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

BY

MISS SOPHANA BURAPRATHEP

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE PROGRAM IN FINANCE (INTERNATIONAL PROGRAM)

FACULTY OF COMMERCE AND ACCOUNTANCY

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Chairman ______________________
(Assistant Professor Suluck Pattarathammas, DBA)

Member and Advisor ______________________
(Professor Anya Khanthavit, Ph.D.)

Member ______________________
(Thananun Siwamogsatham, Ph.D.)

Dean ______________________
(Professor Siriluck Rotchanakitumnuai, Ph.D.)

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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 significant 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

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CHAPTER 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. These forms are dependent on the type of information certain investors use to earn abnormal return from the market. 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 price. 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. There are casual observations, theoretical arguments and empirical findings that suggest the market can be more efficient over time.

From casual observation, as communication networks improve, certain information disclosure is required, investors are better educated and more aware of existing information and competition among traders to service their clients, it takes less time for information to flow to investors today than it did in the past. From a theoretical argument, 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 inevitable changing environments. The competition among market participants also drives the adaptation and innovation to the market. These forces lead to the evolution of the market, which, in turn, improves the degree of efficiency. Finally, from an empirical findings, Lo (2004) also found that degree of efficiency in the US market, measured by autocorrelation coefficients from rolling regression, varied over the sample period. In addition, Lim, Brooks, and Kim (2008) suggested that efficiency in Asian stock markets was damaged by the 1997 financial crisis, but that there was evidence of improving efficiency after the crisis. 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, Hall, and Zalewska-Mitura (1997) was the pioneer study that supported the concept of time-varying degree of market efficiency. They explained that it was difficult for an infant market to be absolutely efficient because agents did not know the price discovery mechanism. But when the market was mature, efficiency improved because the market learned and was developed in such a way that prices quickly absorbed information. Based on weekly data from Bulgarian stock market, Emerson et al. (1997) found evidence of changing auto-regression (AR) coefficients from a regression of stock returns in support of time-varying efficiency. The AR(1) coefficients of return regression play a key role in determining the degree of market efficiency because it implies how fast information disseminates to the asset prices. The lower the magnitude of AR(1) coefficient, the faster information is disseminated to the market. Emerson et al. (1997)'s 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, Jawadi, and Nguyen (2010) employed it to investigate degrees of efficiency in emerging markets before and after liberalization. Aside from this, Anya Khantavit, Natachai Boonyaprapatsara, and Arunsri Saechung (2012) recently applied time-varying smoothed transition autoregressive model (time-varying STAR) to the study of evolving market efficiency using data from Thailand's stock market. The model explains returns process as the combination of more than one AR(p) processes. Their results showed that degree of informational efficiency in Thailand's stock market has been improved as suggested by the lower numbers of days information is relayed and reflected in prices.

Though the aforementioned frameworks are helpful to investigate the changing degree of information efficiency, the author would like to argue that those frameworks have drawbacks at least in three aspects. Firstly, the rolling window estimation method applied by Lo (2004) is inappropriate because autocorrelation coefficient 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, i.e. the magnitude of AR(1) coefficients is getting lower, it is less likely to become less efficient in the future. Lastly, the time-varying STAR model applied by Anya 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 can be measured by tracking the amount of time the market needs to disseminate information, as implied by the size of AR(p) coefficient from the regression of market returns. 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) because the coefficient is stochastic and all observations are taken into consideration when estimates the model. 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 Anya 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 argument that the AR(p) coefficient shall has a negative relationship with time and should move towards a small, 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 weak-form informational efficiency. 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. Because the stochastic AR(p) coefficients cannot be observed, the author will use the Kalman filtering technique to estimate them based on the relationship of the market returns with their lags. The remaining of this paper is organized as follows; Chapter 2 provides the review of literature relevant to time-varying informational efficiency. Chapter 3 discusses the models applied in the previous literatures, the one proposed by this study, and the methodology for model estimation. Next, the empirical results will be reported and discussed in Chapter 4. Finally, Chapter 5 provides conclusions of the study.

CHAPTER 2
REVIEW OF LITERATURE

Efficient Market Hypothesis (EMH) asserts that a financial market is efficient when prices fully reflect all available information. Based on his review, Fama (1970) elaborated on the framework of market efficiency by classifying it into three forms, namely, weak-, semi-strong- and strong-form, each corresponding to a subset of available information the investors can use in their trades. EMH, especially at weak-form level, has been tested by a number of researchers. In the earliest stage, Fama (1965) proposed a test for weak-form efficiency in the market together with random walk process for the stock price. This was due to the empirical evidences of price formation of common stocks in the mid- 1950s to early 1960s which showed that the prices followed random walk process. Thereafter, the test of EMH has been performed based on this underlying assumption and properties of random walk process.

The main purpose of this approach is to test whether or not EMH is rejected for a particular financial market during the observing period. For example, Lo and MacKinlay (1988), employed variance ratio test using weekly data of stock market returns. They rejected the hypothesis that market returns follows random walk. Notwithstanding, they mentioned that their results did not imply that the market was inefficient but should rather be interpreted as a rejection of some economic models for asset pricing that assume efficient price formation.

Worthinton and Higgs (2006) applied three statistical tests, comprising serial correlation test, unit root test and multiple variance ratio test, to test daily market returns from five developed markets and ten emerging markets, including Thailand. Their study yielded different results from different tests. For serial correlation test, efficient market hypothesis was rejected for both developed and emerging markets. However, the results from unit root test contradicted those from serial correlation test in most of their samples, except for two markets (Australia and Taiwan). The results from multiple variance ratio test showed that all emerging markets and two out of five developed markets (Singapore and Australia) were weak-form inefficient. Comparing their results with the earlier studies, Worthinton and Higgs (2006) also cautioned the interpretation of random walk testing, especially the unit root test since the different frequency of data used in the test might yield different conclusions.

Besides, Komain Jiranyakul (2007) applied variance ratio test to investigate EMH in Thailand's stock market using both real and nominal monthly market returns. He inferred that SET index followed random walk, hence, the market was weak-form efficient. The study further suggested that the stock market return could not be predicted due to high and persistent return volatility.

Kim and Shamsuddin (2008) focused on testing weak-form efficiency in Asian markets during periods both pre and post Asian crisis. They found that the Singaporean and Thai markets have become more efficient after the crisis. Further results showed that despite liberalization, there was no evidence of market efficiency in Indonesia, Malaysia or the Philippines.

All of the abovementioned studies focus on the condition whether a financial market is efficient or inefficient, and implicitly assume that level of efficiency is constant during the testing period. Although there were evidences that weak-form efficiency was rejected in several developing and emerging markets, it is still interesting and important to another group of researchers who argued that degree of efficiency can be improved over time. Emerson et al. (1997) introduced autoregressive model with time-varying AR(p) coefficients to test whether the market becomes more efficient. The time-varying AR(p) coefficients were assumed to follow random walk process. These parameters represented the degree of market efficiency as it implied how much time the market needs to disseminate information into stock prices. Based on the weekly data of four shares in Bulgaria, it was found that AR coefficients of these shares exhibited the changing levels of efficiency. The results supported that some shares moved toward a higher efficiency level. They concluded that the market went through three phases. Firstly, the initial phase where there was very little information for market participants to forecast the price, so the market appeared efficient. Secondly, the regular phase where the market was fairly set up and there was enough information, so the systematic pattern of returns appeared and efficient market hypothesis was rejected. Lastly, the market participants learned and absorbed information so the market became efficient.

Zalewska-Mitura and Hall (1999) compared stock returns and market returns from the London Stock Exchange with the returns of five stocks in the Hungarian market. Their study relied on time-varying AR(p) model suggested by Emerson et al. (1997). The results showed that there was no evidence of changing degrees of efficiency in the London market throughout the observing period, whilst none of AR coefficients from regression of stock returns in Hungarian market were constant. AR coefficients of only two out of five stocks in Hungarian market were insignificantly different from zero. For the remaining three stocks, there were no signs of a movement towards efficiency. Among these three stocks, it was noticeable that one of them exhibited an increasing trend of AR coefficients, while another showed a fluctuating pattern of the coefficient. The study concluded that even in the same exchange, the time path of efficiency levels differs from stock by stock.

Instead of using firm-level data, Rockinger and Urga (2000) employed market returns from four emerging exchanges including Hungary, the Czech Republic, Poland and Russia. The results showed the Hungarian market was unpredictable, i.e. weak-form efficient, while data from the Russian market illustrated opposite results. The study also suggested a link between the degree of efficiency and liquidity, as evidenced by evolving AR coefficients from the Czech and Polish markets.

In relation to Asian markets, Li (2003a) studied evolving market efficiency using data from two stock exchanges in China: the Shanghai Stock Exchange and the Shenzhen Stock Exchange. It was shown that some degree of inefficiency existed in both markets at initiation, but the value was lower in the Shenzhen Stock Exchange. Furthermore, the Shenzhen Exchange moved toward efficiency faster than the Shanghai Stock Exchange due to having more liquidity, quicker removal of a ban on institutional investors and never suffered from price limits. Li (2003b) subsequently investigated time-varying degree of efficiency in two sub-markets of the Shanghai and Shenzhen Stock Exchanges, that is, A-share and B-share markets. The results showed that the A-share markets of both Exchanges performed better than the B-share markets in becoming weak-form efficient.

The concept of changing degree of market efficiency is consistent with the Adaptive Market Hypothesis (AMH) proposed by Lo (2004). AMH explains that irrational behaviors are actually the evolutionary of individuals to adapt themselves to changing environments. This adaptations as well as competition among market participants help improve degree of market efficiency. To support the AMH, Lo (2004) applied rolling window regression model with monthly returns from S&P Composite Index and showed that AR(1) coefficients from the model varied through time.

A different framework in literatures of time-varying efficiency was proposed by Anya Khanthavit et al. (2012). They employed time-varying smoothed transition autoregression model (time-varying STAR) to investigate informational efficiency in Thailand's stock market. Following this model, the current period return is explained by a combination of two AR(4) processes. The model is able to detect either gradual or sudden structural changes in the level of efficiency. Furthermore, Anya Khanthavit et al. (2012) applied π-Absorption Time measurement (AT) to identify numbers of days for information dissemination. They found that the degree of efficiency in Thailand's stock market was gradually improved, supported by the fact that number of days the information was spread out to the market in the current period was lower than that in the past.

Some researchers also attempted to identify economic factors that make a market become more efficient. As mentioned above, Li (2003a) pointed out some market restrictions that could obstruct the convergence to efficiency. Based on results from simulation, Easley and O'Hara (1992) suggested three factors that affect the process by which prices adjust to their true value: market depth (indicated by the average number of uninformed trades), variance of trading volume of uninformed trades and the number of informed traders. The smaller the market depth, the lower the trading variance and the higher the number of informed traders, the faster the speed of adjustment of prices towards their true value. In addition, Arouri et al. (2010) investigated the effect of market liberalization on degree of efficiency in five emerging stock markets. Proxy variables related to market liquidity, market developments, market integration, as well as other control variables, were taken into consideration in their study. The results showed that liberalization had a significant effect on the degree of efficiency in most samples. However, the direction of this effect was country-specific. The results also indicated that changes in the degree of efficiency were strongly influenced by changes of inflation and exchange rates.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Models for Investigating Time-varying Market Efficiency

3.1.1 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 window estimation applied by Lo (2004). However, this methodology assumes that autocorrelation coefficient is constant in each estimation window. Arouri et al. (2010) suggested that the fixed parameter model cannot describe the evolution of a financial market and time-varying characteristic of efficiency.

The second one is a time-varying AR(p) model proposed by Emerson et al. (1997). The model is expressed as follows:

$$r_t = \beta_{0t} + \sum_{i=1}^{p} \beta_{it} r_{t-i} + \nu_t, \; \nu_t \sim N(0, \sigma_\nu^2) \qquad (3.1)$$

$$\beta_{it} = \beta_{it-1} + \omega_t, \; \omega_t \sim N(0, \sigma_\omega^2) \qquad (3.2)$$

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. (3.2). 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 measurement (HL) 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. $h = \frac{-\ln 2}{\ln|\beta_1|}$. The lower AR(1) coefficient, the faster a half of a particular amount of information is relayed to the market.

Some studies provide argument on using random walk process to describe dynamic behavior of β_{it}. Since this latent parameter is unknown, Rockinger and Urga (2000) suggested that the best predictor of the future value of a parameter is its present value. Accordingly, random walk process seemed to be the most appropriate choice. Li (2003a) agreed with this idea and mentioned that the random walk process was flexible enough to nest two possibilities of AR coefficients to be a constant or time-varying in one specification. He also argued that by assuming other processes rather than random walk, β_{it} would be forced to change and the possibility of constancy could not be detected, if it did indeed exist.

Though numbers of empirical studies that applied this specification found that the estimated AR coefficients had a falling trend, the author argues that the random walk specification of AR coefficients is inaccurate. This is mainly due to the assumption of Gaussian white noise disturbance term, ω_t. It is obvious that AR coefficient will have no directional trend and is likely to have any value. Without a mechanism to relate β_{it} with time, it is allowed to bounce back to a higher level. Intuitively, when a market has achieved a certain level of efficiency, it shall not turn back to being less efficient any further.

Apart from random walk, Li (2003b) imposed general auto-regression of order one (GAR(1)) process to describe AR coefficients. 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 coefficients and time, and again, it is allowed a reversion to a higher value.

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

$$
\begin{aligned}
r_t = & \{\rho_0^1 + \textstyle\sum_{i=1}^{p} \rho_i^1 r_{t-i}\} \\
& + \{(\rho_0^2 - \rho_0^1) + \textstyle\sum_{i=1}^{p} (\rho_i^2 - \rho_i^1) r_{t-i}\} G(s_t; \theta_1, c_1) \\
& + \ldots + \{(\rho_0^m - \rho_0^{m-1}) + \textstyle\sum_{i=1}^{p} (\rho_i^m - \rho_i^{m-1}) r_{t-i}\} G(s_t; \theta_{m-1}, c_{m-1}) \\
& + \varepsilon_t
\end{aligned}
\tag{3.3}
$$

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 at any point of time via a combination of autoregressive processes. AR(p) processes are related to each other by a monotonic function of time, $G(s_t; \theta_k, c_k)$, which accommodates a smooth transition between each of them. Anya Khanthavit et al. (2012) proposed a strictly statistical test to determine the optimal orders of lag term. All lag orders of AR coefficients were taken into consideration via general impulse response function of AT measurement in order to infer the improvement of degree of efficiency. In short, 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 framework facilitates the investigation of time-varying degree of efficiency, especially when returns processes are described by AR(p) where p > 1. Nevertheless, specification of autoregressive process of time-varying STAR model is deterministic so that, with a particular set of parameters, market return at each period can be specified with certainty.

3.1.2 The Proposed Stochastic AR(p) Coefficient Models

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

$$r_t = \beta_0 + \sum_{i=1}^{p} \tilde{\beta}_{it} r_{t-i} + \nu_t \quad (3.4)$$

$$\tilde{\beta}_{it} = \mu^i + \lambda^i f(t) + \sum_{j=1}^{k} \alpha_j^i \beta_{it-j} + \omega_t^i \quad (3.5)$$

where r_t denotes logarithm return at time t,

β_0 denotes long-term mean rate of return,

$\tilde{\beta}_{it}$ denotes stochastic AR coefficient of returns in the i^{th} lag order for i = 1,…,p,

ν_t denotes white noise disturbance, $\nu_t \sim N(0, \sigma_\nu^2)$,

μ^i denotes drift term or long-term mean of $\tilde{\beta}_{it}$,

λ^i denotes time coefficient,

α_j^i denotes coefficient of the j^{th} lag order of $\tilde{\beta}_{it}$ for j = 1,…,m,

$f(t)$ denotes a function which relates $\tilde{\beta}_{it}$ with time, and

ω_t^i denotes white noise disturbance, $\omega_t^i \sim N(0, \sigma_\omega^2)$.

Similar to the previous studies, the magnitude of $\tilde{\beta}_{it}$ is related to degree of market efficiency as it reflects how much time the market takes to relay certain amount of information. In the case where AR(1) specification is imposed, such as in Rockinger and Urga (2000) and Arouri et al. (2012), HL measurement can be applied. And in the case where lag order p is greater than one, such as Anya Khanthavit et al. (2012), AT measurement can be applied. Beside, this model makes improvements from Emerson et al. (1997)'s 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 coefficients, $\tilde{\beta}_{it}$, are dropped, r_t will also collapse to random walk, which is inconsistent with theory of time series model in which returns are stationary.

Secondly, eq. (3.5) 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 p equals to one, μ^i and λ^i equal zero, and α_j^i equals to one, the reduced-form specification will facilitate a random walk process. Again, if μ^i and λ^i are restricted to zero, but the absolute value of α_j^i is less than one, the reduced-form will accommodate auto-regressive specification. In addition, if λ^i and α_j^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, the specification in eq. (3.5) is general in that the number of lag order k is not specified. However, this study proposes lag order k 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. (3.5) are statistically significant, they will be the evidence to support the argument that neither random walk nor GAR(1) is correctly specified.

Lastly, a functional relationship with time, $f(t)$, is imposed to describe dynamic behavior of $\tilde{\beta}_{it}$. This is consistent to what suggested by theoretical perspective and empirical evidences that degree of market efficiency improves through time. With a particular set of parameter values, $\tilde{\beta}_{it}$ shall be decreased time when time passes. As the true relationship of $\tilde{\beta}_{it}$ with time is unknown, $f(t)$ in eq. (3.5) can be a constant, increasing function or decreasing function. This study, however, proposes three functional forms as follows;

$$f^1(t) = t \tag{3.6}$$

$$f^2(t) = \frac{1}{t} \tag{3.7}$$

$$f^3(t) = 1 - \frac{1}{1+e^{-\theta(t-\tau)}} \tag{3.8}$$

The function of time in the eq. (3.6) linearly relates AR coefficients with time variable t. In case degree of efficiency has relationship with time in this manner, parameter λ^i should be significant and negative. On the other hands, eq. (3.7) relates AR coefficients 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 λ^i should be significant and positive. In such a case, $\tilde{\beta}_{it}$ will dramatically drop to an insignificant value within a few sample periods.

In eq. (3.8), the author applies the logistic function proposed by Anya Khanthavit et al. (2012) to relate $\tilde{\beta}_{it}$ with time. In opposite to the specification in eq. (3.7), this specification facilitates either gradual or rapid improvement of degree of efficiency, as indicated by the size of parameter θ that will 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 Anya Khanthavit et al. (2010), it is more likely that the degree of efficiency would be slowly improved through time.

3.2 Model Estimation

3.2.1 Kalman Filter

Since AR coefficient of the proposed model is stochastic, rolling regression and time-varying STAR cannot be applied. Therefore, this study will apply Kalman filter technique to estimate the parameters of the model. This technique was usually applied by the literatures that followed Emerson et al. (1997)'s framework. Rockinger and Urga (2001) mentioned that Kalman filter is preferable to switching regression method for estimating the stochastic coefficient since the latter method is numerically burdensome and its hypothesis testing is very complicated.

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 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) model in equation (3.5) and (3.6) can be put in state space form as follows:

$$r_t = \boldsymbol{R_t B_t} + \beta_0 + \nu_t \tag{3.9}$$

$$\boldsymbol{B_t = AB_{t-1} + D_t + \omega_t} \tag{3.10}$$

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 the stochastic AR(p) coefficient, e.g. $[\tilde{\beta}_{1t} \quad \cdots \quad \tilde{\beta}_{pt}]'$

$\boldsymbol{A}$ denotes transition matrix. This matrix contains lag coefficient of eq. (3.5), e.g. α_j^i, on its main diagonal, and

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

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, $\psi = \{\beta_0, \mu^i, \lambda^i, \alpha_j^i, \theta, \tau, \sigma_\nu^2, \sigma_\omega^2\}$. 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:

$$Log\ L = -\frac{1}{2} T log 2\pi - \frac{1}{2}\sum_{t=1}^{T} log|F_t| - \frac{1}{2}\sum_{t=1}^{T} v_t' F_t^{-1} v_t \tag{3.11}$$

Denote $\mathrm{v_t}$ as prediction error and denote $\mathrm{F_t}$ as prediction error covariance. Maximum likelihood estimation finds the value of unknown parameter ψ so that log likelihood function in eq. (3.11) is maximized.

3.2.2 Lag Order Identification

As number of lag order p of the stochastic AR(p) coefficient 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 apply information criteria to identify the appropriate order of p 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 Anya 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:

$$AIC = T \times ln(\textstyle\sum_{t=1}^{T} v_t^2) + 2(p+1) \tag{3.12}$$

$$SBIC = T \times \ln(\textstyle\sum_{t=1}^{T} v_t^2) + (p+1) \times ln(T) \tag{3.13}$$

T denotes total number of observations, v_t denotes disturbance term of the auto-regressive process, and p denotes 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 inconsistent conclusions, 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 the tests here are preliminary because in the tests the AR(p) coefficients are assumed to be constant under testing procedures, whereas they are stochastic in the proposed model.

3.2.3 Model Comparison

This study proposes three functional forms to relate the degree of market efficiency with time. If the proposed functions of time in eqs. (3.6) to (3.8) are substituted in eq. (3.5), it is noticed that all of them are general and nest with random walk specification. However, neither of them are nested to each other. Thus, conventional tests for parameter restriction and model comparison cannot be performed. This calls for an alternative statistical test to compare the proposed specifications with each other. In this paper, the author will follow the test 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 any two competing models; namely the null model and the alternative model, one's KLIC is subtracted from another, and the result can be either positive or negative. Therefore, in order to make conclusion, Voung (1989) suggested the following test statistic:

$$V = \frac{\sqrt{n}\left(\frac{1}{n}\sum_{i=1}^{n} m_i\right)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i-\bar{m})^2}} = \sqrt{n}(\bar{m}/s_m), \quad m_i = \ln L_{i,0} - Ln\ L_{i,1} \tag{3.14}$$

$ln\, L_{i,0}$ denotes log likelihood value 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.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Data and Descriptive Statistic

This study employs 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 the 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 is available since January 2nd, 2002, while the SET Index is available since April 30th, 1975, (the opening of the Exchange). The longer the 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, the 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 the 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, are used for model estimation. The descriptive statistics of logarithm returns are summarized in Table 4.1.

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

Table 4.1 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)

Following the information reported in Table 4.1, the logarithm returns are characterized as negative skewness and leptokurtosis, with a skewness of -0.1066 and kurtosis of 11.7664. 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. Even if the returns are non-normal, the estimates are still the best linear projection.

Table 4.2 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

The results of AIC and SBIC tests are demonstrated in Table 4.2. 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 they can be applicable to the stochastic AR(p) coefficient model because the constant AR coefficient can be considered as the average value of all stochastic AR 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 stock market.

4.2 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;

$$r_t = \beta_0 + \tilde{\beta}_{1t} r_{t-1} + \nu_t \tag{4.1}$$

$$\tilde{\beta}_{1t} = \mu^1 + \lambda^1 f(t) + \alpha_1^1 \beta_{1t-1} + \omega_t \tag{4.2}$$

The proposed functions of time in eqs. (3.6) to (3.8) are substituted in $f(t)$ in eq. (4.2). Next, $\tilde{\beta}_{1t}$ is the smoothed estimate from Kalman filter and other unknown parameters of the model are then derived from maximum likelihood estimation. Besides, when restriction is imposed such that μ^1 and λ^1 equal to zero, and α_1^i equals to one, the restricted model represents random walk specification applied in the previous literatures. 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 4.3 Estimation Results of Random Walk and Stochastic AR(1) Coefficient Models

Parameters	Random walk model	Stochastic AR(1) coefficient model with		
		linear function of time (eq. (3.6))	inverse function of time (eq. (3.7))	logistic function of time (eq. (3.8))
Panel A				
$\hat{\beta}_0$	0.0240	0.0191	0.0195	0.01806
	(1.6402)	(1.5047)	(1.5415)	(1.4155)
$\hat{\mu}^1$	-	0.3980***	0.1837***	0.0643
		(12.4538)	(12.3323)	(1.4436)
$\hat{\lambda}^1$	-	-0.3756***	4.3810***	0.2813***
		(-7.4787)	(3.3986)	(3.3700)
$\hat{\alpha}_1^1$	-	0.0285	0.0369**	0.0285
		(1.5886)	2.0582	(1.0809)

Table 4.3 Estimation Results of Random Walk and Stochastic AR(1) Coefficient Models (cont'd)

Parameters	Random walk model	Stochastic AR(1) coefficient model with linear function of time (eq. (3.6))	inverse function of time (eq. (3.7))	logistic function of time (eq. (3.8))
Panel A (cont'd)				
$\hat{\theta}$	-	-	-	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 z-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 = dfU – dfR; where dfU and dfR represent numbers of free parameters of the unrestricted and restricted models, respectively.

Table 4.3 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. (4.2); the results show that drift parameters, $\hat{\mu}^1$, 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, $\hat{\mu}^1$ 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, the coefficients of trend element, $\hat{\lambda}^1$, are statistically significantly different from zero in all three specifications. This evidence is very important because they indicate that the degree of market efficiency has a true statistical relationship with time, which is consistent with the hypothesis of this study. The sign of $\hat{\lambda}^1$ 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, these results 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 large 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 $\hat{\lambda}^1$, 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 $\hat{\sigma}_{\nu}$ and is statistically significant. This indicates that $\hat{\beta}_{1t}$ is not constant, but 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 models are 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.

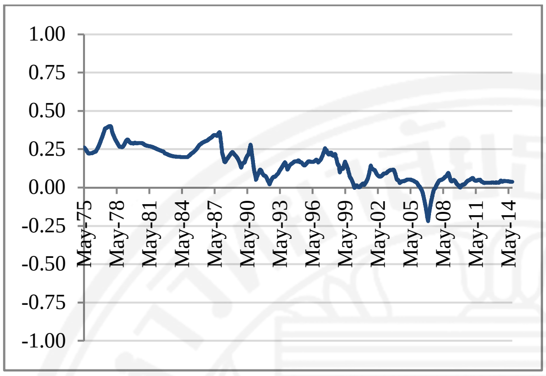

Figure 4.1 (a) The smoothed estimate of $\hat{\beta}_{1t}$ from random walk model

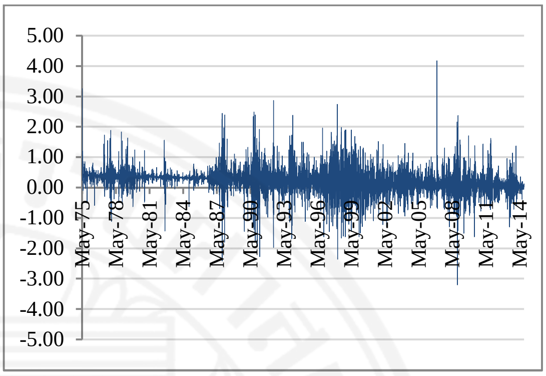

Figure 4.1 (b) The smoothed estimate of $\hat{\beta}_{1t}$ from stochastic AR(1) model with linear function of time

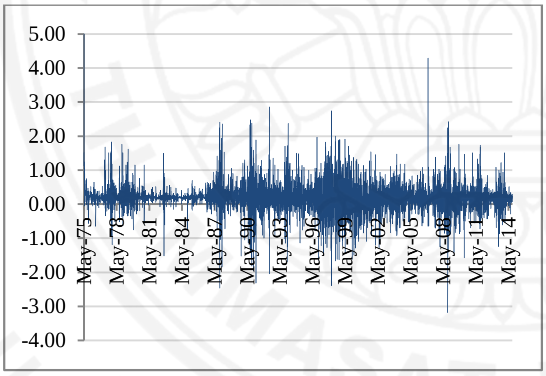

Figure 4.1 (c) The smoothed estimate of $\hat{\beta}_{1t}$ from stochastic AR(1) model with inverse function of time

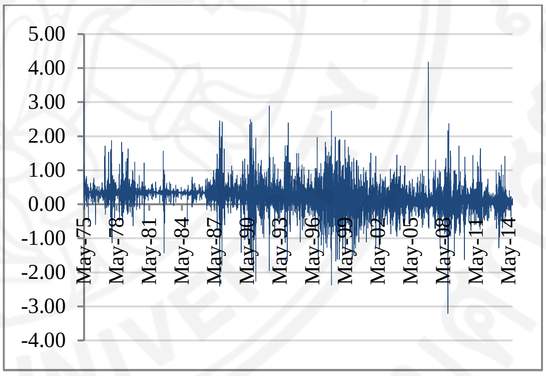

Figure 4.1 (d) The smoothed estimate of $\hat{\beta}_{1t}$ from stochastic AR(1) model with logistic function of time

From Figure 4.1 (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 estimates of $\hat{\beta}_{1t}$ from their stochastic AR(1) coefficient models. 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 this evidence can be explained in three folds. Firstly, coefficients $\hat{\lambda}^1$ are strongly statistically significant, which in turn indicate that values of $\hat{\beta}_{1t}$ from the stochastic AR(1) coefficient models are implicitly diminishing in the long-run. Secondly, it should be emphasized that the specification of random model allows a reversion of $\hat{\beta}_{1t}$ to a higher level at any point of time in the future. The random walk model might provide more agreeable result for this particular sample, but the specification allows $\hat{\beta}_{1t}$ to revert to very large positive or negative values in the future. Lastly, 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 the random walk specification to describe dynamic process of degree of efficiency. 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 difference 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 demonstrates this improvement using the number of days for information dissemination in the stock market, which will be discussed later.

4.3 Model Comparison

Table 4.4 below presents V statistics computed from each pair of the 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 model are favorable to the random walk model in describing the dynamic behavior of the degree of market efficiency. This is consistent to the likelihood ratio test in Table 4.3, which indicates that the stochastic AR(1) coefficient models are better fitted to the data than random walk model.

Table 4.4 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 models 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 three specifications of the stochastic AR(1) coefficient model 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 them is statistically 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 $\hat{\lambda}^1$ 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. Given the parameter estimates, when time increases, $\hat{\beta}_{1t}$ will possibly be a large negative value. In such a case, it implies that once the degree of efficiency improves, it can deteriorate in the future because the large negative value of $\hat{\beta}_{1t}$ suggests 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 to $\hat{\beta}_0$.

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 a large 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.

4.4 Numbers of Days for Information Dissemination

The magnitude of AR(p) coefficient implies how much time the market takes to disseminate information. Following the AR(1) specification in In this study, 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 how fast 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 4.3, the point of time corresponds to $\hat{\tau}$ = 0.5245 is at the 5079^{th} 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 were interested in measuring units of time to dissipate a piece of information throughout the market generally used a half of information as a benchmark, so called half-life 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 one-fourth and three-fourth of information. Briefly, take for example a conventional AR(1) model, $r_t = \beta_0 + \sum_{i=1}^{p} \beta_i r_{t-i} + \nu_t$, when one would like to make a prediction of random variable r_t in h time units ahead, so called $\widehat{r_t}(h)$. By letting the $\hat{x}_t(h)$ is the a prediction h time units ahead, it becomes $\hat{x}_t(h) = \widehat{r_t}(h) + E[\nu_t]$, then it can be obtain that $\hat{x}_t(h) = {\beta_1}^h \cdot x_t$. If the period of time under consideration is that when the process needs to halve its distance from the mean, then $\hat{x}_t(h) = {\beta_1}^h \cdot x_t = 0.5x_t$. Taking logarithm on both side of equation we will obtain $h = \frac{-\ln 2}{\ln|\beta_1|}$. Following this ground concept, when the number of periods required for a unit shock to dissipate by one-fourth and three-fourth, the distances are therefore chosen at 75% and 25%, respectively.

The empirical results are tabulated in the Table 4.5 below.

Table 4.5 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**
	$h = \frac{ln(3) - ln(4)}{\ln\lvert\beta_1\rvert}$	$h = \frac{-ln\,2}{ln\lvert\beta_1\rvert}$	$h = \frac{-ln(4)}{\ln\lvert\beta_1\rvert}$
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.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

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, the research framework on this topic focuses on investigating the time-varying degree of market efficiency, particularly on informational efficiency of emerging financial markets.

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, it is found 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.

REFERENCES

Books and Book Articles

1. Arouri, M. E. H., Jawadi, F., & Nguyen, D. K. (2010). Contributions to management science: The dynamics of emerging stock markets: Empirical assessments and implications. New York: Physica-Verlag.
2. Commandeur, J. J. F., & Koopman, S. J. (2007). Practical Econometrics: An introduction to state space time series analysis. Oxford University Press.
3. Durbin, J., & Koopman, S. J. (2012). Time Series Analysis by State Space Methods. Oxford University Press.
4. Greene, W. H. (2012). Econometric analysis (7 th. ed.). New Jersey: Prentice Hall.
5. Gujarati, D. N., & Porter, D. C., (2008). Basic Econometrics (5 th. ed.). New York: McGraw-Hill/Irwin.
6. Harvey, A. C. (1991). Forecasting, structural time series models and the Kalman filter. Cambridge University Press.
7. Heij, C., de Boer, P., Franses, P. H., Kloek, T., & van Dijk, H. K. (2004). Econometric Methods with applications in business and economics. Oxford University Press.

Articles

1. Anya Khanthavit, Natachai Boonyaprapatsara, & Arunsri Saechung. (2012). Evolving market efficiency of Thailand's stock market. Applied Economics Journal, 19(1), 46-67.
2. Chanwit Phengpis. (2006). Are emerging stock market price indices really stationary? Applied Financial Economics, 16(13): 931-939.
3. Costa, R. L., & Vasconcelos, G. L. (2003). Long-range correlations and nonstationarity in the Brazilian stock market. Physica A, 329(1-2), 231-248.

4. Easley, D., & O'Hara, M. (1992). Time and the process of security price adjustment. The Journal of Finance, 47(2), 577-605.

5. Emerson, R., Hall, S. G. & Zalewska-Mitura, A. (1997). Evolving market efficiency with an application to some Bulgarian shares. Economics of Planning, 30(2-3): 75-90.

6. Fama, E. F. (1965). The behavior of stock-market prices. Journal of Business, 38(1): 34-105.

7. Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2): 383-417.

8. Grossman, S. J. & Stiglitz, J. E. (1980). On the impossibility of informational efficient markets. American Economic Review, 70(3): 393-408.

9. Kim, J. H., & Shamsuddin, A. (2008). Are Asian stock markets efficient? Evidence from new multiple variance ratio tests. Journal of Empirical Finance, 15(3): 518-532.

10. Komain Jiranyakul. (2007). Behavior of stock market index in the stock exchange of Thailand. NIDA Economic Review, 2(2): 47-57.

11. Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74(1), 119-147.

12. Li, X.-M. (2003a). China: Further evidence on the evolution of stock markets in transition economies. Scottish Journal of Political Economy, 50(3): 341-358.

13. Li, X.-M. (2003b). Time-varying informational efficiency in China's A-share and B-share markets. Journal of Chinese Economic and Business Studies, 1(1): 33-56.

14. Lim, K.-P., Brooks, R. & Kim, J. H. (2008). Financial crisis and stock market efficiency: empirical evidence from Asian countries. International Review of Financial Analysis, 17(3): 571-591.

15. Lim, K.-P., & Brooks, R. (2011). The evolution of stock market efficiency over time: A Survey of the empirical literature. Journal of Economic Surveys, 25(1): 69-108.

16. Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from and evolutionary perspective. Journal of Portfolio Management, 30(5): 15-29.

17. Lo, A. W. (2005). Reconciling efficient markets with behavioral finance: The adaptive markets hypothesis. Journal of Investment Consulting, 7(2): 21-44.

18. Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. Review of Financial Studies, 1(1): 41-66.

19. Rockinger, M., & Urga, G. (2000). The evolution of stock markets in transition economies. Journal of Comparative Economics, 28(3): 456-472.

20. Taylor, Alan M, (2001). Potential Pitfalls for the Purchasing-Power-Parity Puzzle? Sampling and Specification Biases in Mean-Reversion Tests of the Law of One Price. Econometrica, Econometric Society, 69(2),: 473-98

21. van Dijk, D., Franses, P. H., & Boswijk, H. P. (2007). Absorption of shock in nonlinear autoregressive model. Computational Statistic & Data Analysis, 51(9): 4206-4226.

22. Vuong, Q. H. (1989). Likelihood Ratio Tests for Model Selection and non-nested Hypotheses. Econometrica, 57(2): 307–333.

23. Worthington, A. C., & Higgs, H. (2006). Weak-form market efficiency in Asian emerging and developed equity market: Comparative tests of random walk behaviour. Accounting Research Journal, 19(1): 54-63.

24. Zalewska-Mitura, A., & Hall, S. G. (1999). Examining the first stages of market performance: A test for evolving market efficiency. Economics Letters, 64(1): 1-12.

25. Zalewska-Mitura, A., & Hall, S. G. (2000). Do market participants learn? The case of the Budapest Stock Exchange. Economics of Planning, 33(1-2): 3-1.

BIOGRAPHY

Name	Miss Sophana Buraprathep
Date of Birth	October 17, 1985
Educational Attainment	2015: Master of Science in Finance, Thammasat University, Thailand
	2007: Bachelor of Business Administration (Finance), Thammasat University, Thailand
Work Position	Vice President
	Equity Derivatives Thailand Department, CIMB Securities (Thailand) Co., Ltd.
Work Experiences	2012-Current: Vice President, Equity Derivatives Thailand Department, CIMB Securities (Thailand) Co., Ltd., Thailand
	2011-2012: Risk Management Officer, Center Auto Lease Co., Ltd., Thailand
	2008-2011: Associate Investment Banking, JayDee Partners Limited, Thailand
	2007-2008: Account Officer, Special Assets Management, Bangkok Bank PCL, Thailand