, and 1,856.6937 for the stochastic AR(1) coefficient model with linear, inverse, and logistic function of time, respectively. The results suggest that the stochastic AR(1) coefficient model is significantly better than random walk model in terms of goodness-of-fit. The drift and trend terms are, therefore, meaningful to be incorporated into the model to explain the behavior of degree of market efficiency. Following these evidences, it shall be inferred that neither random walk nor GAR(1) specification applied in the previous studies is correctly specified.

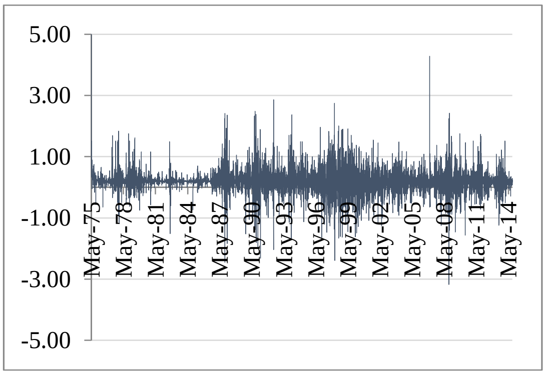
Figure 1
The smoothed estimate of $\hat{\beta}_{1t}$



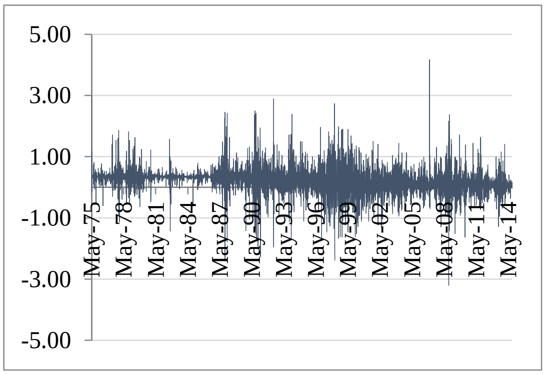
(a) The random walk model



(b) The stochastic AR(1) coefficient model with linear function of time



(c) The stochastic AR(1) coefficient model with inverse function of time



(d) The stochastic AR(1) coefficient model with logistic function of time

From Figures 1 (a) to (d), it can be seen that the smoothed estimate of $\hat{\beta}_{1t}$ from random walk model has a decreasing trend, while such a trend is not visually presented in the smoothed estimate of $\hat{\beta}_{1t}$ from the stochastic AR(1) coefficient model. Also, it is noticed that the absolute values of $\hat{\beta}_{1t}$ from random walk model are less than one, but some of $\hat{\beta}_{1t}$ from the stochastic AR(1) coefficient model are not. However, the arguments for these evidences can be explained in two folds. Firstly, coefficient $\hat{\alpha}_1^1$ are strongly statistically significant, which in turn indicate that values of $\hat{\beta}_{1t}$ from the stochastic AR(1) coefficient model are implicitly diminishing in the long-run.. Secondly and most importantly, the fluctuation pattern of $\hat{\beta}_{1t}$ is due to a Gaussian white noise property of the disturbance. However, the numbers of times that the absolute values of $\hat{\beta}_{1t}$ are greater than one is, on average, 2.78% of total observations. This is considerably small and shall be ignored.

Previously, Arouri et al. (2012) studied time-varying degree of efficiency in Thailand's stock market using a random walk model. Their results differ from the results of the stochastic AR(1) coefficient model in two respects. Firstly, Arouri et al. (2012) demonstrated that $\hat{\beta}_{1t}$ were very stable, while this study finds that $\hat{\beta}_{1t}$ are volatile, but decreasing with time. This is possibly due to the less frequency of data and shorter sampling period since Arouri et al. (2012) used monthly returns from January 1976 to March 2000. The different in model specification is also crucial. As discussed earlier, the random walk model is inferior to stochastic AR(1) coefficient model, hence, $\hat{\beta}_{1t}$ from the latter model shall be more accurate and well described the true process of time-varying degree of market efficiency in Thailand. Secondly, Arouri et al. (2012) asserted that Thailand's stock market was weak-form efficient, but did not indicate how much the degree of efficiency improved. In contrast, this study will demonstrate this improvement using the number of days for information dissemination in the stock market. The details will be discussed later.

5.2 Models Comparison

Table 4 below presents V statistics computed from each pair of models. Recall that a large negative value implies that the alternative model is preferred to the null model, while a large positive value implies otherwise. Comparing between the null random walk model and the alternative stochastic AR(1) coefficient model with three forms of function of time, the results show that all three specifications of the alternative stochastic AR(1) coefficient modes are favorable to the random walk model in describing the dynamic behavior of the degree of market efficiency. This is consistent to likelihood ratio test in Table 3, which indicates that the stochastic AR(1) coefficient model is better fitted to the data than random walk model.

Table 4
Summary of Model Comparison using Voung (1989)'s Test

Alternative models	**Null models**			
		Stochastic AR(1) coefficient models with		
	Random walk model	**linear function of time**	**inverse function of time**	**logistic function of time**
Stochastic AR(1) coefficient model with				
linear function of time	-10.3570***			
inverse function of time	-10.1283***	3.3277***		
logistic function of time	-10.3673***	-0.6272	-3.2556***	

Note. *, ** and *** denote the estimated parameter is significant at 10%, 5% and 1% level.

When comparing the three specification of the stochastic AR(1) coefficient models with one another, the results show that the model with linear function of time is superior to that with inverse function of time, indicated by a significant and positive V statistic of 3.3277. In addition, the model with logistic function of time is also superior to that with inverse function of time, indicated by significant and negative V statistic of -3.2556. Finally, when comparing between the models with linear and logistic functions of time, the sign of V statistic suggests that the model with logistic function of time would be more superior, however, the value of the test statistic, e.g. -0.6272, is not statistically significant. As a result, it can only be inferred that neither of the models with linear nor logistic functions of time are distinguished.

This result is understandable. With particular set of parameters, the logistic function is able to accommodate the linear function of time, especially when the magnitude of $\hat{\alpha}_1^1$ is small as observed in this study. Accordingly, these two specifications are almost identical in terms of describing dynamic behavior of degree of market efficiency. Nevertheless, it should be noted that the model with linear specification has a drawback. When time increases to infinity, $\hat{\beta}_{1t}$ will possibly be a huge negative value. In such a case, it implies that once the degree of efficiency improves, it can deteriorate in the future because the higher value of $\hat{\beta}_{1t}$, the greater time to disseminate information to the market. Opposite to the model with logistic function of time, the magnitude of $\hat{\beta}_{1t}$ estimated from this specification will tend to decrease continuously in the long run.

Furthermore, the model with the logistic function of time is more intuitive than the model with the linear function of time when it is applied to explain time-varying degree of market efficiency. In this regard, it suggests that degree of market efficiency gradually and continuously improves. At the opening of the stock market, degree of efficiency is low as indicated by the big magnitude of $\hat{\beta}_{1t}$. Thereafter, the developments of the stock market, such as improvements in the trading system, enforcement of disclosure rules, establishment of derivatives exchanges, etc., will lead to improvement in degree of informational efficiency. Rather than abruptly happens, this process arises moderately because it takes time for market participants to accumulate experience, learn, and adapt themselves. This process is reflected in the characteristic of the slowly decreasing trend of $\hat{\beta}_{1t}$ proposed by this model. Once the market participants gain more knowledge, combined with better price discovery mechanisms, the degree of market efficiency will then be improved.

Consequently, this study would suggest that the stochastic AR(1) coefficient model with logistic function of time is the most appropriate model specification to explain the dynamic behavior of degree of efficiency in Thailand's stock market.

5.3 Numbers of Days for Information Dissemination

The magnitude of AR(p) coefficient can be related to the degree of market efficiency as it implies how much time the market takes to disseminate information. In this study, results from the statistical test suggest that AR(1) specification is appropriate, therefore, HL measurement can be applied to investigate how much time, in numbers of days, information is disseminated to the market. Based on discussion above, the author will employ the smoothed estimate of $\hat{\beta}_{1t}$ from the stochastic AR(1) coefficient model with logistic function of time. In order to illustrate whether the numbers of days for information dissemination decrease, the calculation will be done at three points of time.

The first point of time is when t = 1, which is the opening of the stock market. The second point of time is when $t = \hat{\tau}$, and the last point of time is when t = 9,682, which is the latest sample of this study. As for the second point of time, the author proposes using $t = \hat{\tau}$ instead of using t equal to half of total observations because $\hat{\tau}$ provides an indicative point of time where trend element of degree of efficiency decreases by a half. Therefore, the estimation of half-life measure at this point of time is more informative. From Table 3, the point of time corresponds to $\hat{\tau}$ = 0.5245 is at the 5079th observation (variable t in this study is scaled by dividing by total number of observation), or approximately 20 years after the opening of the stock market.

Previously, the studies that interested in measuring units of time to dissipate a piece of information throughout the market generally use a half of information as a benchmark, so called HL measurement. In this study, being enthusiastic to see the different results if the other magnitudes of information are applied, the author develops the measurements to gauge the unit of time in order to spread out 25%, 50% and 75% of information. The empirical results are tabulated in the Table 5 below.

Table 5
Numbers of Days for Information Dissemination

Time	**Numbers of days for the magnitudes of information are disseminated to the market**		
	One-fourth	**Half**	**Three-fourth**
t = 1	0.3574	0.8612	1.7223
t = 5,079	0.1100	0.2651	0.5301
t = 9,682	0.1035	0.2494	0.4988

The results illustrated above support that degree of informational efficiency in Thailand's stock market has been improved as indicated by the decreasing numbers of days that the market utilizes to relay either one-fourth, a half, or three-fourth of information. Particularly, the numbers of days to spread out three-fourth of information decrease from 1.7223 days at the opening of market to 0.5301 day and 0.4988 day at the points of time t = 5,079 and t = 9,682, respectively. Considering the utilization of time to dissipate a half of information, it is interesting that the market employs less than one day at all three points of time. At t = 1, the market uses 0.86112 day to disseminate a half of information. Then, the period of time declines to 0.2651 day and 0.2492 day at t = 5,079 and t = 9,682, respectively. Moreover, the dissemination speed is also improving. For example, at t = 1, the market requires additional 0.8162 day in order to relay further information from a half to three-fourth (1.7223 – 0.8612), while it needs additional 0.2494 day at t = 9,682 (0.4988 - 0.2494).

However, numbers of days for information dissemination at the latest observation are not much different from those at the second point of time, i.e. at t = 5,079. This could be explained that, for the given data, the stock market has been developed until it has reached the long run level of market efficiency to so that the number of day for information dissemination at the second and the latest points of time is very close to each other.

6. Conclusions

Efficient market hypothesis has been studied and tested in a numbers of literatures. This hypothesis is important in economic and financial theories since it is a foundation in developing asset pricing models, investment strategies, as well as risk assessment. Recently, research framework on this topic focuses on investigating the time-varying degree of market efficiency, particularly on informational efficiency of an emerging financial market.

This study proposes the stochastic AR(1) coefficient model and imposes relationship of degree of efficiency with time in order to correct the drawback of the model specification applied in the previous studies. Based on the sample from daily returns of the SET index from April 30th, 1975 to September 19th, 2014, this study finds that the degree of market efficiency has a statistically significant relationship with time, at least in three functional forms. This evidence leads to the conclusion that both the random walk and GAR(1) models are mis-specified. Further statistical test also shows that the stochastic AR(1) model with linear and logistic functions of time are the best two models in describing the dynamic behavior of degree of market efficiency in Thailand. Finally, the results of HL measurement indicate that number of day for information dissemination decreases through time.

This study not only is an evidence of improving degree of market efficiency, but also contributes to research methodology of the study in this topic. For one who is interested in time-varying degree of market efficiency, further study can be performed to expand the edge of knowledge on this field. One of the interesting results from this study is that behavior of degree of market efficiency in Thailand's stock market is highly volatile. It would be interesting to find out the determinants to explain such dynamic behavior.

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