Thesis Proposal

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1. Thesis title

FORECASTING IN FINANCIAL MARKET WITH MARKOV REGIME SWITCHING AND PRINCIPAL COMPONENT ANALYSIS.

การพยากรณ์ในตลาดทางการเงินด้วยวิธีสับเปลี่ยนสถานะมาร์คอฟ และ การวิเคราะห์องค์ประกอบหลัก.

2. Introduction

The characteristic that all stock markets have in common is the uncertainty, which is related with their short and long-term future state. This feature is undesirable for the investor but it is also unavoidable whenever the stock market is selected as the investment tool. The best that one can do is to try to reduce this uncertainty is forecasting. Stock market forecasting (or prediction) is one of the instruments in this process.

The financial market forecasting task divides researchers and academics into two groups: those who believe that we can devise mechanisms to predict the market and those who believe that the market is efficient and whenever new information comes up the market absorbs it by correcting itself, thus there is no space for prediction. Furthermore they believe that the financial market follows a *random walk,* which implies that the best prediction you can have about tomorrow's value is today's value.

Type of forecasting such that qualitative and quantitative method. The first is qualitative forecasting techniques are subjective, based on the opinion and judgment of appropriate when past data is not available. It is usually applied to intermediate-long range decisions (e.g. Informed opinion and judgment, Delphi method, Market research, Historical life-cycle analogy). Another one is quantitative forecasting models are used to estimate future demands as a function of past data; appropriate when past data is available. It is usually applied to short-intermediate range decisions (e.g. Time series methods, Causal econometric forecasting methods).

3. Literature Review

3.1 Time Series methods

Most financial studies involve returns, instead of prices, of assets. Campbell, Lo, and MacKinlay (1997) give two main reasons for using returns. First, for average investors, return of an asset is a complete and scale-free summary of the investment opportunity. Second, return series are easier to handle than price series because the former have more attractive statistical properties. There are, however, several definitions of an asset return.

In time series, let $\{P_t\}$ denote the series of the financial price at time *t* is transformed to logarithm return series (in percent) $\{r_t\}_{t>0}$, r_t be a sequence of random variables on a probability space (Ω, F, P), i.e.

$$r_t = 100 \cdot \ln(\frac{P_t}{P_{t-1}}) . \qquad (1)$$

The return series is stationary process which looked like *white noise*. and to put the volatility models in proper perspective, it is informative to consider the conditional mean and variance of r_t given F_{t-1}; that is,

$$\mu_t = E(r_t \,|F_{t-1}),\ h_t = Var(r_t \,|F_{t-1}) = E[(r_t - \mu_t)^2 \,|F_{t-1}] \qquad (2)$$

where F_{t-1} denotes the information set available at time $t-1$. Typically, F_{t-1} consists of all linear functions of the past returns. Therefore, the equation for μ_t in (2) should be simple, and many authors assume that r_t follows a simple time series model, e.g.

Mehmet A. (2008), Marcucci J. (2005) assume μ_t is constant, Easton and Faff (1994), and Kyimaz and Berument (2001) assume returns with a one week delay into the regression model and Supot C.(2003) assume returns with Autoregressive process.

4. Research Problems

Most financial returns depend concurrently and dynamically on many economic and financial variables. The fact that the return r_t has a statistically significant lag-l autocorrelation indicates that the lagged return r_{t-l} might be useful in predicting r_t (Tsay:2005).

This thesis assume that r_t follows a simple time series model such as a stationary ARMA(*p, q*) model with some explanatory variables i.e.

$$r_t = \mu_t + \varepsilon_t, \mu_t = \phi_0 + \sum_{i=1}^{k} \beta_i X_{it} + \sum_{i=1}^{p} \phi_i r_{t-i} - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (3)$$

for r_t, where *k*, *p*, and *q* are non-negative integers, and X_{it} are explanatory variables.

Nevertheless three serious problems arise with this approach as following:

4.1 *Heteroskedasticity*: This problem is that the variances of the residuals are not constant and possibly time-dependent.

4.2 *Spurious high persistence*: This problem occur when volatility high in long time.

4.3 *Multicolinearity*: This problem is occur in the explanatory variables are correlated with each other or high correlation between the explanatory variables in a regression equation.

4.1 Heteroskedasticity

Mehmet A. (2008) said financial returns have *three characteristics*. The first is *volatility clustering* that means large changes tend to be followed by large changes and small changes tend to be followed by small changes such that variance of returns are time vary dependent we call *heteroskedasticity*. The second is *fat tailedness* (excess kurtosis) which means that financial returns often display a fatter tail than a standard normal distribution and the third is *leverage effect* which means that negative returns result in higher volatility than positive returns of the same size.

The generalized autoregressive conditional heteroskedasticity (GARCH) models mainly capture three characteristics of financial returns. The development of GARCH type models was started by Engle (1982). Engle introduced ARCH to model the heteroskedasticity by relating the conditional variance of the disturbance term to the linear combination of the squared disturbances in the recent past. Bollerslev(1986) generalized the ARCH (GARCH) model by modeling the conditional variance to depend on its lagged values as well as squared lagged values of disturbance.

The GARCH (1, 1) model is as follows,

$$r_t = \mu_t + \varepsilon_t = \mu_t + \eta_t \sqrt{h_t} \;,\; h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{4}$$

where η_t is iid distribution with zero mean and unit variance, $\alpha_0, \alpha_1 > 0$ and $\beta_1 > 0$ to ensure positive conditional variance. Bollerslev proposed that the inequality $\alpha_1 + \beta_1 < 1$ must be satisfied for stationary covariance process of returns.

The Exponential GARCH (EGARCH) model proposed by Nelson(1991) to cope with the skewness often encountered in financial returns. The main problem of standard GARCH model is that positive and negative shocks have the same effects on volatility. However, impacts of positive and negative shocks on the volatility may be asymmetric. Several alternative GARCH models have been proposed to capture the asymmetric nature of volatility responses. One of them is the exponential GARCH (EGARCH) model of Nelson. In this specification, conditional variance is modeled in logarithmic form, which means that there is no restriction on parameters in the model to avoid negative variances. The conditional variance equation of EGARCH(1,1) is defined as

$$\ln(h_t) = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \beta_1 \ln(h_{t-1}) + \xi \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{5}$$

where ξ is the asymmetry parameter to capture leverage effect. The EGARCH process is covariance stationary if the condition $\beta_1 < 1$ is satisfied.

Led to GJR-GARCH which was introduced independently by Glosten, Aganathan, and Runkle (1993) to account for the leverage effect. Model that allows for different impacts of positive and negative shocks on volatility. The GJR-GARCH(1, 1) model takes following form,

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 (1 - I_{\{\varepsilon_{t-1} > 0\}}) + \beta_1 h_{t-1} + \xi \varepsilon_{t-1}^2 (I_{\{\varepsilon_{t-1} > 0\}}) \quad (6)$$

where $I_{\{\varepsilon_{t-1} > 0\}}$ is equal to one when ε_{t-1} is greater than zero and another is zero. The conditions $\alpha_0 > 0, (\alpha_1 + \xi)/2 > 0$ and $\beta_1 > 0$ must be satisfied to ensure positive conditional variance.

4.2 Spurious high persistence problem

Hamilton and Susmel(1994) stated that the spurious high persistence problem in GARCH type models can be solved by combining the Markov Regime Switching (MRS) model with ARCH models (SWARCH). The idea behind regime switching models is that as market conditions change, the factors that influence volatility also change.

4.2.1 Markov Regime Switching (MRS)

Hamilton(1989,1990) has suggested Markov Regime Switching techniques as a method for modelling non-stationary time series. In the Hamilton approach, the parameters are viewed as the outcome of a discrete-state Markov process. For example, expected returns in the stock market may be subject to occasional, discrete shifts.

A potentially useful approach to model nonlinearities in time series is to assume different behavior (structural break) in one subsample (or regime) to another. If the dates of the regimes switches are known, modeling can be worked out with dummy variables. For example, consider the following model

$$r_t = \mu_{S_t} + \varepsilon_t, t = 1, ..., T \quad (7)$$

where $\varepsilon_t \sim iid(0, \sigma_{S_t}^2)$ and $S_t = 1, ..., N$. Thus under regimes the coefficient parameters are μ_{S_t} and $\sigma_{S_t}^2$.

The unobserved regime variable s_t are governed by a first order Markov Chain with constant transition probabilities given by

$$\Pr(s_t = j | s_{t-1} = i) = p_{ij} \;\; ;\text{i,j}=1,\ldots,\text{N} \quad \text{with } p_{i1} + p_{i2} + ... + p_{iN} = 1. \quad (8)$$

In matrix notation,

$$P = \begin{pmatrix} p_{11} & p_{21} & \cdots & p_{N1} \\ p_{12} & p_{22} & \cdots & p_{N2} \\ \vdots & \vdots & \vdots & \vdots \\ p_{1N} & p_{2N} & \cdots & p_{NN} \end{pmatrix}. \quad (9)$$

The conditional probability density function for the observations r_t given the state variables S_t, S_{t-1} and the previous observation F_{t-1} is $f(r_t | S_t, S_{t-1}, F_{t-1})$

The chain rule for conditional probabilities yields then for the joint probability density function for the variables r_t, S_t, S_{t-1} given past information F_{t-1} is

$$f(r_t, S_t, S_{t-1} | F_{t-1}) = f(r_t | S_t, S_{t-1}, F_{t-1}) \cdot \Pr(S_t, S_{t-1} | F_{t-1}),$$

such that the log-likelihood function to be maximized with respect to the unknown parameters becomes

$$l(\theta) = \sum_{t=1}^{T} l_t(\theta) \qquad (10)$$

where $l_t(\theta) = \log[\sum_{S_t=1}^{N} \sum_{S_{t-1}=1}^{N} f(r_t | S_t, S_{t-1}, F_{t-1}) \cdot \Pr(S_t, S_{t-1} | F_{t-1})]$, and $\theta = (p_{ij}, \mu_{S_t}, \sigma^2_{S_t})$.

4.2.2 Markov Regime Switching GARCH Model

The MRS-GARCH model we expected with two regimes simply can be represented as follows. Let $\{r_t\}_{t\geq 0}$ is a sequence of random variables on the probability space (Ω, F, P) whenever we write $t \geq 0$ that mean $t \in [0, T]$;

$$r_t = \mu_{t,S_t} + \varepsilon_t, \varepsilon_t = \eta_t \sqrt{h_{t,S_t}} \text{ and } h_{t,S_t} = \alpha_{0,S_t} + \alpha_{1,S_t} \varepsilon^2_{t-1} + \beta_{1,S_t} h_{t-1} \qquad (11)$$

where S_t = 1 or 2 , μ_{t,S_t} is the conditional mean and h_{S_t} is conditional variance ,both are measurable function of $F_{t-\tau}$ for $\tau \leq t-1$, and the error term η_t is iid. with mean zero and unit variance. In order to ensure easily the positive of conditional variance we impose the restrictions $\alpha_{0,S_t} > 0, \alpha_{1,S_t} \geq 0$ and $\beta_{1.S_t} \geq 0$. The sum $\alpha_{1,S_t} + \beta_{1,S_t}$ measures the persistence of a shock to the conditional variance.

Many author use MRS-GARCH to forecast in Stock Market, Marcucci J. (2005) use MRS-GARCH forecast volatility of S&P 100 and Mehmet A.(2008) use MRS-GARCH forecast volatility of Turkish Stock Market.

4.3 Multicollinearily

For the mean equation (3) from financial returns depend on explanatory variables then multiple regression analysis is one of the most widely used methodologies for expressing the dependence of a response variable on several explanatory (independent) variables.

Multiple linear regression (MLR) attempts to model the relationship between two or more explanatory variables and a response variable, by fitting a linear equation to the observed data. The response variable (Y_t) is given by:

$$Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i X_{ti} + \varepsilon_t \qquad (12)$$

where $X_{it}, i = 1,..., p$ are the explanatory variables at time t, $\beta_i, i = 0,1,..., p$ are the regression coefficients, and ε_t is is a white noise series.

The predicted value given by the regression model (Y_t) is calculated by:

$$Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i X_{ti} \qquad (13)$$

The most common method to estimate the regression parameters $\beta_i, i = 0,1,..., p$ is ordinary least square estimator (OLS). MLR is one of the most used methods for forecasting. This method is widely used to fit the observed data and to create models that can be used for the prediction in many research fields such as biology, medicine, psychology, economic and environment.

In spite of its evident success in many applications, however, the regression approach can face serious difficulties when the explanatory variables are correlated with each other. *Multicollinearity*, or high correlation between the explanatory variables in a regression equation, can make it difficult to correctly identify the most important contributors to a physical process. One method for removing such multicollinearity and redundant explanatory variables is to use multivariate data analysis (MDA) techniques. MDA have been used for analyzing voluminous environmental data.

One method is principal component analysis (PCA), which start has been employed in air-quality studies to separate interrelationships into statistically independent basic components. They are equally useful in regression analysis for mitigating the problem of multicollinearity and in exploring the relations among the explanatory variables, particularly if it is not obvious which of the variables should be the predictors. The new variables from the PCA become ideal to use as predictors in a regression equation since they optimize spatial patterns and remove possible complications caused by multicollinearity.

4.3.1 Principal Component Analysis (PCA)

PCA is a method to study the structure of the data, with emphasis on determining the patterns of covariances among variables. Thus, PCA is the study of the structure of the variance-covariance matrix. In practical terms, PCA is a method to identify variable or sets of variables that are highly correlated with each other.

Step to find PCA.

Consider a vector of *p* random variable $X = (X_1,....,X_p)'$ with mean $\mu = (\mu_1,...,\mu_p)'$, $(\cdot)'$ denotes transpose, $\mu_i < \infty (i = 1,..., p)$ and variance $\Sigma = (\sigma_{ij}), \sigma_{ij} < \infty (i, j = 1,..., p)$. Assume that the rank of Σ is *p* and $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_p \geq 0$ are the *p* eigenvalues of Σ.

In the PCA we want to find uncorrelated linear function of $X_1,....,X_p$, say, $Z_1,...,Z_m,(m \leq p)$, such that variances $V(Z_1),...,V(Z_m)$ account for most of the total variances among $X_1,....,X_p$. Also, we require $V(Z_1) > V(Z_2) > ... > V(Z_m)$. Algebraically, principal components are particular linear combinations of $X_1,....,X_p$. Geometrically, the principal component represent a new coordinate system obtained by rotating the original axes $X_1,....,X_p$. The new axes represent the directs with maximum variability.

Let $\alpha_i = (\alpha_{i1},...,\alpha_{ip})'$, $i = 1,...,m$ be a $p \times 1$ vector of weights for the respective components of X . More specifically:

1. The first principal component (PC) is the linear function

$$Z_1 = \alpha_1' X = \sum_{i=1}^{p} \alpha_{1i} X_i \ . \tag{14}$$

Our aim is to find α_1 such that $V(Z_1)$ is maximum subject to the condition $\alpha_1{}'\alpha_1 = 1$.

2. The second PC,

$$Z_2 = \alpha_2' X = \sum_{i=1}^{p} \alpha_{2i} X_i \ , \tag{15}$$

maximizes $\alpha_2'\Sigma\alpha_2$ subject to being uncorrelated with $Z_1 = \alpha_1' X$, or equivalently subject to

$$Cov[Z_1, Z_2] = Cov[\alpha_1' X, \alpha_2' X] = 0 \, , \tag{16}$$

where $Cov[x, y]$ denotes the covariance between the random variables x and y .

3. In general, the *k*th PC of X is

$$Z_k = \alpha_k{}' X = \sum_{i=1}^{p} \alpha_{ki} X_i \ , \tag{17}$$

we are to find α_k such that $V(Z_k)$ is maximum subject to the condition $\alpha_k{}'\alpha_k = 1$, $\alpha_k{}'\alpha_{k'} = 0 (k \neq k', k, k' = 1,...,m)$ .Clearly,

$$Cov[Z_k, Z_{k'}] = Cov[\alpha_k{}' X, \alpha_{k'}{}' X] = 0.(k \neq k') \tag{18}$$

By Spectral Decomposition Theorem, we can write $\Sigma = \mathrm{A\Lambda A'}$ where $A = (\alpha_1,...,\alpha_p)$, $\Lambda = Diag.(\lambda_1,...,\lambda_p)$. Note that some of the λ_i ’s may be zeros. Therefore, the total population variance among $X_1,...,X_p$ is

$$\sum_{i=1}^{p} V(X_i) = \mathrm{tr}\,\Sigma = \mathrm{tr(A\Lambda A')} = \mathrm{tr(\Lambda A A')} = \mathrm{tr}(\Lambda) \text{ (since AA}'\text{=I) } = \sum_{i=1}^{p} \lambda_i = \sum_{i=1}^{p} V(Z_i). \tag{19}$$

The total population variance among $Z_1,...,Z_p$ is the same as the total population variance among $X_1,...,X_p$. The proportion of the total variance accounted for by the *k*th PC is $\lambda_k \big/ \sum_{i=1}^{p} \lambda_i$. The first m PC’s with the m largest variance account for $\sum_{i=1}^{m} \lambda_i \big/ \sum_{i=1}^{p} \lambda_i$ proportion of the total variance of X . If, therefore, most (80-90%) of the total variance in X is accounted for by the first m components $Z_1,...,Z_m$, then for large p ,these components can replace the p original $X_1,...,X_p$ for explaining the variability among the variables and the subsequent component $Z_{m+1},...,Z_p$ can be discarded.

4.3.2 Multiple regressions base on principal components analysis.

Let $\{X_{it}, t \in T\}$ and $\{Y_t, t \in T\}$ be $p+1$ discrete time stochastic processes defined on $T = \{1, 2, ..., n\}, n \in \mathbb{Z}^{+}, i = 1, ..., p$. Let us assume the parallel evolution of processes to be known until a given instant of time. We deal with the problem of forecasting the process $\{Y_t\}$ (output process) by using the additional information of the process $\{X_{it}\}$ (input process).

If $\{X_{it}\}$ process have multicollinearity then forecasting procedure can be performed by means of the PCA of processes. So, a multiple regression by principal components model states how the output is related to the values of the input through the random variables in the orthogonal decomposition for output process.

A multiple regression with PCA model consists of expressing the output process Y, as a function of the input process, in a similar way to its orthogonal decomposition through the principal components, by the equation:

The predicted value given by the regression model (Y_t) is calculated by:

$$Y_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i Z_i \qquad (20)$$

where $Z = \{Z_1, ..., Z_m\}$ is the PCA matrix of X, $\alpha_i, i = 0,1,...,m, m \le p$ is the regression parameters.

5. Research Objectives

The objectives of the research are the following:

1. To forecast return with mean equation as follow

   1.1 Constant mean equation.

   1.2 Mean equation (3).

2. To forecast volatility of mean equation using GARCH, EGARCH, GJR-GARCH, and MRS-GARCH

3. To compare models from loss function in forecast financial return and volatility.

**Note:

- Paper 1. Use constant mean equation forecast return and using GARCH, EGARCH, GJR-GARCH, and MRS-GARCH forecast volatility of financial market and application in Future Market.(*Ref*: N. Sopipan, P. Sattayatham and B. Phemanode, "*Forecasting Volatility of Gold Price using Markov Regime Switching and Trading Strategy*", Journal of mathematical finance. Vol. 2(1), pp 121-131 , 2012.)

- Paper 2. Use mean equation use the day of the week effect and ARMA process forecast return and using GARCH, EGARCH, GJR-GARCH, and MRS-GARCH forecast volatility of financial market and comparing interval time of performance. (*Ref*: P. Sattayatham, N. Sopipan and B. Phemanode (2012), "*Forecasting the Stock Exchange of Thailand using Day of the Week Effect and Markov Regime Switching GARCH.*", Journal of Forecasting. (in progress))

6. Scope and limitations

The forecasting in Markov Regime Switching for simplicity, this thesis assume presence of two regimes and order of the GARCH-type is (1,1). The standardized errors follow student-t, generalized error distributions (GED) and normal distribution.

7. Research Methodology

The research work will proceed as follows:

1. Investigate the GARCH-type, MRS-GARCH and mean equation (3) models.

2. Forecast returns with mean equation (3) and volatility with the GARCH-type and MRS-GARCH.

8. Expected results

This thesis expect to construct model for forecast return and volatility of financial market.

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10. Research plan

N	Year	2011		2012	
	Activities	Jan-May	June-Dec	Jan-May	June-Dec
1	Studying the theoretical background and literature research.				
2	Study the Markov Regime Switching model to solve spurious high persistence and heteroskedasticity in volatility and numerical model for forecasting data.				
3	Study the PCA model to solve multicolinearity problem in explanatory variables in mean equation and numerical model for forecasting data.				
4	Comparison various models				
5	Preparation of the thesis				

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