TIME-VARYING SYSTEMATIC RISK IN THE STOCK EXCHANGE OF THAILAND : EVIDENCE FROM MULTIVARIATE GARCH AND KALMAN FILTER ESTIMATES

Muttalath Kridsadarat

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ABSTRACT

Title of Dissertation	Time-Varying Systematic Risk in the Stock Exchange of Thailand : Evidence from Multivariate GARCH and Kalman Filter Estimates
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The purpose of this study was to use multivariate GARCH and the Kalman filter to estimate the time-varying systematic risk or beta. Much research has found that estimating systematic risk with a market model using the traditional regression approach violated classical assumptions regarding both the stationary assumption and independent identically distributed of the innovations. This study focuses on using various models of multivariate GARCH and the Kalman filter to improve this beta estimation. As the GARCH model is a popular model used in volatility clustering data. The model allows for the forecasting of the variance of return to vary systematically along periods. Further, the Kalman filter approach recursively estimates the beta series from the time update function, which can create a series of conditional betas that vary through time from the market model. Therefore, systematic risk of the market can be estimated more precisely by using these two models. The model also allows for conditional variances and conditional covariance between individual portfolio returns, which in this study uses equity sector indexes and the market portfolio returns to respond asymmetrically to past innovations, depending on their sign as well.

The data used in this study were the daily return of the Thailand Stock Exchange Industries Group Indexes fromJanuary 2007 to June 2014. There are eight groups of equity sector indexes: agriculture and food industry, consumer products industry, financial sector, industrial sector, property and construction sector, service sector, and the technology sector.First, this study estimates the beta using ordinary least squaresin order to ascertain the characteristics of each sector in the Thai stock market. The study also found the ARCH effect and autocorrelation in traditional regression. Next, the study used the multivariate GARCH model in the VECH model and BEKK model specification to estimate time-varying beta. The results showed that all of the sector indexes revealed a time-varying variance. Moreover, the pattern of asymmetries in the covariance of returns was also found, which is evidence that covariance will be higher during a market decline. After that, three models of the Kalman filter, the random walk model, the random coefficient model, and the autoregressive model, were used to estimate the time-varying beta. The results showed that most of the equity sector indexes revealed a time-varying pattern with the Kalman filter model except for the consumer product industry. Moreover, the study also compared the forecasting accuracy among the models. In terms of in-sample forecasting, the multivariate GARCH VECH model performed the best among the models. In terms of out-sample forecasting, the results also confirmed that the multivariate GARCH VECH model and the Kalman filter AR(1) model were superior to rolling OLS according to lower MAE and RMSE. However, the evidence indicating which methodology is the best estimator between these two models is not clear.

This study contributes to financial participants a more precise estimation of systematic risk, which is one of the most important risks in the financial market, by using more proper methodologies, multivariate GARCH, and the Kalman filter framework. The results of the study can provide greater understanding of time-varying systematic risk that is useful information for investors and all financial market participants as well.

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AR(1) Model	Autoregressive Kalman Filter Model
RMSE	Root Mean Squares Error
MAE	Mean Absolute Error

ABBREVIATIONS

Abbreviations	Equivalence
ASEAN	Association of Southeast Asian Nations
GARCH Model	Generalized Autoregressive Conditional Heteroskedasticity Model
MGARCH Model	Multivariate Generalized Autoregressive Conditional Heteroskedasticity Model
CAPM	Capital Asset Pricing Model
SET	Stock Exchange of Thailand
AGRO	Agriculture Products and Food Equity Sector
CONSUMP	Consumer Products Equity Sector
FIN	Financial Equity Sector
INDUS	Industrial Equity Sector
PROPCON	Property and Construction Equity Sector
RESOURCE	Resource Equity Sector
SERVICE	Service Equity Sector
TECH	Technology Equity Sector
OLS	Ordinary Least Squares
ARCH	Autoregressive Conditional Heteroskedasticity
VECH Model	Vectorized Generalized Autoregressive Conditional Heteroskedasticity Model
BEKK Model	Baba, Engle, Kraft and Kroner Generalized Autoregressive Conditional Heteroskedasticity Model
RW Model	Random Walk Kalman Filter Model

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 Motivation and Research Question

Since the recent global financial crisis has drawn attention to the fragility of the financial market, understanding market risks precisely is an advantage for all investors and financial market participants in order to meet the challenges of the volatility of the market. One of the most important risks of the financial market is systematic risk which means the risk associated with market returns. From the view of the modern theory of finance, systematic risk is an extremely essential risk because it is the only on type of risk that should be rewarded (Sharp, 1964; Black, 1972; Lintner, 1965; Mossin, 1966). Moreover, utility as a risk measure in a portfolio is unquestionable and systematic risk or beta is also the general sensitivity to market swing measurement (Grundy and Malkiel, 1996). Therefore, the proper methodology that can estimate systematic risk is the essential financial instrument of investors and market participants.

Normally, systematic risk measurement is a market model under the ordinary least squares, which provides simplicity of estimation. This model has been widely accepted in beta estimation in both academic research and actual business decision making for many years. However, several studies have found the violations of stationary assumption and independent identically distributed returns in the simple regression model. The nonstationarity in parameters, nonstationarity of error terms and the intertemporal dependences in the number of outliers can be found in the ordinary least squares regression model (e.g. Bey and Pinches, 1980) These imply that the model is non-Gaussian. There is an alternative hypothesis that allows systematic risk to vary through time (Bos and Newbold, 1984; Fabozzi and Francis, 1978) and this study will follow this idea to find the methodology that allows these conditions in estimation. Therefore, the systematic risk of the market can be estimated more precisely by using more proper models. The market participants will understand more the beta that represents the characteristics of the firms better, and these essentially are the motivation behind this study. The study will contribute to the understanding of time-varying systematic risk by using a proper model and by providing more precise beta as well that can be applied in portfolio management and portfolio performance measurement.

The study focuses on a better understanding and quantifying systemic risk by using the appropriate econometric model and by comparing the performance of each model using the econometric method and the results of applications. Therefore, the study will provide an explanation of the volatile beta of each equity sector. A good understanding of precise systematic risk would be an improvement for both academic and market participations to prompt for ASEAN Trading Link as well.

1.2 Literature Review

According to the essential of systematic risk estimation, much of the research has attempted to find proper models to evaluate the time-varying beta. Normally, there are two approaches that are used in time-varying systematic risk estimation. The first one follows the alternative hypothesis, which allows the conditional variance to vary over time, which is known as the multivariate GARCH model. Another approach uses the state space model to describe the system that varies through time. This method is well-known as the Kalman filter.

Choudhry and Wu (2007) has studied the forecasting time-varying beta of UK companies using the GARCH model and the Kalman filter method. This article investigates the forecasting ability of three different GARCH models and the Kalman filter method. According to Bollerslev et al. (1988), investors expect the same future returns on particular moments; however, these are conditional expectations, which means that the expectations are random variables rather than constant variables. For this reason, the paper supports the idea that systematic risk of risky assets should be time-varying variables as well, and one of the models that is properly used for forecasting time-varying systematic risk is the GARCH model. The advantage of

GARCH models is that they incorporate heteroscedasticity into the estimation procedure and they also capture the tendency for the volatility clustering of financial and economic data. Moreover, this paper also studies the forecasting ability of the non-GARCH method, the Kalman filter approach. This approach recursively estimates the beta series from an initial set of priors, generating a series of conditional alphas and betas in the market model.

In terms of the GARCH model, this article compares the results of the time-varying systematic risk of three types of GARCH models: the bivariate GARCH, BEKK GARCH, and GARCH-GJR. The multivariate BEKK GARCH model is considered to be more stable than the standard multivariate GARCH since the BEKK formulation specifies that conditional variance is guaranteed to be positive along a period of time. Another formulation is GARCH-GJR, which is an asymmetric GARCH model that considers leverage effect. This model allows conditional variance to respond differently to positive and negative returns. Moreover, this article also compares the results of various GARCH models with the Kalman filter Method as both of these methodologies match with time-varying beta.

The data used in this article were the weekly returns of 20 UK firms, from January 1989 to December 2003. Twenty UK firms were selected based on size (market capitalization), equity sector, the product/service provided by the firm, and the availability of the data. The methodology of the article is to compare the forecasting accuracy of these three GARCH models. The study evaluates the performance of the model by calculating the mean squared error (MSE) and mean absolute error (MAE). The article uses modified Diebold-Mariano comparison tests to compare the performances of these models. To avoid the sample effect, three forecast horizons were considered, including two one-year forecasts, 2002 and 2003, and one two-year horizon from 2002 to 2003. Among the GARCH models, the GARCH-GJR model appears to provide more accurate forecasts than the bivariate GARCH or BEKK models, followed by the bivariate GARCH. However, when compared with the Kalman filter, the results found that the Kalman filter approach is superior.

Another paper that compares these two approaches of time-varying systematic risk estimation is that of Nieto, Orbe and Zaragga (2014), which compares the performance of nine time-varying beta estimates taken from three different methodologies that are least-square estimators, including nonparametric weights, GARCH-based estimators, and the Kalman filter estimators. The data used in this article were based on42 stocks traded on the Mexican Stock Exchange from January 2, 2003 to December 31, 2009, The Mexican Stock Exchange was selected because of its high dispersion of beta in terms of both level and variability. The stocks were sorted and grouped into portfolios according to individual money-trading volume. This article uses two different MGARCH structures, which are the BEKK and DCC model. Moreover, according to the evidence that negative shocks have a greater impact on the volatility of returns than positive shocks, this article also deals with this point in the estimation of beta by adding the asymmetric effect to both two models, denoted by BEKK-A and DCC-A, respectively. Next is the modeling of the Kalman filter. There are two formats that are mostly used for time-varying beta estimation, the random walk model (KF-RW) and the random coefficient (KF-RC). With random walk model, betas are determined by their own previous value plus an error term, while the betas in the random coefficient model vary randomly around a fixed value, with some variance. Therefore, this paper estimated nine betas for each portfolio and all of the descriptive analyses and results designated that the patterns of the time-varying in these nine models were noticeably different.

This paper compares the accuracy in the forecasting of these three methodologies, which are dynamic estimators based on ordinary least squares (OLS), time-varying estimators based on the multivariate GARCH model that allow the conditional variance of the errors to vary through time, and the Kalman filter estimators. There are two frameworks used to compare the accuracy of estimations. The first framework is an asset-pricing perspective, which is the CAPM, and the second one is mean-variance space for returns for portfolio management purposes. In the first case beta estimates are compared using different measures of the time-series fit of the model and looking at the cross-sectional relationship between mean returns and market betas (Nieto, Orbe, and Zaragga, 2014). In the second framework, the mean-variance context, the study compared the results of the minimum variance portfolio to sell the performance of out-of-sample forecasting from various beta estimations. This paper concluded that the Kalman filter model with random coefficient was the best estimator according to the capability to reduce the adjustment errors in both the market model and the CAPM; and for the cross-section data, this model also produced a good fit. However, this study also suggested that the Kalman filter random walk model and the multivariate GARCH estimation performed better in highly-volatile markets than estimation in lower volatility environments. According to these models are more appropriate in terms of risk diversification, which infer to estimating the composition of the portfolio with minimum risk. Moreover, this paper also suggested that here are different conclusions depending on whether betas or risk premia are estimated, and this can be the improvement point to propose a new possible estimator that combines the advantages of these different models.

Besides selecting superior methodologies and choosing a proper model for estimating these two approaches, the scope of the data used in time-varying systematic risk estimation are also important. The first related literature was a paper by Koutmos and Knif (2002), which reports on research estimating systematic risk using time varying distributions by comparing the sector returns from the stock market in four countries. The research extends the work of Bekaert and Wu (2000) and Braun et al. (1995) by providing additional evidence about time-varying systematic risk. The model develops time-variation in the variance-covariance matrix of asset returns and market portfolio returns, and the model also allows for asymmetries in variances and covariances. The data used were the daily prices of five sector portfolios and the market index of the stock market in Germany, Japan, the UK and the USA. These five sectors are the basic sector, the Cyclical Sector, the Energy sector, the Financial sector, and the Industrial sector.

This research uses the vector GARCH model to estimate the time varying beta since this model is a way of modeling volatility clustering. Moreover, conditional variances and the conditional variance between individual portfolio returns and market portfolio returns are allowed to respond asymmetrically to past innovations. Since the ordinary least square need many assumptions and most studies found that the beta yields from a single index model using ordinary least square violate these assumptions. The research uses the vector GARCH model to handle it.

This research begins by using the traditional regression approach. The results from this estimation also confirm the misspecification of the simple regression model.

The squared error terms are correlated. Next, this research estimates the single beta model by using the bivariate GARCH model. The results were not surprising. All of the portfolios expressed time varying variance. The coefficients that linked current variance to its own past history were statistically significant. Moreover, one of the most interesting things in this research was testing for the asymmetry in the covariances. However, not all of the cases showed such asymmetry. The results of the bivariate GARCH estimation showed no evidence of misspecification but they did not explain how well the estimation of variance-covariance matrix reflected the information related to the sign and size of past innovations. The research followed the sign bias test, the negative size bias test, and positive size bias test for the specification of conditional variance of Engel and Ng (1993) The results supported the idea that the covariance estimates correctly reflected the sign and size of past residuals. However, there was no clear evidence of asymmetry in the betas. Finally, the research compared the performance of the vector GARCH model with the static market model by calculating the Root Mean Square Error (RMSE), the Mean Percent Error (MPE), and the Mean Absolute Error (MAE). The results revealed that the time varying beta was superior to the static market model.

In addition to applying the time-varying beta to the stock market, some research has estimated the time-varying systematic risk in treasury bills and bonds. One of the articles that supported the evidence of time-varying beta in this area is that of Bollerslev, Engle, and Wooldrige, who did research on the capital asset pricing model with time varying variance in 1988. The data used in this article consisted of bills (6-month Treasury bills), bonds (20-year Treasury bonds), and stocks to represent the market portfolio. The data were collected by quarterly percentage returns from the first quarter of 1959 to the second quarter of 1984. One hundred and two observations were provided for this test. The article estimated for trivariate CAPM for bills, bonds and stocks. The article explained the importance and success of the CAPM model. As the CAPM model originally proposed by Sharpe (1964) and Lintner (1965) under the mean variance optimization in Markowitz (1952). The assumption of CAPM is that all investors choose mean variance efficient portfolios in each period, although they need not have identical utility functions. Another assumption is that all investors have the same subjective expectations regarding the means, variances, and covariances of returns. The last assumption concerns the market. The CAPM assumes that the market is efficient, which means that no transaction costs, no taxes, or no restriction for borrowing and lending at risk free rate. However, this article focuses on the possibility that investors have the same expectation in each particular moment but that this expectation changes or when future returns change. As a result, conditional expectations are random variables rather than constants.

Therefore, when investors receive newly-revealed surprises for the last period's asset returns, they update their estimation of the mean and covariances of returns in each period. Therefore, this belief and the specification that investors' expectations of returns are static may lead to the poor performance of systematic risk estimation. This causes the approaching to multivariate GARCH in systematic risk estimation.

The results of the estimation revealed that the beta of the bills and bonds were similar; they had positive premiums. The beta of the stocks was close to one. In summary, the results of this study supported the notion that expected returns are influenced by the conditional variance of returns. The risk premia are better represented by the covariance implied by the market than its own variance. Moreover, the new information added in past innovations is important in explaining premia and heteroscedasticity as well.

According to the previous studies discussed above, it can be concluded that proper model for estimating systematic risk should be studied in greater detail. . In conclusion, most of the research supports the idea that the two well-known methodologies, the multivariate GARCH and the Kalman filter estimation, with various specifications of models, can be used to estimate the time-varying betas properly. However, the models and the specifications of these two methods require further research. The performance of forecasting accuracy can be compared to finding out the superior model among the others. To make the study simple and do not require large number of individual stock data scope of analysis the equity sector index returns of Thailand as a preliminary study. Moreover, the issue of asymmetry in covariance will be addressed in this study as well.

1.3 Scope of the Study

The scope of data was the daily closing price of the Thailand Stock Market equity sector indexes from January 2007 to June 2014. There were eight industries Indices separated by the Thailand Stock Market, which are Agriculture Products and Food Equity sector (AGRO), Consumer Products (CONSUMP), Financials (FIN), Industrials, Property and Construction (PROPCON), Resource (RESOURCE), Services (SERVICE). and Technology (TECH). The market representative is the SET index. During the period of the data as mentioned, 1,824 observations were used to calculate the return of each equity sector index in beta estimation. There were three main methodologies estimated in this study: Ordinary least squares, multivariate GARCH, and Kalman filter. In chapter two, the beta is first estimated using the Ordinary least squares method (OLS) in order to ascertain the static value of systematic risk and the character of each equity sector. Next, this study improve the performance of the OLS by using the small window of data and by rolling the window along the period. The beta that was estimated from this method was also the time-varying beta. The pattern of the time-varying beta was expected to move up and down along the static beta using the OLS.

There are two famous methodologies for estimating time-varying beta that are normally used. Chapter three and four will explain the theoretical background and estimation results of these two methodologies. Chapter three will explain the first method, which is the multivariate GARCH. Using the multivariate GARCH model allows the forecasting variance of returns to vary systematically during the periods. Then, the beta is also varying through time that is consistent with this hypothesis. Therefore, the systematic risk of the market can be estimated more precisely by using the multivariate GARCH model. However, since there are several forms of multivariate GARCH models, (Choudhry and Wu, 2007) and all of them can capture the volatility clustering of the stock index data very well. However, there are some specifications for each model that provide an advantage for time-varying beta calculation. This study thus focuses on two types of multivariate GARCHs, which are the VECH model multivariate GARCH and the BEKK model multivariate GARCH. Later the results will be compared in terms of both advantages and disadvantages and also in terms of the accuracy of these potential GARCH models in calculating more precise time-varying beta. Another way to estimate systematic risk is by using a form of feedback control. Chapter four will provide and explanation and the results of beta estimation from the Kalman filter, which is a set of equations that provides a capable recursive solution of the least squares method. This approach recursively estimates the beta series from an initial set of priors, generating a series of conditional alphas and betas in the market model. The algorithm can be applied in stock return calculations by representing the CAPM equation. According to the equity sector index return depends on the market return multiply by the function of time update which can be plugged into the model using the time equation and this time update equation is the time varying beta that is being observed. As with the multivariate GARCH, there are many forms of the Kalman filter model. In this study, there are three models used for time-varying estimation. The first one is the Kalman filter random walk model (RW model), the time update in this model depends on the function of previous value of itself. The second one is the Kalman filter random coefficient model (RC model), The time update function does not depend on the lag of itself but depends on the coefficient which random through time. The last one is the Kalman filter autroregressive (1) model (AR(1) model) in which the time update function is formed by the AR(1) model.

Chapter five contains a comparison of the forecasting accuracy of these various methodologies. It was expected that the results would show the benefit of the time-varying beta and find the superior model among the others that could respond to market movement better. The last chapter is the conclusion of this study.

CHAPTER 2

SYSTEMATIC RISK ESTIMATION BY MARKET MODEL

2.1 Capital Asset Pricing Model (CAPM)

According to the essential of systematic risk estimation, financial market participants try to find the best way to estimate it. One of the typical measurements of asset riskiness is the beta estimation using the capital asset pricing model or CAPM. The capital asset pricing model introduced by Sharpe (1964) and Lintner (1965) expressed the idea that the expected return of an asset or a portfolio equals the rate on a risk-free asset plus the risk premium of the particular asset. In other words, this model quantifies the asset's sensitivity to non-diversify risk or systematic risk as beta. The riskier asset should reward the expected return greater than one time of the systematic risk. If this expected return is lower than the market return, it implies that this particular asset provides lower risk than the market as well.

From CAPM

$$r_i - r_f = \beta_i (r_m - r_f) \text{--------------(2.1)}$$

Where r_i is the return of the asset

r_f is the return of the risk free asset

r_m is the expected market return

β_i is the beta of security

In beta estimation, normally, investors can use the simple linear regression with ordinary least squares to estimate systematic risk However, there are six conditions required to make OLS is a good estimator according to Gauss-Markov assumption

1) Linearity in parameters: The dependent variable is assumed to be a linear function of the variables specified in the model.

2) The expected value of the error term is zero.

3) Homoskadasticity: The conditional variance of the error term is constant all the time.

4) The error term is independently distributed and not correlated.

5) The independent variable is not correlated with the error term.

6) There are no other problems, i.e. multicollinearity.

These six ideal conditions make the OLS the best linear unbiased and efficient (BLUE). This means that the variance of the OLS estimator is minimal and the value from the estimation is not different from the true value between dependent variable and independent variable (two values of estimation).

2.2 Systematic Risk Estimation Using OLS

According to the CAPM, the beta or systematic risk is commonly estimated using the OLS applied to the linear regression for each asset or portfolio. Therefore, this model will provide one value of beta and the graph will be the horizontal line along the period.

The data used in this study for the beta estimation were the same set of data for the other following methods. The data were the daily closing prices for the industry index of the Thailand stock market itself. In this study, the SET Index is used as the market representative. For the equity sector index, there were eight equity sectors indexes separated by the Thailand Stock Market, which were agriculture product and food industry (AGRO), consumer products (CONSUMP), financials (FIN), industrials, property and construction (PROPCON), resource (RESOURCE), services (SERVICE), and technology (TECH). According to the closing price of these equity sector index and market index, the returns from market and equity sector index must be calculated before being plugged into the equation. Further, the returns ofthe equity sector index (i) and the market were calculated using the continuous compound return method. Then the daily returns were computed using the following formula.

$$Ri = 100*\log(Pi,t / Pi,t-1)$$

From the general form of CAPM in section 2.1, it was applied to the ordinary least squares estimation as shown below:

From CAPM

$$r_i – r_f = \beta_i(r_m – r_f) \text{-------------- } (2.2)$$

Where r_i is the return of the equity sector index i

r_f is the return of the risk free asset

r_m is the expected market return (SET)

β_i is the beta of the equity sector index i

The methodology of estimation is simple. The daily return of each equity sector as well as the daily return of the market is regressed using the least squares method. The results revealed that all of the betas were significantly different from zero in all industry groups at a 99% confident interval, which means that the systematic risk or market risk had a significant effect on equity sector returns. Next, the study tested Q^2-Stat (Ljung-Box Statistic) to examine the ARCH effect in the estimation to investigate whether the OLS violated the Gauss-Markov assumption or not.

Table 2.1 Results of Traditional Regression Approach Estimation

Industry Group	Beta	Prob	Q_sqt(5)		Q_sqt(10)		Q_sqt(20)	
			Q_sqt(5)	Prob.	Q_sqt(10)	Prob.	Q_sqt(20)	Prob.
Agro&Food	0.616509***	0.0000	200.66	0.0000	261.15	0.0000	330.07	0.0000
Consumer	0.265784***	0.0000	5.0626	0.4080	7.3581	0.6910	8.8988	0.9840
Financial	1.09571***	0.0000	86.848	0.0000	124.68	0.0000	225.07	0.0000
Industrial	0.984954***	0.0000	204.89	0.0000	220.78	0.0000	386.25	0.0000
Property&Construction	0.945035***	0.0000	135.47	0.0000	222.13	0.0000	357.2	0.0000
Resource	1.186272***	0.0000	208.78	0.0000	312	0.0000	415.2	0.0000
Service	0.724114***	0.0000	117.15	0.0000	158.05	0.0000	198.72	0.0000
Technology	0.823219***	0.0000	28.82	0.0000	46.477	0.0000	95.887	0.0000

Note: *Significant at 90% confident interval

**Significant at 95% confident interval

***Significant at 99% confident interval

Q^2 (n) is the Ljung-Box Statistic calculated for the squared standardized residuals using n lags.

According to the results table, all of the equity sectors' betas were seen to be significant at a 99% confidence interval. It was confirm on CAPM that the beta of each equity sector was the portion of the equity sector's sensitivity to non-diversify risk or systematic risk. According to CAPM, it is known that the beta is the ratio of the expected return of the asset (in this case is equity sector index) over or under the returns of the market and return. Further, according to the results in table 2-1, the resource equity sector was the only equity sector that had a beta higher than 1, which means that this equity sector contributed higher risk and also expected return than the market. The lowest beta among industries was the consumer product industry. The beta was quite low at 0.265. This implies that this equity sector had the lowest systematic risk and a low correlation with the market among the others.

When we take a look at the Ljung-Box Statistic, most of Ljung-Box statistics for all five, ten, and twenty lags were significant in estimation, except for the consumer product industry. Therefore, most of the industries presented the ARCH effect or conditional heteroskadasticity, except for the consumer product industry. This implies that there was a problem of heteroskadasticity in the estimation, which violated the Gauss-Markov assumption. Overall, estimating GARCH (1,1) in these equations can be used to improve precise of beta estimations by using multivariate GARCH models, which will be tested in the next chapter

2.3 Systematic Risk Estimation Using the Rolling OLS

As the result from section 2.2 indicate, there was one value for the beta along the period. This does not explain the market responsiveness of each equity sector, which may vary according to each period of time. Another approach to improving the beta estimation using the OLS as proposed by Fama and MacBeth (1973) is to use a rolling OLS estimation of the market model. This is one simple way to obtain time series estimates of betas and it also is time-varying. In this study, the data were separated into a small period or window where each window contained 60 observations of the data. In each window, one value of the beta was regressed using the OLS and the window of data was rolled along the period.

From the 1,842 observations, there were 1,782 time-varying beta provided from this method because the first 60 observations were used to calculate the first beta. To illustrate the benefit of the time-varying beta of the rolling estimation, this study compared the rolling beta with the static beta from the ordinary least squares by plotting a graph of the beta by equity sector to see the pattern of the market's sensitivity for each equity sector index.

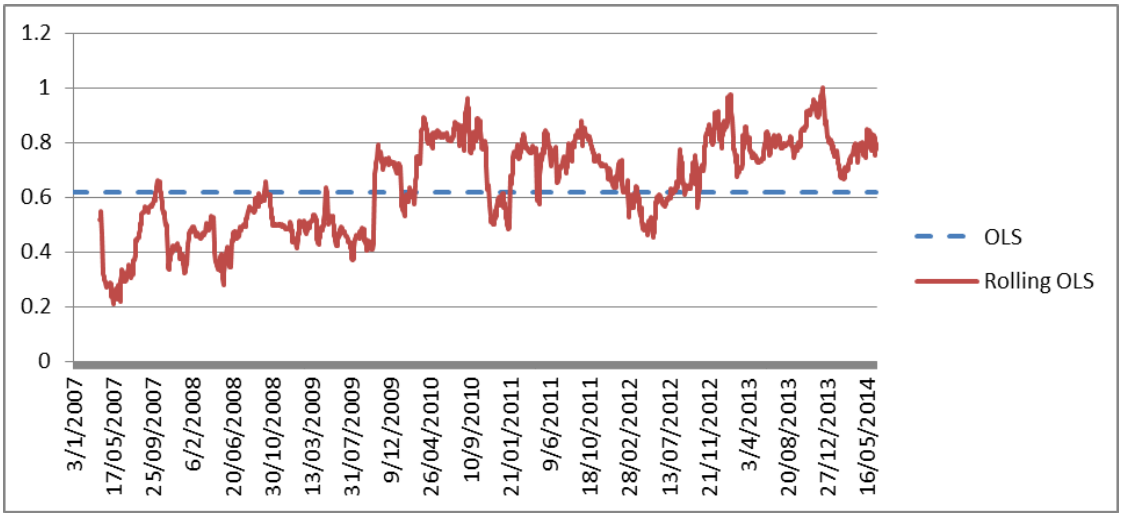

Figure 2.1 OLS and Rolling OLS AGRO Equity Sector Beta Plotted

Figure 2.1 compares the betas of the AGRO equity sector by the OLS and Rolling OLS methods. From the plot, it was found that there was an increasing trend of beta in this equity sector and the beta from the OLS was 0.6165, which was around the mean of the time-varying beta from the rolling estimate. Specifically, we can detect a noticeable increasing trend from June 2009 to September 2010. One explanation for this increase is the increase in food and commodity prices in 2010. Thailand faced a scarcity of cooking oil and pork prices also increased. That increased the risk in this equity sector. As a result, the betas showed an increasing trend. Moreover, the rolling estimation showed a declining trend in some short periods of this equity sector such as the decline from the third quarter of 2010 to the beginning of 2012.

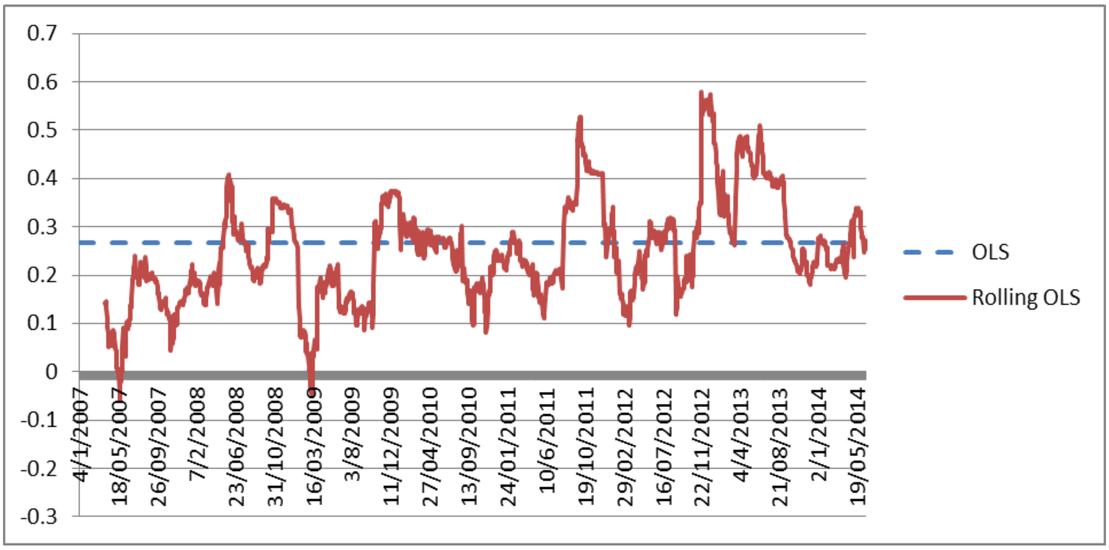

Figure 2.2 OLS and Rolling OLS CONSUMP Equity Sector Beta Plotted

Figure 2.2 is a comparison between the OLS and the rolling beta of consumer product industry (CONSUMP). According to the OLS, the beta of this equity sector was around 0.2657. This equity sector contributed the lowest systematic risk among the other equity sectors. There were three sectors in this equity sector: fashion, household and office supplies, and personal and medical supplies. The dominant sector was personal and medical supplies, which contained drug and medical product companies. Since these products are necessary goods, the systematic risk of this equity sector was low. In addition, this equity sector produced medical products the demand for which had a low relationship with the risk of the market. Even during the market crash, the demand for drugs and medical equipment stayed the same. Therefore, the time-varying betas of this equity sector were quite small. However, when we take a look at the plot of the rolling estimate, there was an increasing trend of the beta and the beta was quite volatile in some short periods as well.

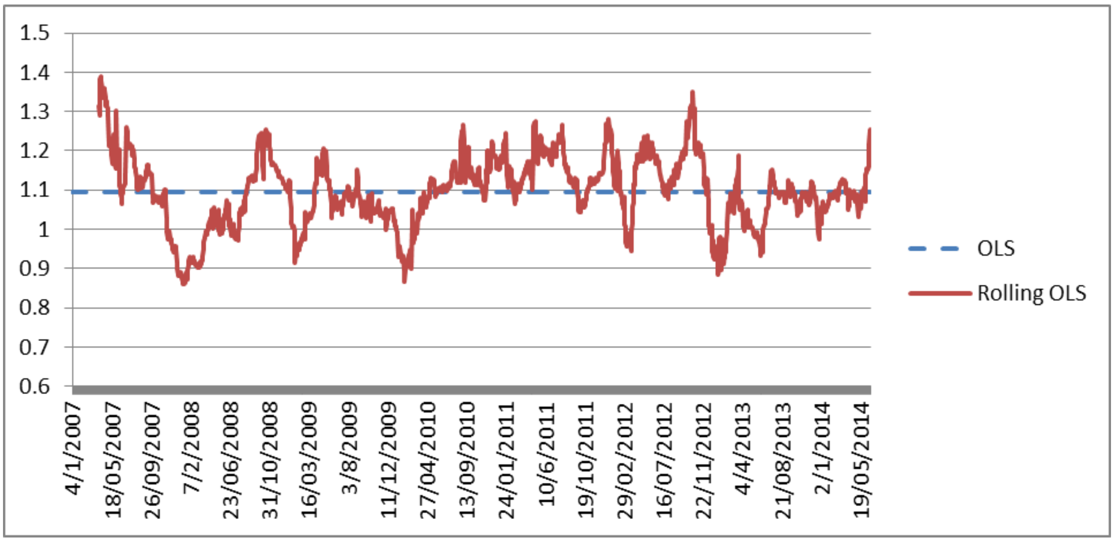

Figure 2.3 OLS and Rolling OLS FIN Equity Sector Beta Plotted

Figure 2.3 comparesthe beta from the OLS and the rolling beta of the financial equity sector (FIN). According to the OLS, the beta or systematic risk of this equity sector was 1.0957, which is similar to the market risk, which had a systematic risk equal to 1. This equity sector shareda high volume of trade in the market and was composed of banks and finance company stocks, which were the companies that had high impacton the market. Conversly, even though this equity sector had a systematic risk similar to the market, there was an obvious declining trend in 2007 and an increasing trend from the beginning of 2008 to mid-year. Overall, the systematic risk of this equity sector was around the market risk but there was a slight up and down trend along the period.

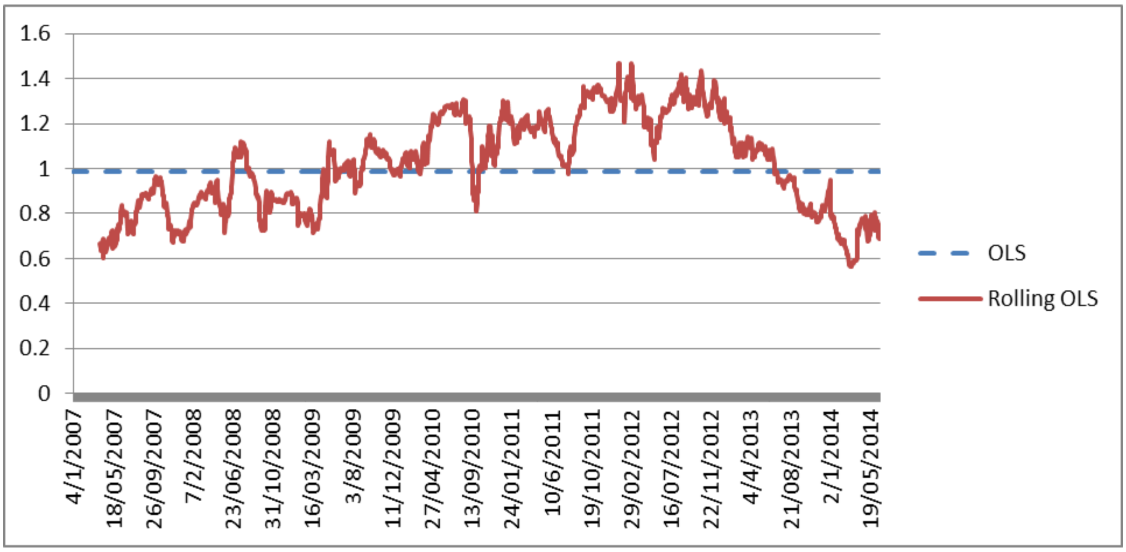

Figure 2.4 OLS and Rolling OLS INDUS Equity Sector Beta Plotted

Figure 2.4 compares the beta from the OLS and the rolling beta of the industial equity sector (INDUS). The comparison plotting between the beta from OLS and the rolling beta of this equity sector is the good evidence of trend observing from rolling OLS. The static beta estimation for the industrial equity sector (INDUS) using the OLS was 0.9849. Nevertheless, there was a noticable increasing trend of systematic risk in this equity sector from 2007 to mid-year of 2012 from around 0.6 to 1.4 and a decling trend right after that.

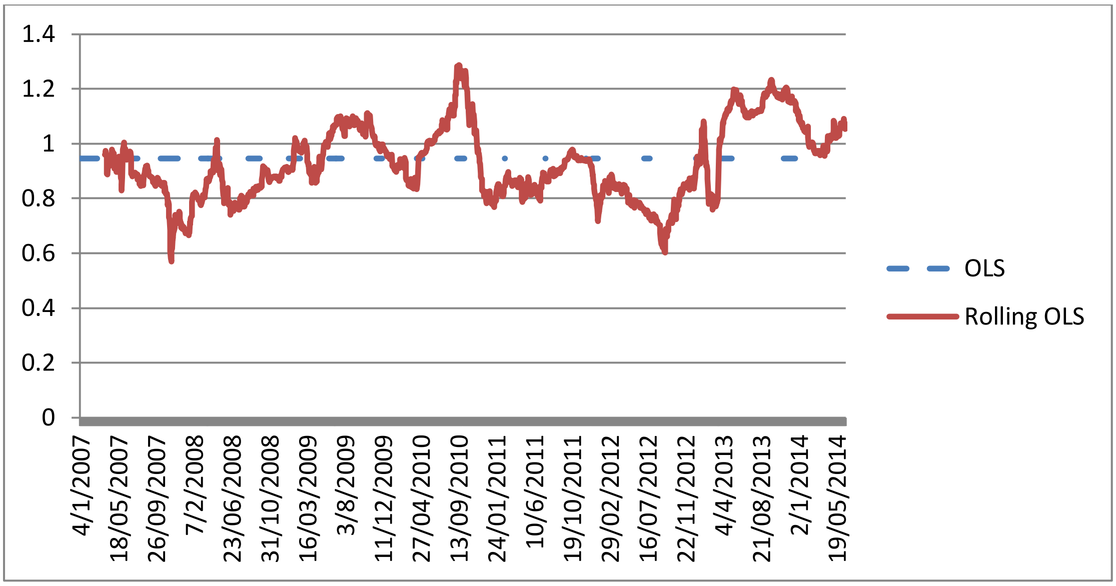

Figure 2.5 OLS and Rolling OLS PROPCON Equity Sector Beta Plotted

Next is the beta comparison between the OLS and rolling OLS methods of the property and construction equity sector (PROPCON). The systematic risk of this equity sector was quite similar to the market risk, which was around 0.9450. The dominated sector is construction material that is high volume traded stock is in this industry sector. Therefore, the beta of this equity sectorwas close to the market beta. However, according to the rolling OLS, there was an increasing trend of systematic risk in the property and construction equity sector from September 2007 to September of 2010. However, there was a sharp decline at the end of 2010 and a slight decrease after that until mid-year of 2012. After that, there was a high jump of the beta because of the economic recovery.

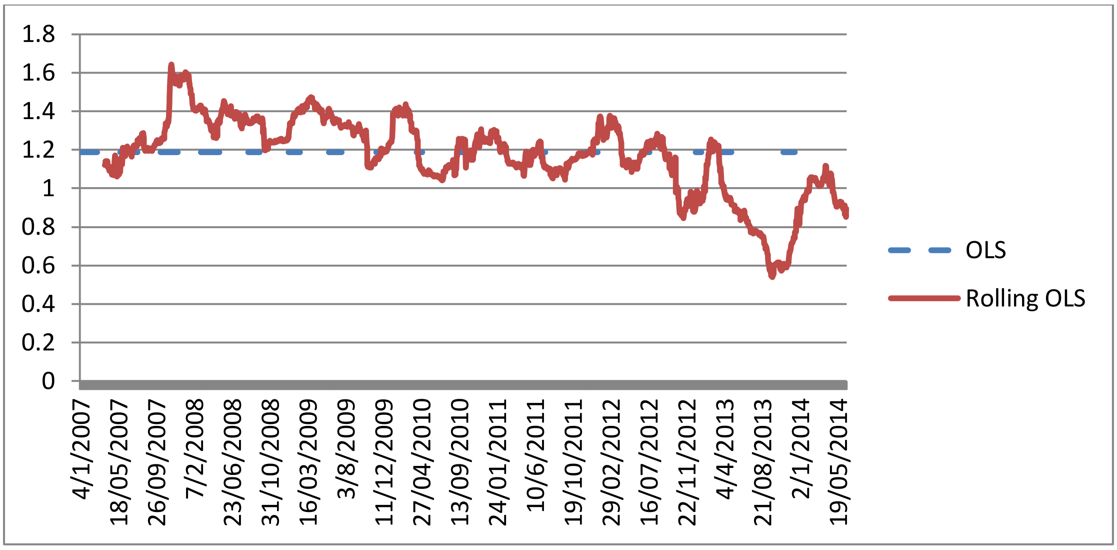

Figure 2.6 OLS and Rolling OLS RESOURCE Equity Sector Beta Plotted

Figure 2.6 shows the beta comparison between the OLS and rolling OLS methods of the resource equity sector. This equity sector can be considered the market driver of Thailand's stock market. The resource equity sector contains two sectors, energy and mining. The energy sector is composed of oil companies and utility suppliers. In the past the oil prices fluctuated all the time because of many problems, and as we know the energy sector is one of the most important sectors that drives Thailand's stock market. For this reason, it aligns with the intuitive sense that this equity sector will have higher systematic risk than the market. Even if there is a short volatile along the period, the beta from the rolling estimate showed a declining trend of systematic risk in the resourceequity sector. This result is different from the static beta from the OLS, which provided a beta equal to 1.1862, which was higher than market risk. When looking closely, it can be seen that there was a sharp decline of systematic risk from the second quarter of 2013 to the beginning of 2014 and a rebound after that.

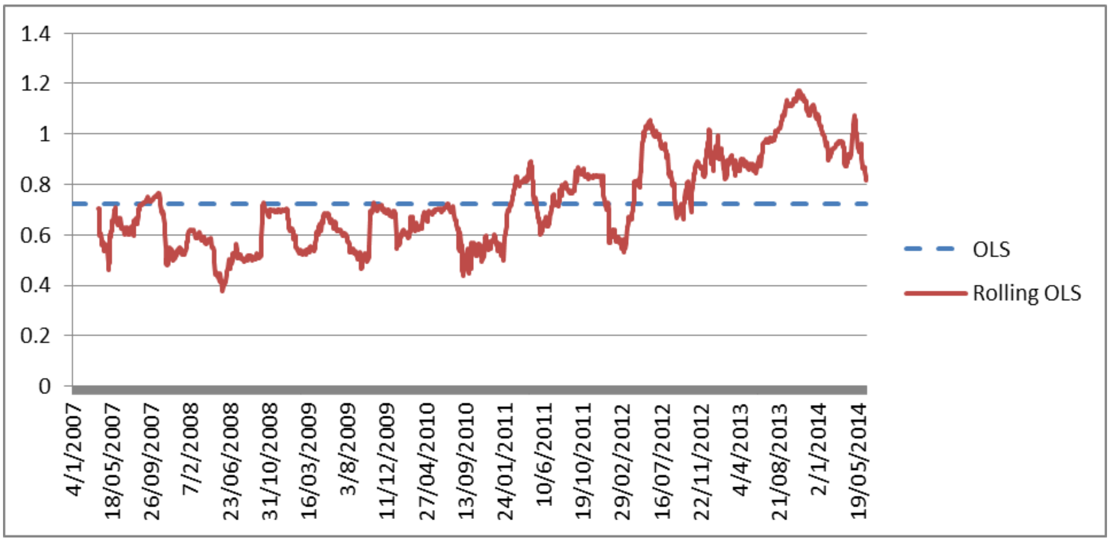

Figure 2.7 OLS and Rolling OLS SERVICE Equity Sector Beta Plotted

Figure 2.7 is a comparison of the beta between the OLS and rolling OLS methods in the service equity sector (SERVICE). According to the OLS, the beta of the equity sector was 0.7241. The service equity sector comprises various sectors—commerce, medicine, media and publications, professional service, tourism and leisure, and transportation and logistics. When we look at the beta from the rolling estimation, it can be seen that it was volatile at around 0.6 from 2007 to 2010 and there was an increasing trend after that.

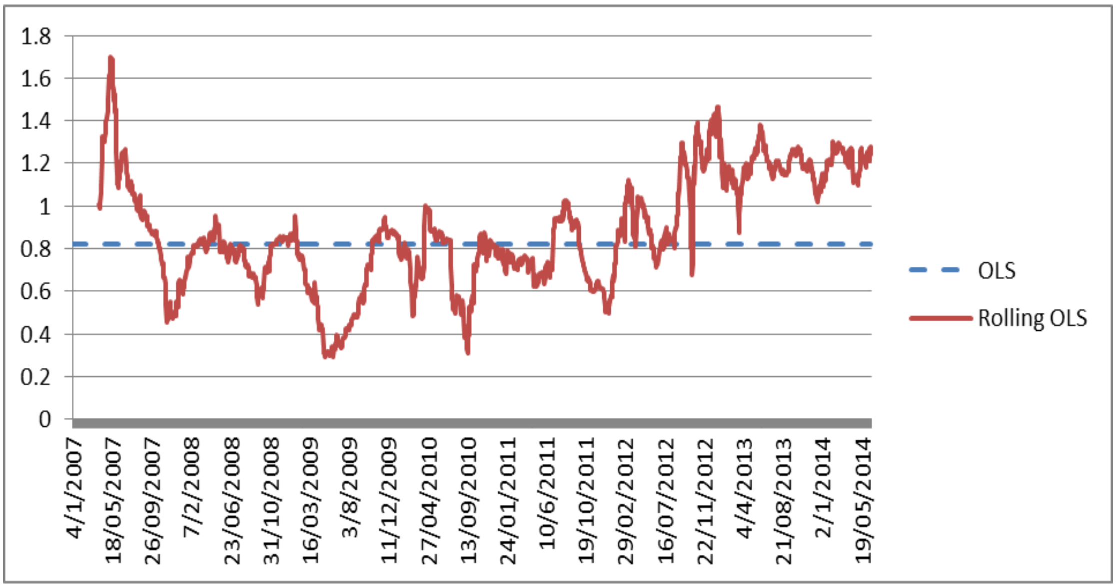

Figure 2.8 OLS and Rolling OLS TECH Equity Sector Beta Plotted

Figure 2.8 is a comparison between the static beta from the OLS and the rolling beta estimation in the technology equity sector (TECH). This comparison was also a good illustration of the benefit of the rolling estimate. The beta or systematic risk of the technology equity sector from the OLS was 0.8232. However, this equity sector beta was quite volatile according to the main sector in this equity sector was mobile phone service providers. Further, there were many important events in the telecommunication industry such as the 3G system bidding problem in 2012. Therefore, there was instability in the returns of this equity sector. The beta from the rolling estimate swung from 0.3 to around 1.4 and moved up and down quite fast during the short period.

In conclusion, though the OLS regression is a simple way to estimate beta, there is a drawback in term of trend and volatility observing and violation of the Gauss-Markov assumption. Regarding the observation of the trend or trends, we can improve the method of beta estimation by using a rolling OLS estimation of the market model. The beta plotted from rolling OLS in section 2.3 can explain the market responsiveness of each equity sector index better than static OLS. However, the problem of the violation of the Gauss-Markov assumption is still a problem. According to table 2.1, there was an ARCH effect, which means that the conditional variance of the error term was not constant all the time. The next two chapters will resolve this problem and contribute time-varying systematic risk which is proper model to use.

CHAPTER 3

TIME-VARYING SYSTMATIC RISK USING MULTIVARIATE GARCH

3.1 Theoretical Background of Multivariate GARCH

Multivariate GARCH is a model that is based on the fact that the contemporaneous shocks to variables can be correlated with each other. Moreover, the model has been used to investigate volatility and correlation transmission and spillover effects in various studies. For example, instead of modeling the variance of two-time series data separately, the researcher can also expect the volatilities of the two series to be interrelated. Therefore, the increasing volatility of one series is likely to increase the volatility of another series.

Assume that there are two variables y_{1t} and y_{2t}; the error processes can be illustrated as shown below:

$$\varepsilon_{1t} = v_{1t}(h_{11t})^{0.5}$$
$$\varepsilon_{2t} = v_{2t}(h_{22t})^{0.5}$$

As with the univariate case, if we assume $var(v_{1t}) = var(v_{2t}) = 1$, we can think of h_{11t} and h_{22t} as the conditional variances of ε_{1t} and ε_{2t} respectively. Since the shocks can be correlated, the notation of h_{12t} is the conditional variance between these two shocks.

Let $$h_{12t} = E_{t-1}\varepsilon_{1t}\varepsilon_{2t}$$

According to the notation mentioned above, the multivariate GARCH model can be written down in the general form of two variables, as shown below:

$$h_{11t} = c_{10} + \alpha_{11}\varepsilon^2_{1t-1} + \alpha_{12}\varepsilon_{1t-1}\varepsilon_{2t-1} + \alpha_{13}\varepsilon^2_{2t-1} + \beta_{11}h_{11t-1} + \beta_{12}h_{12t-1} + \beta_{13}h_{22t-1} \quad \text{-----} \ (3.1)$$

$$h_{12t} = c_{20} + \alpha_{21}\varepsilon^2_{1t-1} + \alpha_{22}\varepsilon_{1t-1}\varepsilon_{2t-1} + \alpha_{23}\varepsilon^2_{2t-1} + \beta_{21}h_{11t-1} + \beta_{22}h_{12t-1} + \beta_{23}h_{22t-1} \quad \text{-----} \ (3.2)$$

$$h_{22t} = c_{30} + \alpha_{31}\varepsilon^2_{1t-1} + \alpha_{32}\varepsilon_{1t-1}\varepsilon_{2t-1} + \alpha_{33}\varepsilon^2_{2t-1} + \beta_{31}h_{11t-1} + \beta_{32}h_{12t-1} + \beta_{33}h_{22t-1} \quad \text{-----} \ (3.3)$$

According to the multivariate GARCH (1,1) process, the conditional variance of each variable comes from the lagged squared error (ε^2_{1t-1} and ε^2_{2t-1}), and the product of lagged errors ($\varepsilon_{1t-1}\varepsilon_{2t-1}$). However, there are drawbacks to these general forms of multivariate GARCH (1,1) processes. The main disadvantage of them is the number of parameters necessary for the estimation can be quite large. From this case of two variables, there were 21 parameters. When the number of variables becomes larger, complication in the estimation can become a problem of the model.

In order to solve the problem of a large number of parameters, many researchers have tried to minimize the size of the model by finding a suitable restriction on the general form, and one of the most popular restriction is to diagonalize the system. In this way the conditional variance (h_{ijt}) contains only lags of itself and the cross products of $\varepsilon_{it}\varepsilon_{jt}$. This specification is called the diagonal VECH model. Therefore, the diagonal VECH model changes the set of equations (3.1)-(3.3) into:

$$h_{11t} = c_{10} + \alpha_{11}\varepsilon^2_{1t-1} + \beta_{11}h_{11t-1} \quad \text{-----} \ (3.4)$$

$$h_{12t} = c_{20} + \alpha_{22}\varepsilon_{1t-1}\varepsilon_{2t-1} + \beta_{22}h_{12t-1} \quad \text{-----} \ (3.5)$$

$$h_{22t} = c_{30} + \alpha_{33}\varepsilon^2_{2t-1} + \beta_{33}h_{22t-1} \quad \text{-----} \ (3.6)$$

With this specification, the model is easy to estimate even if there are large numbers of variables. However, the model assumes that there are no interactions among the variances, which is the problem of this specification.

3.2 Methodology

The scope of this study focuses on the systematic risk in the Thailand stock exchange. Therefore, the data used were collected from the closing prices of the equity sector index of the Thailand stock exchange and market index (SET). Eight industry indexes were separated in the Thailand stock market: agriculture products and food industry (AGRO), consumer products (CONSUMP), financials (FIN), industrials, property, and construction (PROPCON), resource (RESOURCE), services (SERVICE) and technology (TECH). The frequency of the data collected was daily and the data used were collected from January 2007 to June 2014. Therefore, there were 1,842 observations provided for the test. This study used the closing price of each equity sector to compute the return for each equity sector and used the closing price of the SET to compute the market portfolio return. This follows the market or single index model. Further, the return of equity sector index (i) and market were calculated using the continuous compound return method, and then the daily returns were computed with the following formula:

$$R_i = 100*\log(P_{i,t} / P_{i,t-1})$$

3.2.1 Multivariate GARCH VECH model

The first model used in this study was the multivariate GARCH VECH model following Bollerslev (1990). The diagonal VECH model or V ECH model specification has an important advantage in capturing the contemporaneous correlation between the various error terms. Then the coefficients that are estimated with this extended multivariate GARCH model will be more efficient than using a set of single equation estimations. The VECH model diagonalizes the system by letting the variance and covariance equations contain only lags of itself and the cross product of residuals ($\varepsilon_{i,t}\varepsilon_{j,t}$).

The VECH model used in this study was modified to capture asymmetry in the covariance and can be shown in these following sets of equations.

$$R_{i,t} = \mu_{i,t} + \sigma_{i,t}Z_{i,t} \quad \text{-----(3.7)}$$

$$R_{m,t} = \mu_{m,t} + \sigma_{m,t}Z_{m,t} \quad \text{-----(3.8)}$$

$$\sigma^2_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}\sigma^2_{i,t-1} + \delta_i S_{i,t-1}\varepsilon^2_{i,t-1} \quad \text{-----(3.9)}$$

$$\sigma^2_{m,t} = \alpha_{m,0} + \alpha_{m,1}\varepsilon^2_{m,t-1} + \alpha_{m,2}\sigma^2_{m,t-1} + \delta_m S_{m,t-1}\varepsilon^2_{m,t-1} \text{-----(3.10)}$$

$$\sigma_{i,m,t} = \lambda_0 + \lambda_1\varepsilon_{i,t-1}\varepsilon_{m,t-1} + \lambda_{2,}\sigma_{i,m,t} + \delta_{i,m}S_{m,t-1}\varepsilon_{m,t-1} \quad \text{-----(3.11)}$$

However, there wasa different from the normal form of the VECH model multivariate GARCH regarding the term $S_{i,t-1}$ that was designed to capture potential asymmetry in the conditional variance.

Where $S_{j,t-1} = 1$; if $\varepsilon_{j,t-1} < 0$

And $S_{j,t-1} = 0$; otherwise

3.2.2 Multivariate GARCH BEKK model

The next multivariate GARCH model used was the BEKK model, which was popularized by Engle and Kronos (1995). The model ensures that the conditional variances are always positive by putting the model in quadratic forms. Therefore, the conditional variances and conditional covariance equation depend on the square of the residual or innovation and cross product of residuals. To make the results more precise, this study allowed all of the matrixes to be full matrixes and did not reduce the number of coefficients in the estimation. The model can be illustrated as shown.

$$R_{i,t} = \mu_{i,t} + \sigma_{i,t}Z_{i,t} \quad \text{-----(3.12)}$$

$$R_{m,t} = \mu_{m,t} + \sigma_{m,t}Z_{m,t} \quad \text{-----(3.13)}$$

$$\sigma^2_{i,t} = \gamma^2_{i,i} + \gamma^2_{i,m} + \alpha^2_{i,i,1}\varepsilon^2_{i,t-1} + \alpha^2_{i,m,1}\varepsilon^2_{i,t-1} + \beta^2_{i,i}\sigma^2_{i,t-1} + 2\beta_{i,m}\beta_{i,i}\sigma_{i,m,t-1} + \beta^2_{i,m}\sigma^2_{m,t-1} \quad \text{-----(3.14)}$$

$$\sigma^2_{m,t} = \gamma^2_{i,i} + \gamma^2_{i,m} + \alpha^2_{m,m,1}\varepsilon^2_{i,t-1} + \alpha^2_{i,m,1}\varepsilon^2_{i,t-1} + \beta^2_{m,m}\sigma^2_{i,t-1} + 2\beta_{i,m}\beta_{i,i}\sigma_{i,m,t-1} + \beta^2_{i,m}\sigma^2_{m,t-1} \quad \text{-----(3.15)}$$

$$\sigma_{i,m,t} = \gamma_{i,i}\gamma_{i,m} + \gamma_{i,m}\gamma_{m,m} + \alpha_{i,i}\alpha_{i,m}\varepsilon^2_{i,t-1} + \alpha_{i,m}\alpha_{m,m}\varepsilon^2_{i,t-1} + \beta_{i,i}\beta_{i,m}\sigma^2_{i,t-1} + \beta^2_{i,m}\sigma_{i,m,t-1} + \beta_{i,i}\beta_{m,m}\sigma_{i,m,t-1} + \beta_{m,m}\beta_{i,m}\sigma^2_{m,t-1} \quad \text{-----(3.16)}$$

From the raw data which were the daily closing price on the SET index and SET industry index (equity sector index), the daily returns of both market portfolio (SET Index) and industries indexes were computed to continuous compound returns before putting them into the estimation. Therefore, the variable R_i was the return of each industry index and R_m was the return of the SET index.

The step of studies for the multivariate GARCH can be separated into two main steps. First, the time-varying beta was estimated using the multivariate GARCH in two models, which were the VECH model and the BEKK model. Their forms were mentioned previously and the study estimated the systematic risk by using these models. The results were expected to see time-varying in the variance. The coefficients that link the current variance to its own past history as well as past innovations should be statistically significant. Next, the study plotted the beta that was estimated by these two methods to see the pattern of systematic risk in each equity sector and trend and to see how each model captured the change in the market.

3.3 Results and Contribution

The time-varying beta was estimated using the VECH model multivariate GARCH. The results from this estimation are shown in table 3.1.

Table 3.1 Results from the Multivariate GARCH Estimation (VECH Model)

Industry Group	αi,0	αi,1	δi	αi,2	λ1	δi,m	λ2
Agro&Food	0.002121	0.061772***	0.042037	0.882133***	0.068300	0.065918***	0.874203
	0.0000	*0.0000*	*0.0003*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Consumer	0.003748	0.078608***	0.209726	0.538538***	0.062478	0.080293***	0.860203
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Financial	0.003276	0.056108***	0.071534	0.861171***	0.058426	0.074531***	0.861355
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Industrial	0.002489	0.072473***	0.037513	0.885307***	0.072060	0.07894***	0.860993
	0.0000	*0.0000*	*0.0005*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Property&Construction	0.001979	0.06971***	0.028079	0.893232***	0.058033	0.044732***	0.895455
	0.0000	*0.0000*	*0.0070*	*0.0000*	*0.0000*	*0.0001*	*0.0000*
Resource	0.002663	0.054323***	0.068168	0.88443***	0.053760	0.074323***	0.875813
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Service	0.002199	0.078485***	0.045847	0.859287***	0.061541	0.058605***	0.886689
	0.0000	*0.0000*	*0.0002*	*0.0000*	*0.0001*	*0.0000*	*0.0000*
Technology	0.004314	0.067025***	0.050959	0.827018***	0.065880	0.054902***	0.881706
	0.0000	*0.0000*	*0.0020*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Note: *Significant at 90% confidence interval

**Significant at 95% confidence interval

***Significant at 99% confidence interval

The results showed that, not surprisingly, all of the indexes show a time-varying variance. You can see from the significance of $\alpha_{i,2}$ in all of the industries group. The coefficients that linked the current variance and its own past variance were all significantly different from zero. For the evidence that showed whether a past innovation can influence current variance, the results showed that all of the cases were true. The coefficient $\alpha_{i,1}$ of all industries was significantly different from zero. Moreover, for the results of the asymmetries, if the sign of most coefficients$\delta_{i,m}$ was negative and the coefficients $\delta_{i,m}$ were significant, it followed asymmetric responses of the market, which specify that the covariance will be higher during market decline. The results from this study also showed that the coefficient $\delta_{i,m}$ of all industries was significantly different from zero and all of the coefficients were positive. According to the results above, the study can explain that there was asymmetry of the beta in this model.

Table 3.2 Results from the Multivariate GARCH Estimation (BEKK Model)

Industry Group	αi,1 sqrt	αi,2 sqrt
Agro&Food	0.220630***	0.957577***
	0.0000	*0.0000*
Consumer	0.142862***	0.976463***
	0.0000	*0.0000*
Financial	0.266825***	0.958365***
	0.0000	*0.0000*
Industrial	0.282237***	0.951748***
	0.0000	*0.0000*
Property&Construction	0.271323***	0.958962***
	0.0000	*0.0000*
Resource	0.220244***	0.961345***
	0.0000	*0.0000*
Service	0.277828***	0.947477***
	0.0000	*0.0000*
Technology	0.241959***	0.954045***
	0.0000	*0.0000*

Note: *Significant at 90% confidence interval

**Significant at 95% confidence interval

***Significant at 99% confidence interval

The study estimated the multivariate GARCH in the form of the BEKK model. The results showed that all of the equity sectors coefficient $\alpha_{i,2}$ squares were significantly different from zero, which means that all of the indexes showed a time-varying variance. The finding from the BEKK model was consistent with the VECH model. As with the VECH model, the study examined the effect of past innovation on current variance and found that all industries provided a significant coefficient $\alpha_{i,1}$. Consequently, the results explain that past innovation can influence current variance.

Next, the study compared the beta in each equity sector by plotting the beta using the two models of the multivariate GARCH. The first method was the multivariate GARCH with the VECH model and the second method was the multivariate GARCH using the BEKK model. The time-varying beta from these two models of multivariate GARCH can be calculated according to the formula below.

$$B_{i,t} =(\sigma_{i,m,t} /\sigma^2_{m,t})$$

The time-varying market variance and covariance with the equity sector (i)were estimated using the conditional covariance equations divided by the conditional variance equation of the market in each model. The beta calculated by multivariate GARCH method move up and down along the period and it was expected that it would move along the beta calculated using the OLS.

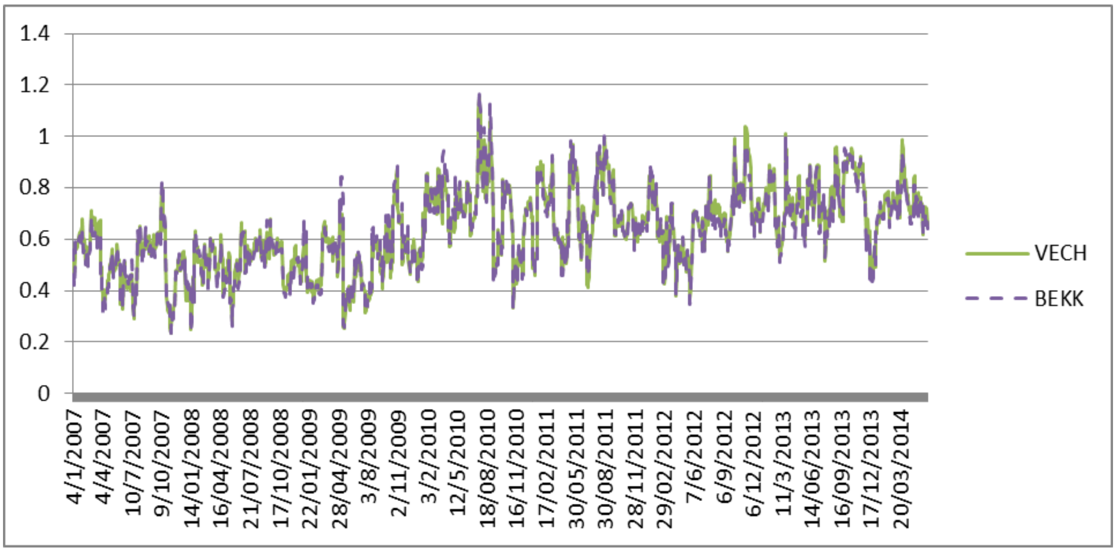

Figure 3.1 Multivariate GARCH AGRO Equity Sector Beta Plotted

According to the results in Chapter 2, the beta of agriculture and food equity sector (AGRO) using the OLS was 0.6165. This result is consistent with characteristic of this equity sector. This equity sector has less systematic risk than the market since the products are necessary goods. These two models of multivariate GARCH, the time-varying beta moved up and down from 0.2 to 1.2 and there was an obvious increasing trend in the time-varying beta, especially from mid-year of 2009 to the third quarter of 2010. Moreover, the time-varying betas using these two models had similar patterns for this equity sector.

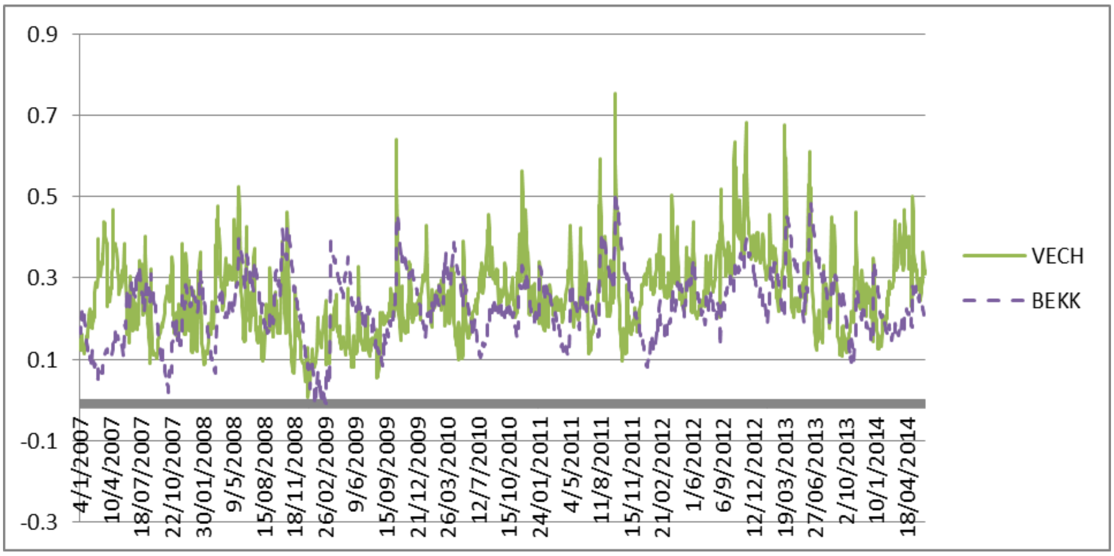

Figure 3.2 Multivariate GARCH CONSUMP Equity Sector Beta Plotted

The results of the plotting also confirmed that this equity sector had the lowest beta in the market. From multivariate GARCH models, the systematic risk fluctuated from -0.05 to 0.7. According to figure 3.2, the beta plotting using the VECH Model fluctuated more than the beta from the BEKK Model. Further, when taking a look closely at the pattern and trend, we can observe that these two models had similar patterns of beta. However, the beta from the VECH exhibited a little lag from the BEKK. This means that the VECH may respond to market sentiment more quickly than the BEKK in this equity sector. Overall, there was a slightly increasing trend of the beta in this equity sector, which implies higher expected returns in the consumer product equity sector.

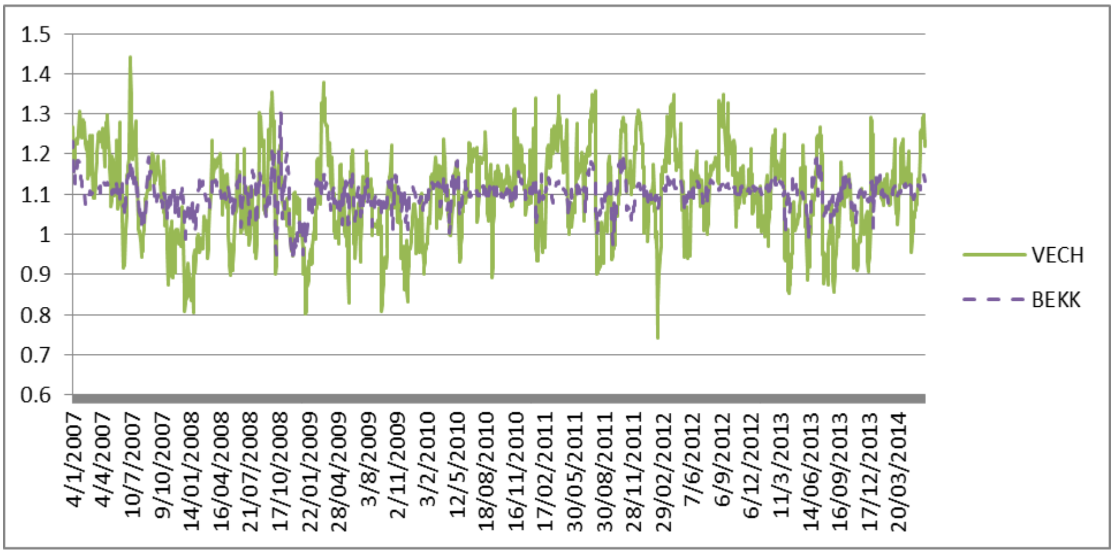

Figure 3.3 Multivariate GARCH FIN Equity Sector Beta Plotted

The beta of this equity sector was greater than the market beta. According to the OLS, financial equity sector beta was 1.0957, which was above but close to the market beta. Therefore, this industrial beta was greater than the market beta, which suggests higher systematic risk. According to these two models multivariate GARCH, the time-varying beta moved up and down along the period and it was obvious that the beta from the VECH fluctuated more than the beta from the BEKK. The time-varying betas from the VECH model moved from 0.8 to 1.4while the betas from the BEKK varied from 0.9 to 1.3. The pattern of higher fluctuation of the VECH was also the same as the result for the consumer product equity sector. Regarding the systematic risk trend, we can see a slight decline from 2007 to the beginning of 2008. Moreover, these two models also exhibited a sharp decline in the beta in third quarter of 2008, which was the effect of the hamburger crisis.

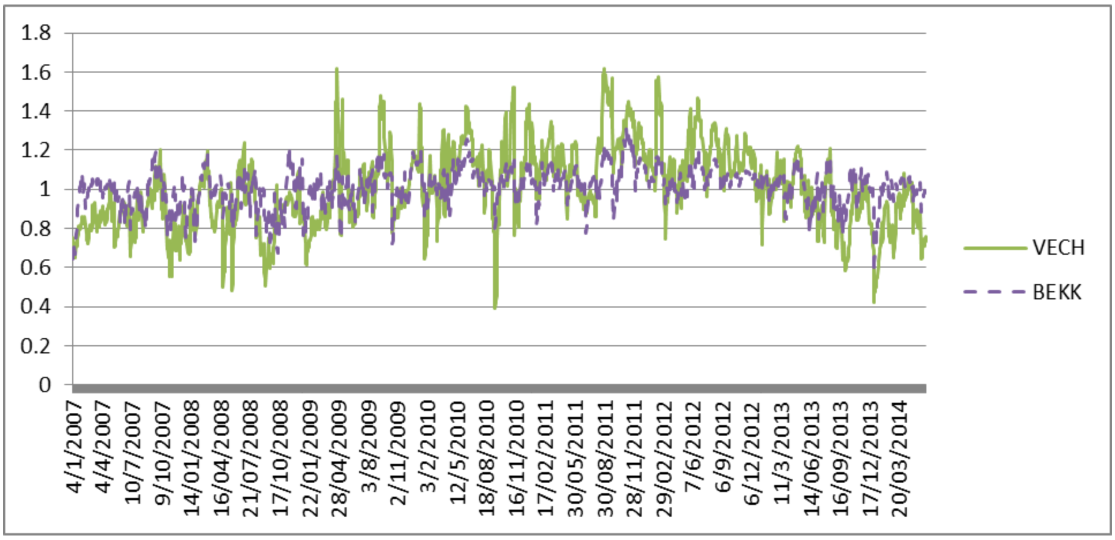

Figure 3.4 Multivariate GARCH INDUS Equity Sector Beta Plotted

According to OLS model, the beta of the industrial sector was 0.97, which was very close to the market index. This implies that this equity sector had similar systematic risk to the market. However, when we consider the time-varying beta calculated using the multivariate GARCH we found that the time-varying beta of both methods fluctuated and an increasing trend could be seen. Again, the time-varying beta from the VECH has larger variation than the BEKK. The betas from the VECH model varied from 0.4 to 1.6 while the betas from the BEKK varied from 0.6 to 1.3. Moreover, according to the VECH model, an increasing trend of the beta was observed from 2007 to 2012 and the betas of this equity sector began a decreasing trend after that.

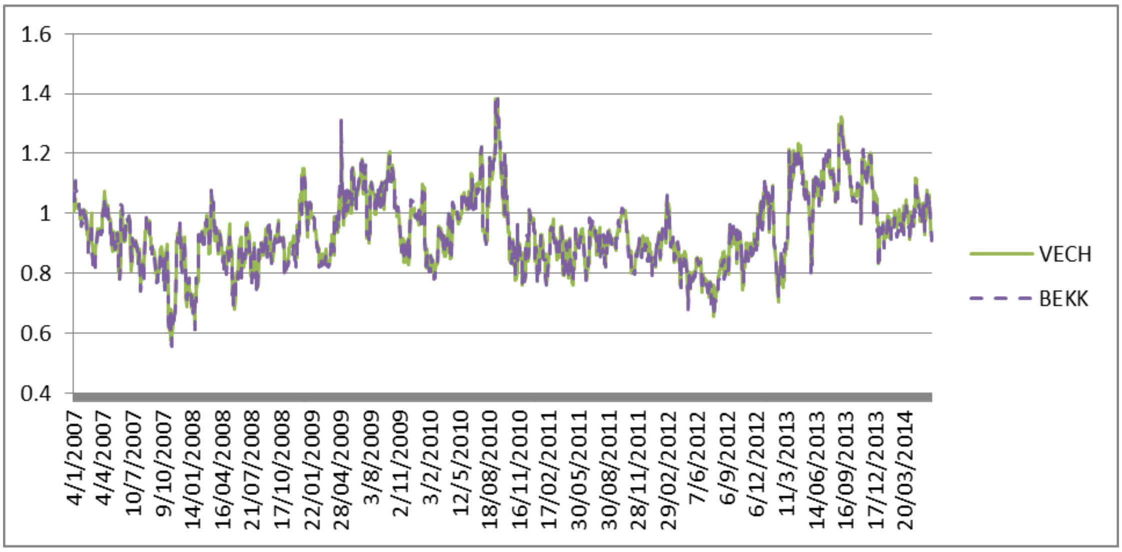

Figure 3.5 Multivariate GARCH PROPCON Equity Sector Beta Plotted

The beta of Property and Construction using the OLS estimation was around 0.9450, which was close to the market beta. However, the time-varying beta calculated using the multivariate GARCH varied from 0.6 to 1.4 and we can observe a pattern of systematic risk that was different in various periods of time. The betas from these two methods moved in the same direction and had similar patterns. There was an increasing trend of systematic risk from the third quarter of 2007 to 2010. After that the beta declined sharply and fluctuated lower than one until the end of 2012. Next, we can see the increasing trend of this equity sector again from 2013 according to the recovery of Thailand’s economy.

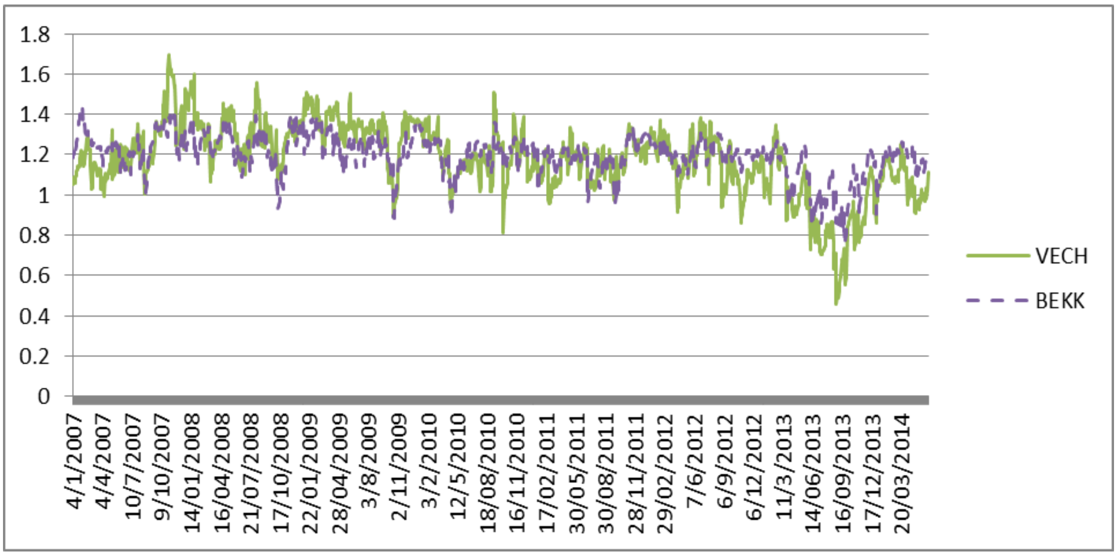

Figure 3.6 Multivariate GARCH RESOURCE Equity Sector Beta Plotted

The beta calculated using the OLS of the resource equity sector was greater than the market beta. The beta was around 1.1862, which means that this equity sector had higher systematic risk than the market. By calculating the time-varying beta using the VECH and BEKK multivariate GARCH model, we can observe the decreasing trend of the beta especially from the beginning of 2013 to the third quarter of 2013 and rebounding again after that. The variation of systematic risk estimated using the BEKK model was lower than the VECH model. The betas from the VECH model varied from 0.5 to 1.6, which was a large range, while the betas from the BEKK varied from 0.8 to 1.4. Even though the VECH model contributed the larger variation, these two models also showed the same patterns of a sharp decline in some periods, such as the third quarter of 2009 and mid-year of 2010.

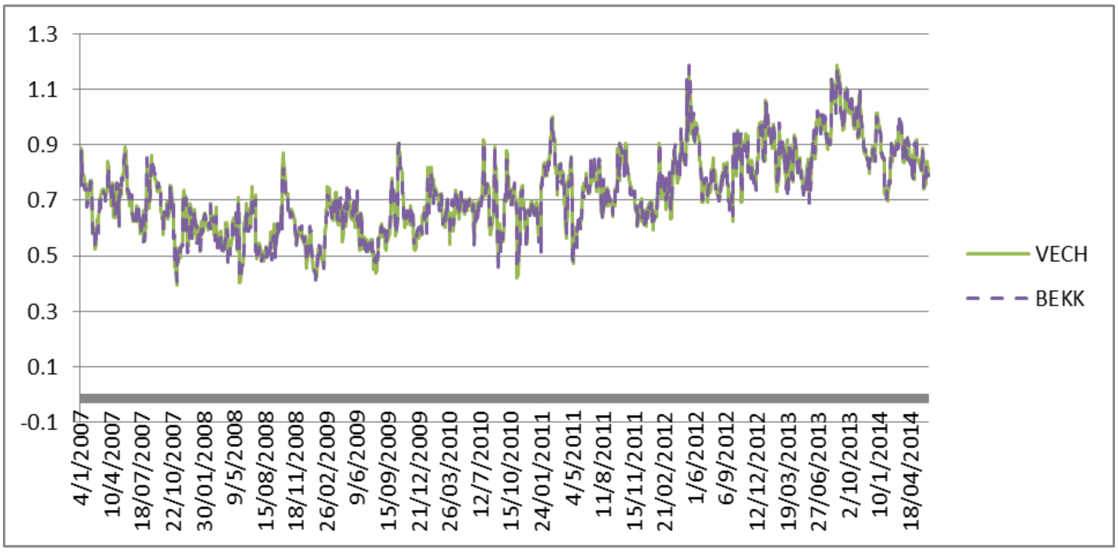

Figure 3.7 Multivariate GARCH SERVICE Equity Sector Beta Plotted

Using the OLS model, the beta of the service equity sector was 0.66, which was lower than the market beta. This means that the service equity sector had lower systematic risk than the market. By using multivariate GARCH, these two models, which were the VECH and BEKK models, betas moved along with the same pattern. The time-varying betas moved along from 0.4 to 1.2, and we can see that the beta exhibited a slight decline from 2007 to 2008. After that there was a rise of systematic risk in this equity sector, which implies a higher expected return from the service equity sector as well.

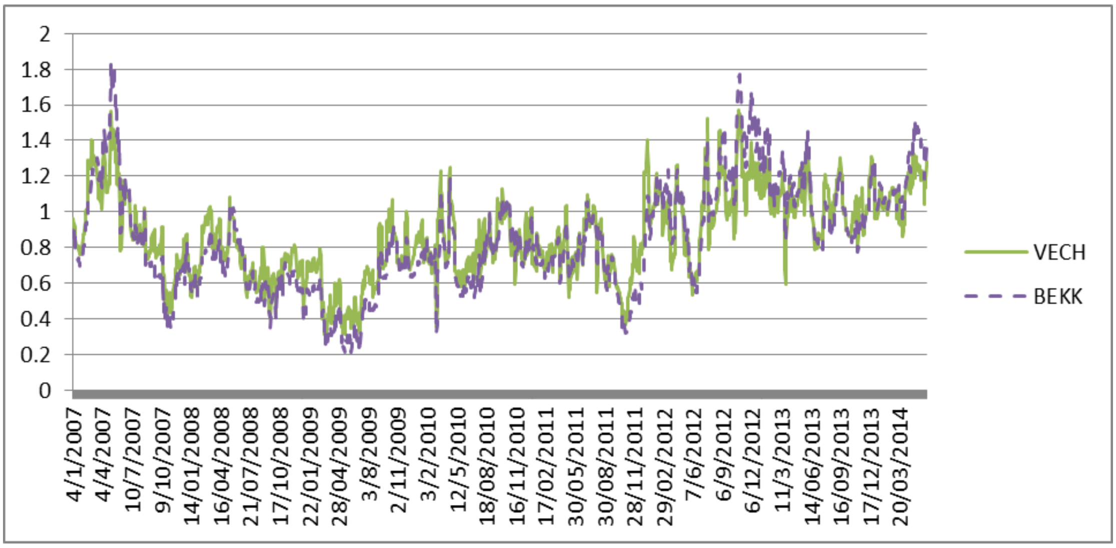

Figure 3.8 Multivariate GARCH TECH Equity Sector Beta Plotted

The last one was time-varying beta of the technology equity sector. The beta of this sector by OLS was 0.8232, which as lower than the market beta. This implies that the technology equity sector had lower systematic risk than the market risk. However, when we consider the time-varying beta calculated using the multivariate GARCH and the beta plotting, it was found that the beta exhibited large variation. They moved from 0.2 to 1.8. There was sharp increase in the beta in the first quarter of 2007 and a noticeable decline after that, which was according the effect of the news in this equity sector, as mentioned in chapter 2. This equity sector also showed a decrease until the mid-year of 2009 and after that there was a rise of the beta even though there were some short periods of regression. The betas from these two methods moved in the same direction and responded to the market quickly.

The plots showed that the two series of betas from the multivariate GARCH model moved up and down along the period as with the plot of the OLS in chapter 2, and the trend of beta could be observed clearly by using the multivariate GARCH. This is the advantage of portfolio adjustment for market participants in using the precise model, which can show the rapid move of systematic risk and trend of the particular equity sector.

According to these results, the time-varying beta using the multivariate GARCH is the good choice for beta estimation for this equity sector since this equity sector return changes all the time and the multivariate GARCH is good at capturing the change.

CHAPTER 4

TIME VARYING SYSTEMATIC RISK USING THE KALMAN FILTER

4.1 Kalman Filter: Theoretical Background

The Kalman filter is a set of mathematical equations that has two groups of equations, which are time update equation and measurement update equations. This algorithm uses the concept of "state space" which was an important notion in engineering in 1960s. It was developed to describe a system that varies through time (Choudhry and Wu, 2005), especially for guidance navigation and the control of vehicles. This set of equations provides a capable recursive solution of the least-squares method.

The process of estimation using the Kalman filter method uses a form of feedback control. Therefore, there are two groups of equations for the Kalman filter: time update equations and measurement update equations. The time update equations are accountable for projecting forward (in time) and the measurement of update equations is accountable for feedback. The algorithm of estimation can then be illustrated according to Figure 4.1, which explains that the time update projects the current state estimate ahead in time. The measurement update adjusts the projected estimate using the actual measurement at that time.

4.2 Methodology

When we apply the theory of the Kalman filter to time-varying beta estimation, we can represent the CAPM equation that explains the return of each equity sector index using a measurement equation. This means that the equity sector index return depends on the market return times with the function of time update, which is explained by the time equation. According to this explanation, it implies that the function of the time update (Θ_t) is the time varying beta that we are observing.

From equation (4.1) and (4.2), which are the sets of two groups of the Kalman filter equation, The model can be specified into the state space model for a time-varying beta estimation. The measurement equation can be the representative of the signal equation and the time update equation is state equation in the state space model.

In this study, there were three forms of state space model: the AR(1) model, the random coefficient model, and the random walk model. The measurement equation or signal equation in these three models are the same unless the time equation for the state equation are varied by differences in the model.

4.2.1 Random Walk Model

This model is one of the simplest model that uses the Kalman filter estimation in this paper. The equity sector return depends on the function of the market return and the time update. Further, the time update depends on the function of the previous value of time update itself. The set of equations can be illustrated by equation (4.3) and (4.4).

$$Y_t = F_t\theta_t + \nu_t \qquad \text{------(4.3)}$$

$$\theta_t = \theta_{t-1} + \omega_t \qquad \text{------(4.4)}$$

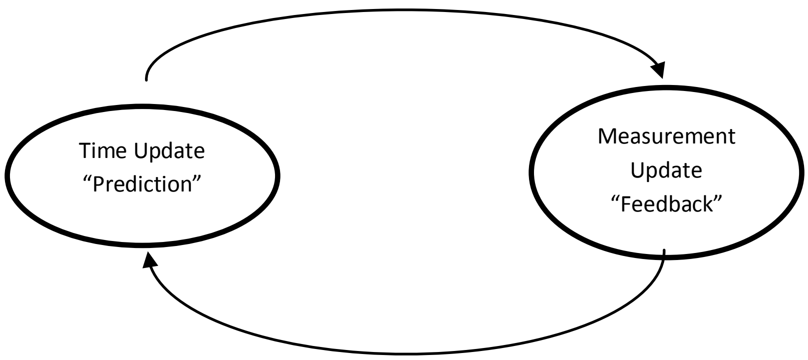

Figure 4.1 The Ongoing Process of the Kalman filter

Let Y be the series of data that vary through time. Then, the series of Y is $Y_{t-n}, \dots, Y_{t-1}, Y_t$. We assume that Y depends on one unobservable datum, which is called the state of nature. Let it be Θ. This state of nature also changes over time and the previous value of the state of nature also affects the next state of nature. Then we can write the relationship between Y_t and Θ as follows:

$$Y_t = F_t\theta_t + \nu_t \qquad \text{----- (4.1)}$$
$$\theta_t = G_t\theta_{t-1} + \omega_t \qquad \text{----- (4.2)}$$

F_t and G_t is the known quantity.

ν_t and ω_t are the observation errors (assumed to be normal distributed, zero mean, and a known variance). Equation (4.1) is known as the measurement equation and equation (4.2) is the time equation.

One good example of the Kalman filer model was considered by Phadke (1981) in the situation of statistical quality control. In that study, the number of defectives observed in a sample obtained at time t was represented by Y_t, while $\Theta_{1,t}$ and $\Theta_{2,t}$ were the true defective indexes of the process and the drift of this index correspondingly. This is an example where both the time equation and measurement equation can be the matrix.

In the equations,

Y_t stands for the equity sector return at time t,

F_t is the market return at time t,

And Θ_t is the time equation or the time varying beta is the function that depends on the lag of itself as shown in equation (4.4).

4.2.2 Random Coefficient Model

This model is different from the random walk model because the time equation does not depend on the lag of the time update itself. It depends on the coefficient $C_{1,t}$, which is random through time. The set of equations can be illustrated by equation (4.5) and (4.6).

$$Y_t = F_t\theta_t + \nu_t \qquad \text{------(4.5)}$$

$$\theta_t = C_{1,t} + \omega_t \qquad \text{------(4.6)}$$

In the equations,

Y_t stands for the equity sector return at time t,

F_t is the market return at time t,

And Θ_t is the time update or the time varying beta is the function that depends on coefficient C_1, as shown in equation (14).

4.2.3 Autoregressive Model (AR(1))

The time equation of this model is the equation of the lag of time update itself. However, it is different from random walk equation as there is coefficient C_1 in the equation. The set of equations can be illustrated by equation (4.7) and (4.8).

$$Y_t = F_t\theta_t + \nu_t \qquad \text{------(4.7)}$$

$$\theta_t = C_1 + C_2\theta_{t-1} + \omega_t \qquad \text{------(4.8)}$$

In the equations,

Y_t stands for the equity sector return at time t,

F_t is the market return at time t,

And Θ_t is the time update or the time varying beta is the function that depends on coefficient C_1 and the time update lag, as shown in equation (4.8).

In this paper, the time varying beta of the equity sector index will be estimated using these three models of the Kalman filter. In each model, the beta will be estimated eight times as there are eight equity sector indexes in Thailand's stock market. The data used are the same set as in chapter 3. In each equity sector, there are 1,842 observations of closing price and also 1,842 observations of closing prices of the market index or SET index. The closing prices need to be transformed to daily returns as in Chapter 3. The state space model in EViews will be used to estimate the time varying beta. In each equity sector, 1,842 betas will be received that vary through time.

4.3 Results and Contributions

There are eight industry time varying betas: the agriculture product and food equity sector (AGRO), consumer products (CONSUMP), financials (FIN), industrials, property and construction (PROPCON), resources (RESOURCE), services (SERVICE), and technology (TECH). In this paper, three models of the Kalman filter were used with 500 iterations in order to generate the time varying beta for each equity sector.

4.3.1 Results from the Kalman Filter Random Walk (RW) Model

The time update and measurement update were estimated with the set of equations (4.3) and (4.4). The results for all eight industries are shown below.

Table 4.1 Results from the Kalman Filter Random Walk Model

Industry Group	Θ1 (Final State)
Agro&Food	0.712961***
	0.0000
Consumer	0.608986***
	0.0000
Financial	1.127611***
	0.0000
Industrial	0.677049***
	0.0000
Property&Construction	1.05672***
	0.0000
Resource	0.916641***
	0.0000
Service	0.908421***
	0.0000
Technology	1.304808***
	0.0000

Note: *Significant at 90% confidence interval

**Significant at 95% confidence interval

***Significant at 99% confidence interval

According to equation (4.3) and (4.4), it can be seen that the time update or betas in this model varied through time in a random walk pattern. The previous beta is also effected the current beta. The results in the table also show that the return on the market index influenced the equity sector index. However, in this model, the consumer product beta was significant, which is different from the two following models.

4.3.2 Results from the Kalman Filter Random Coefficient (RC) Model

In this model, the time update or beta depends on the random coefficient without any effect from the previous value of the beta itself. The time update and measurement update were estimated using the set of equations (4.5) and (4.6). The results for all eight industries are shown below.

Table 4.2 Results from the Kalman Filter Random Coefficient Model

Industry Group	C1	Θ1 (Final State)
Agro&Food	0.621615	0.621615***
	0.0000	*0.0050*
Consumer	0.240251	0.240251
	0.0000	*0.2731*
Financial	1.095396	1.095396***
	0.0000	*0.0000*
Industrial	0.989232	0.989232***
	0.0000	*0.0016*
Property&Construction	0.939568	0.939568***
	0.0000	*0.0000*
Resource	1.183937	1.183937***
	0.0000	*0.0000*
Service	0.712257	0.712257***
	0.0000	*0.0010*
Technology	0.832614	0.832614***
	0.0000	*0.0061*

Note: *Significant at 90% confidence interval

**Significant at 95% confidence interval

***Significant at 99% confidence interval

As we allow the coefficient $C_{1,t}$ to vary through time, it can infer that betas are also time varying. Further, the coefficient $C_{1,t}$ is equal to the beta in the final state as well. According to the table, the results for most of the industries showed significant betas, which can explain that the returns of the market also affected the returns of the equity sector index except for the consumer product equity sector.

4.3.3 Results from the Kalman Filter Autoregressive (AR(1)) Model

The time update and measurement update were estimated using the set of equations (4.7) and (4.8). In this model the time update depends on coefficient C_2 time with a lag (t-1) of the time update (Θ) itself. The results for all eight industries are shown below.

Table 4.3 Results from the Kalman filter AR(1) Model

Industry Group	C1	C2	Ɵ1 (Final State)
Agro&Food	0.067808	0.892194***	0.553034***
	0.0004	*0.0000*	*0.0038*
Consumer	0.165254	0.301422***	0.239453
	0.0000	*0.0023*	*0.2620*
Financial	0.887006	0.190636*	1.080862***
	0.0000	*0.0581*	*0.0000*
Industrial	0.204305	0.795869***	0.909713***
	0.0000	*0.0000*	*0.0010*
Property&Construction	0.141070	0.84997***	0.97201***
	0.0000	*0.0000*	*0.0000*
Resource	0.009226	0.991959***	0.97528***
	0.0533	*0.0000*	*0.0000*
Service	0.007203	0.990282***	0.847243***
	0.0308	*0.0000*	*0.0000*
Technology	0.016028	0.981844***	1.140957***
	0.0180	*0.0000*	*0.0000*

Note: *Significant at 90% confidence interval

**Significant at 95% confidence interval

***Significant at 99% confidence interval

From coefficient C_2, the results showed that the time update or in this study are systematic risks (beta) are time-varying in all industries. In addition, the previous betas also affected the current beta as well. In terms of the significant effect from the market returns to the time update (Θ_t), it is found that the beta of time update are mostly significant except consumer product. This result is consistent with the random coefficient model.

After the table results were explained, the plotting of time varying beta was developed from these three models and they were separated by equity sector, as displayed.

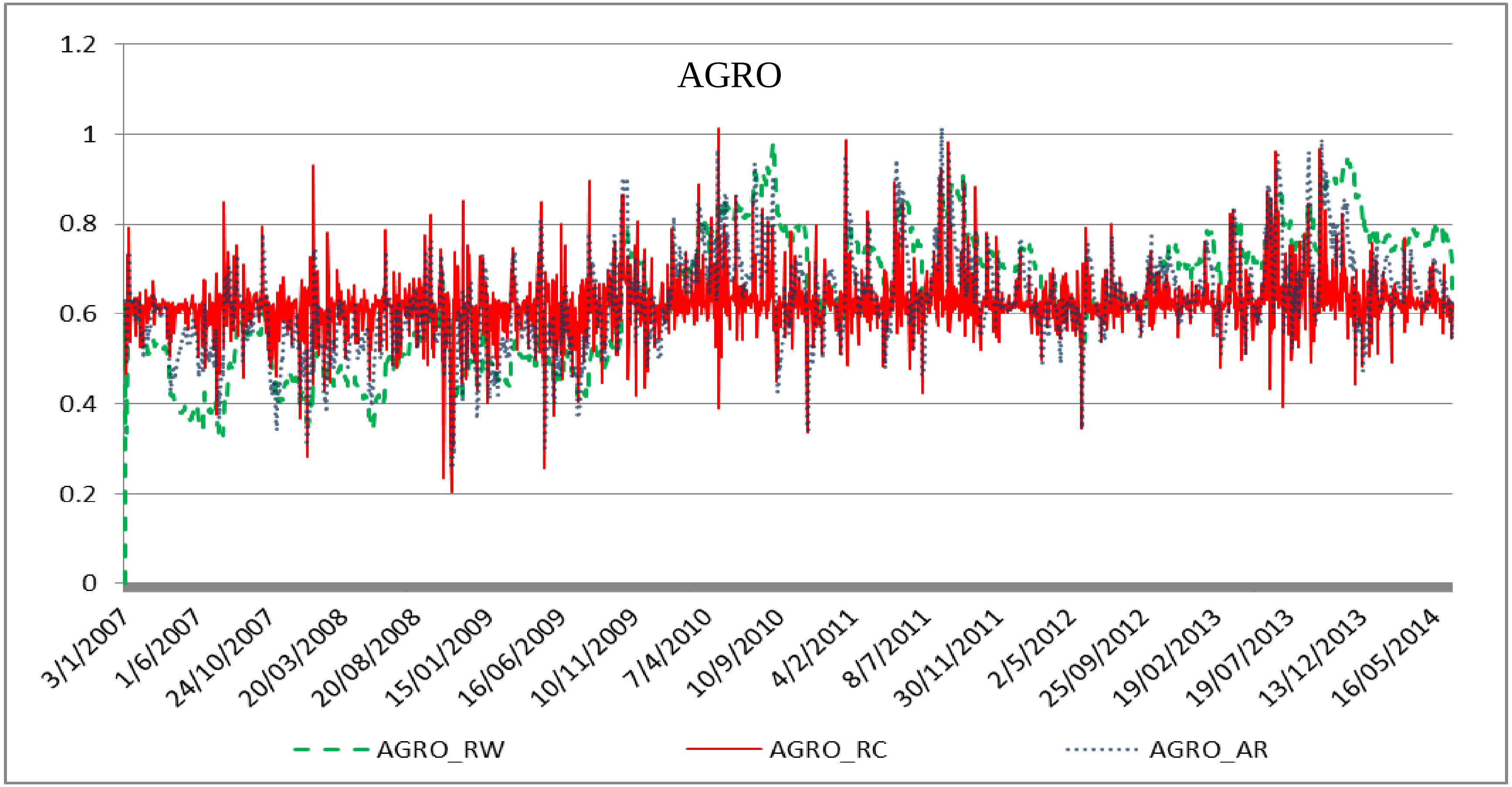

Figure 4.2 Kalman Filter Models: AGRO Industry Beta Plotted

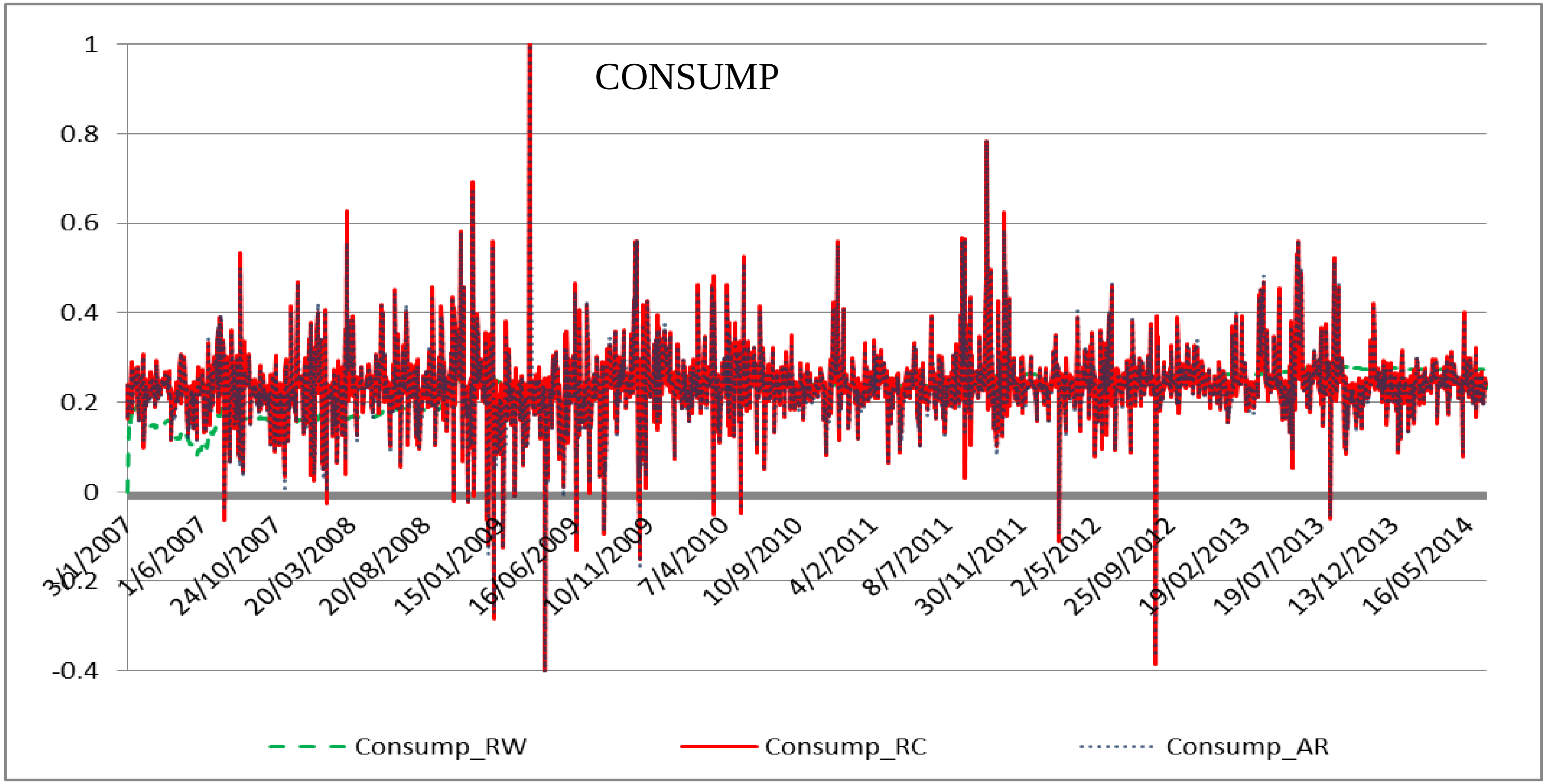

Figure 4.3 Kalman Filter Models: CONSUMP Industry Beta Plotted

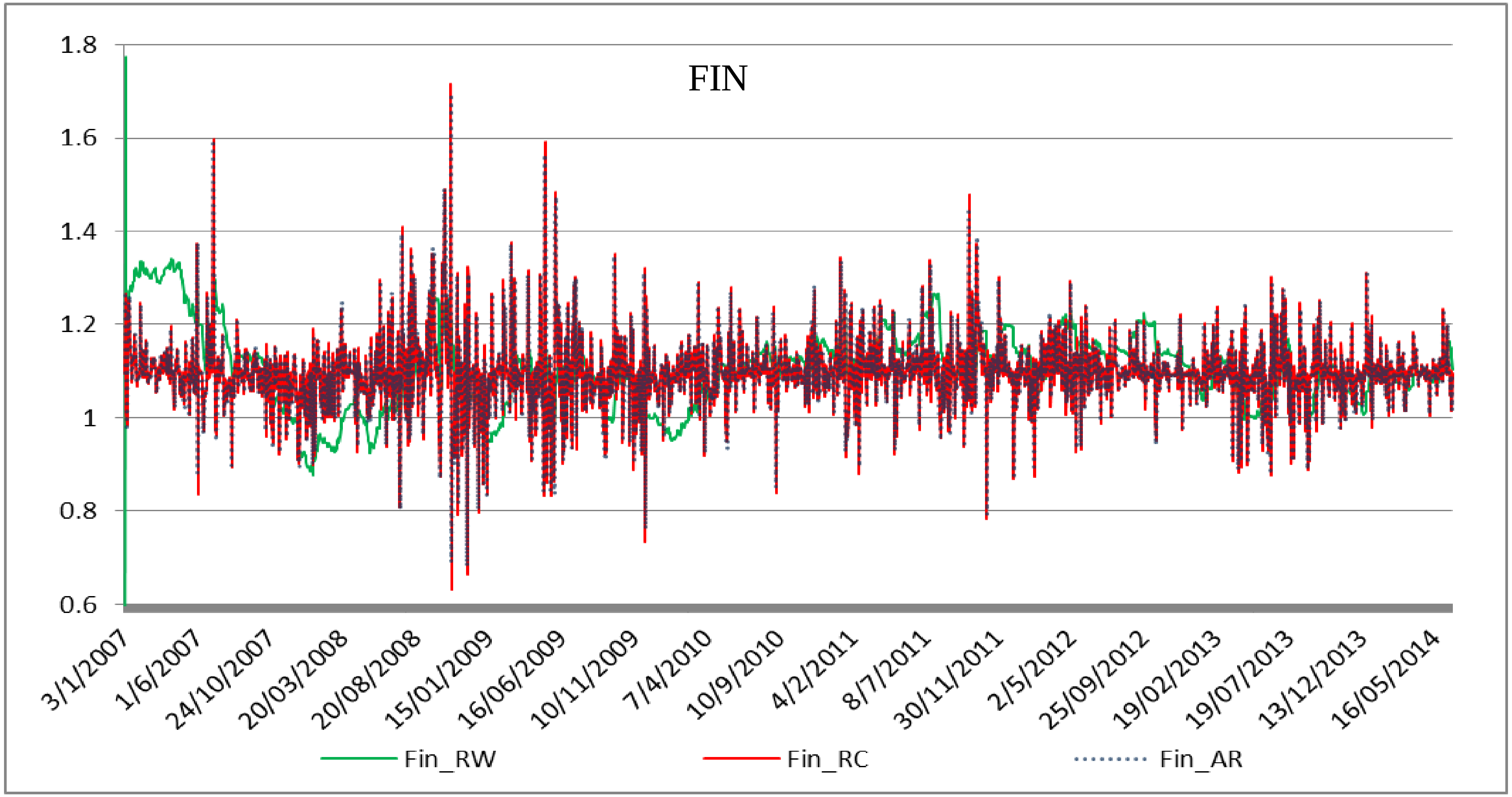

Figure 4.4 Kalman Filter Models: FIN Industry Beta Plotted

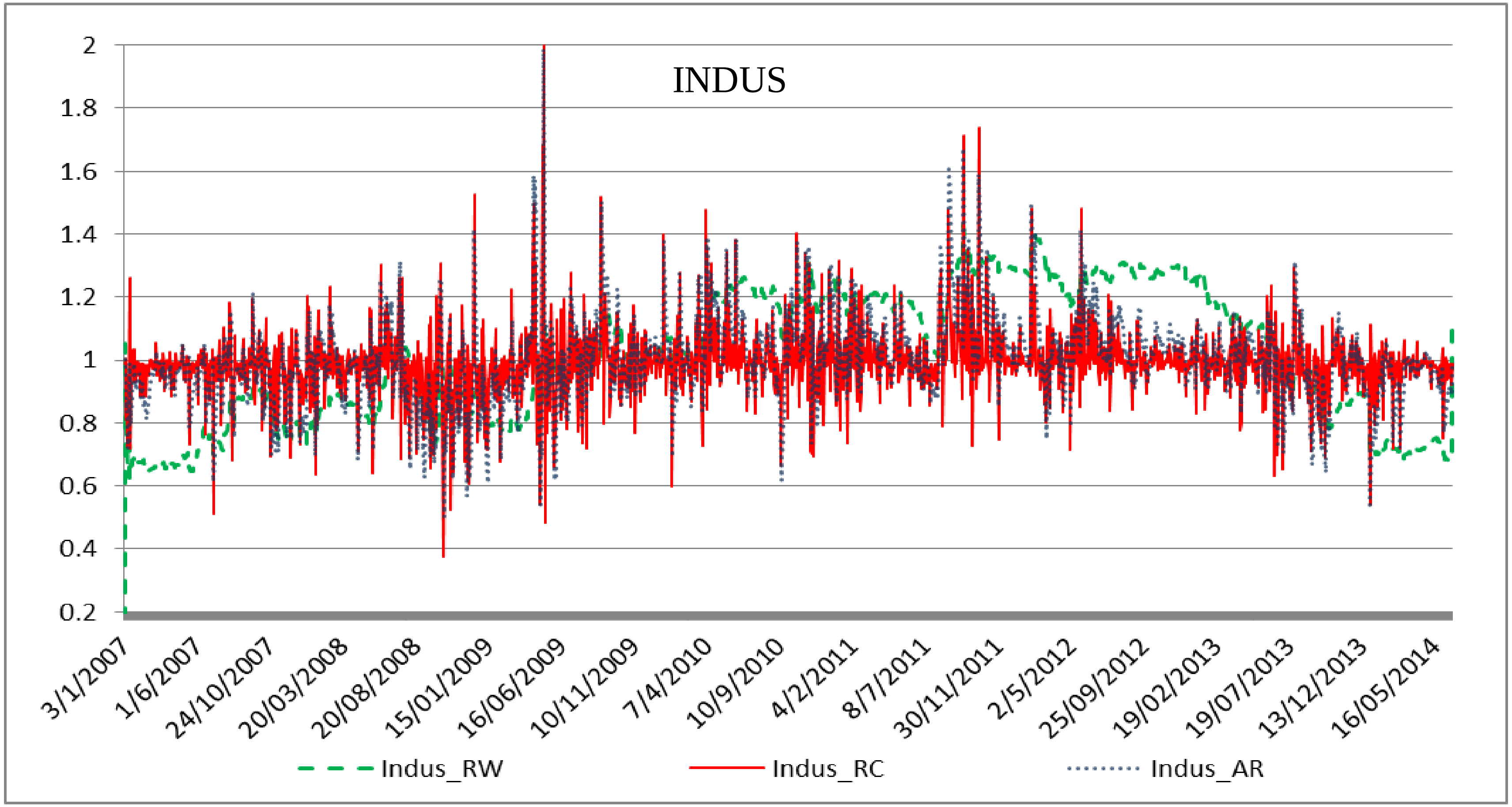

Figure 4.5 Kalman Filter Models: INDUS Industry Beta Plotted

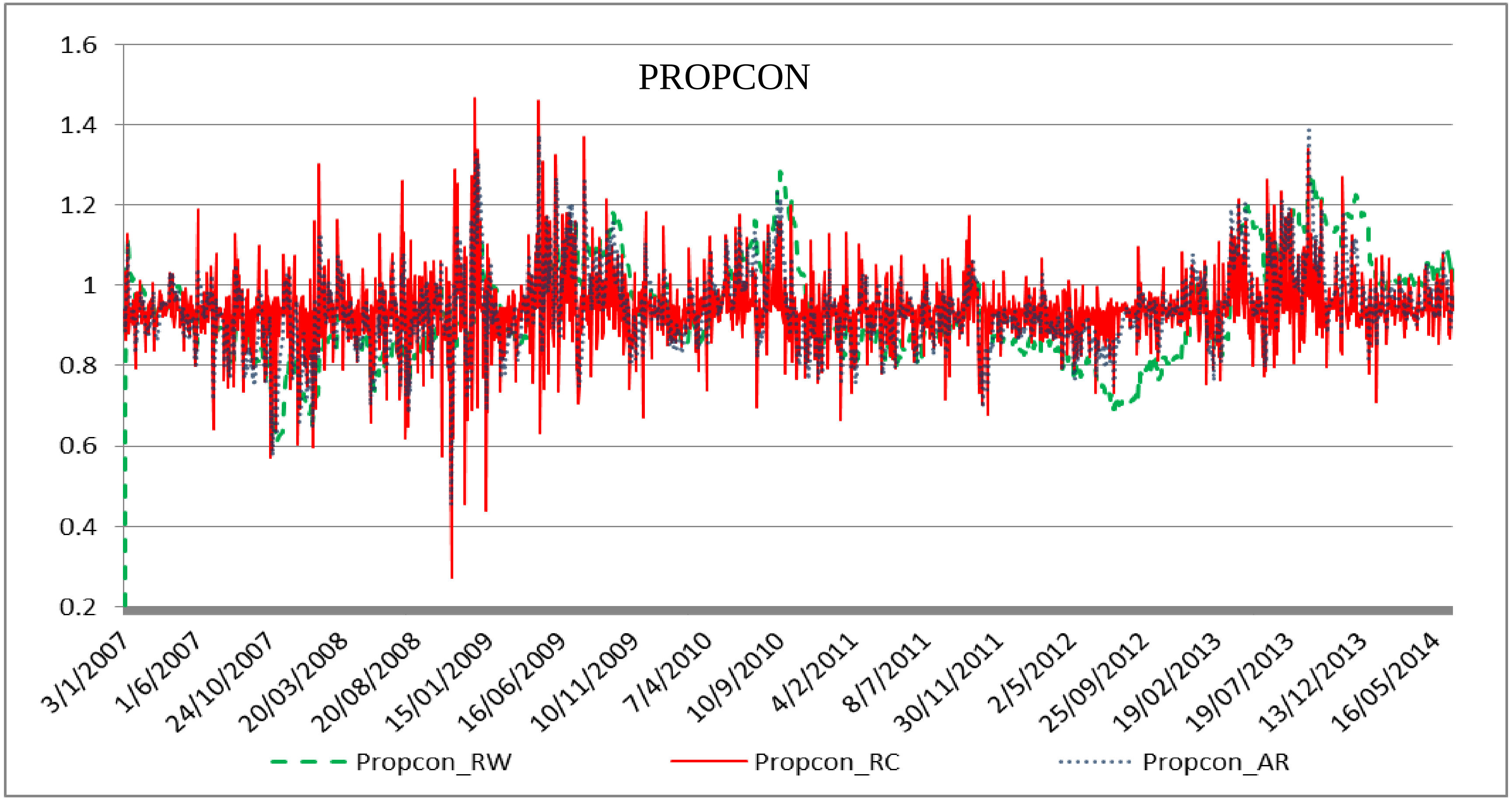

Figure 4.6 Kalman Filter Models: PROPCON Industry Beta Plotted

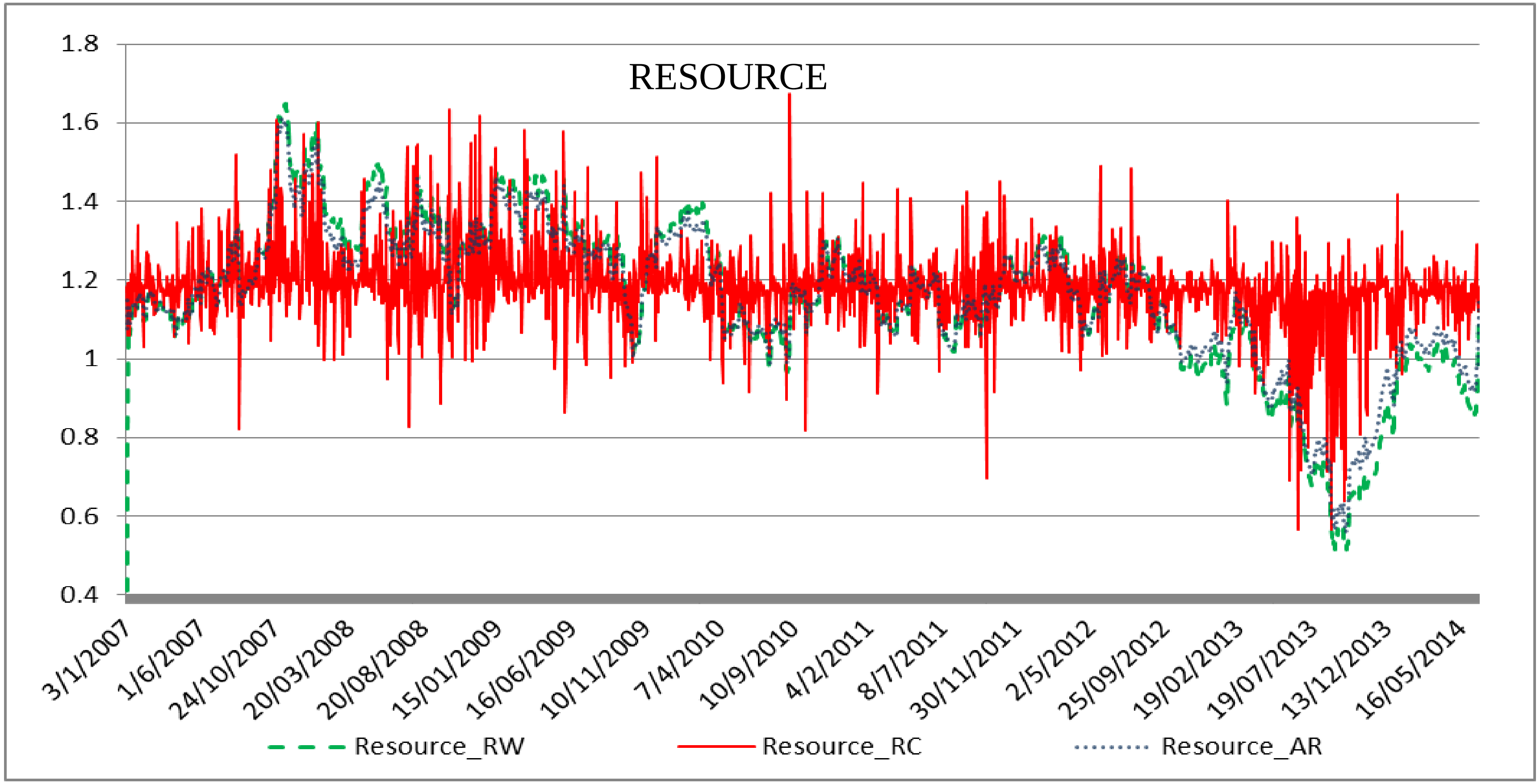

Figure 4.7 Kalman Filter Models: RESOURCE Industry Beta Plotted

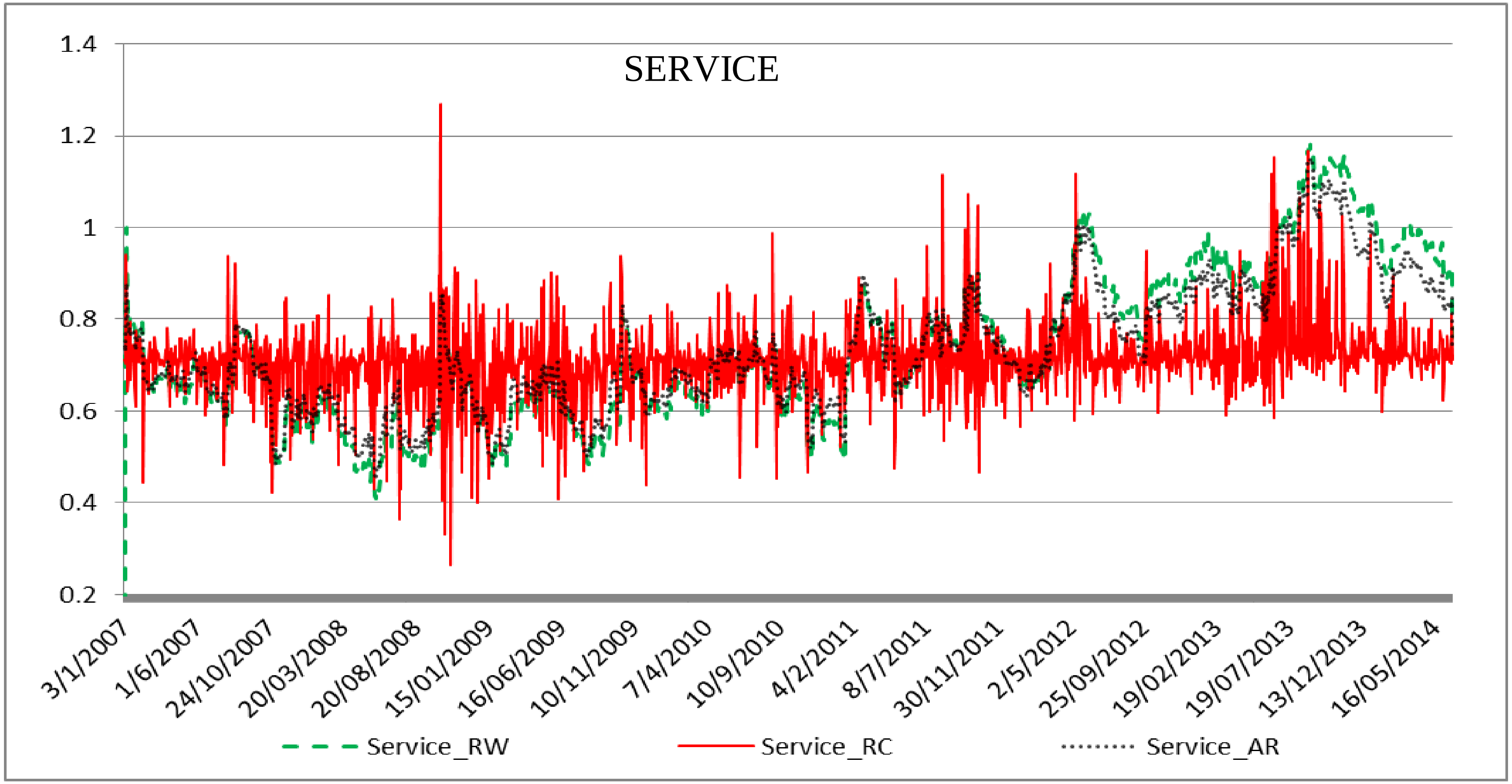

Figure 4.8 Kalman Filter Models: SERVICE Industry Beta Plotted

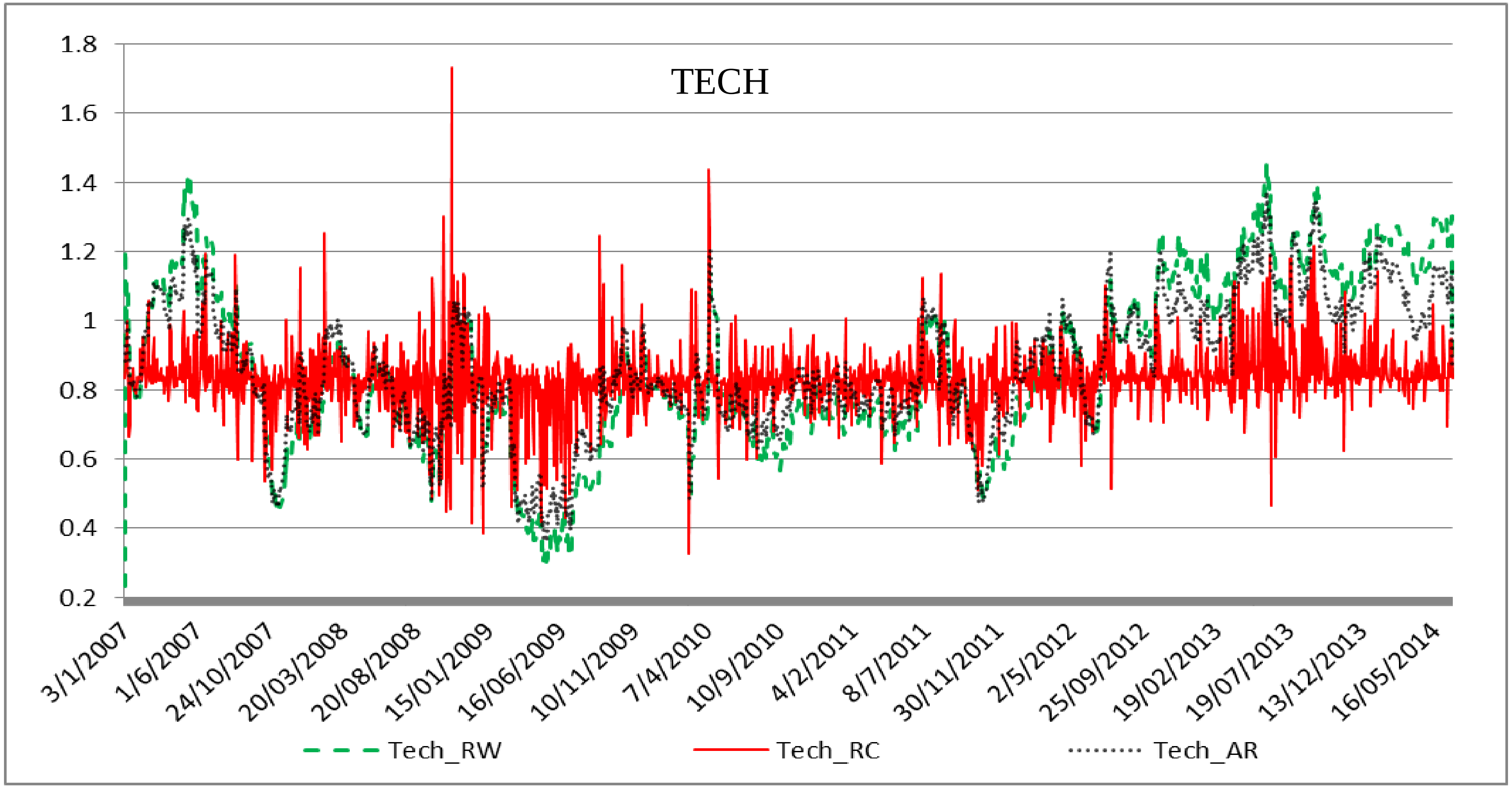

Figure 4.9 Kalman Filter Models: TECH Industry Beta Plotted

In the agriculture and food product equity sector, the time varying betas from the Kalman filter in these three models varied from 0.2 to 1.0. The betas from the random coefficient model were seen to be the most volatile beta. However, an increasing trend can be observed from June 2009 to September 2010 with the random walk and AR(1) model. This increase in the beta in that particular period can be explained by the rise in pork prices and agriculture products in that year. This trend is also consistent with the pattern of time varying beta from the rolling beta estimate in chapter 2 and the multivariate GARCH model in chapter 3.

The consumer product equity sector had the lowest time-varying beta among the others. Normally, the beta swings around 0.2 but there are some spikes of time-varying beta in some periods. In this equity sector, the betas from the random coefficient were still the most volatile among these three models. The time-varying beta from the AR(1) model and the random coefficient model had a similar pattern for this equity sector, while the time-varying beta from the random walk model provided a slightly increasing trend in this equity sector, which is consistent with the results from chapter 2 and chapter 3.

The financial equity sector had an average beta at around 1.1. The range of the beta is normally around 0.8 to 1.4. The time-varying beta from the random coefficient model still be the most volatile beta followed by the AR(1) model. The largest swing period of the beta in this equity sector was from September 2008 to February 2009. It can be observed, according to the plot that the beta from the random coefficient model and the AR(1) model, that the plot of the beta fluctuated dramatically along that period. Further, the beta from the random walk model also showed both a sharp increasing and decreasing trend in this short period. One explanation of this event may be the effect of the hamburger crisis in that period. Moreover, there was the increasing trend from April 2010 to November 2011, which was observed in the plot as well.

Normally the time-varying beta in the industrial equity sector swings at around 0.9 to 1.0. The pattern of the beta from random coefficient and AR(1) still went along the same direction. There was a slightly decreasing trend during the end of 2008 to the beginning of 2009.

The range of the fluctuation for the time-varying beta in property and construction material equity sector is normally from 0.6 to 1.2. The average beta is around 0.95. The time-varying beta was still the most fluctuating beta among these three models, followed by the AR(1) model. Moreover, the beta from the random walk model in this equity sector also went with the trend of these prior two models, but the beta from the random walk was better in providing a clear trend and did not show a large fluctuation. The beta from the end of 2008 to the beginning of 2009 still was the most volatile period due to the hamburger crisis. However, an increasing trend of the beta was observed from 2007 to 2010. This equity sector was on a rising trend again from September 2012 before going down again at the beginning of this year.

The resource equity sector is one of the main equity sectors and is usually called the market driver. The time-varying beta from the random coefficient fluctuated along the time and did not show the well-defined trend of the systematic risk of this equity sector. However, the time-varying beta from the random walk and AR(1) went together and illustrated a distinct trend. A decreasing trend in the time-varying beta of this equity sector can be observed obviously from the end of 2012 to the end of 2013 before going up again at the beginning of 2014.

The service equity sector also has the time-varying beta from the random coefficient model as the most volatile beta. The beta from the AR(1) and random walk model went together and showed an increasing trend after 2009. In contrast with the resource equity sector, this equity sector is on the rising trend and we can observe a dramatic increasing of the beta at the end of 2013.

Normally, the technology equity sector has an average beta at around 0.8. The beta swings from 0.4 to 1.4, which is quite a large range. As can be observed from the time-varying beta from AR(1), there was an obvious increasing trend in the systematic risk of this equity sector from the end of 2011. However, there was a decreasing pattern many times during the period. One explanation is that the main companies and sector in this equity sector are mobile phone service providers and the price of the stocks was highly sensitive to 3G news in Thailand during the period.

From the results of these three models using the Kalman filter method, the trend of systematic risk in each equity sector can be seen better than using the OLS. This is one of the contributions of the Kalman filter in relation to time-varying beta estimations.

CHAPTER 5

COMPARISON OF FORECASTING ACCURACY

5.1 Measure of Forecasting Accuracy

The objective of this chapter is to evaluate the performance of time-varying betas using the various methods that were illustrated in previous chapters, which are the Rolling OLS, the multivariate GARCH VECH model, the multivariate GARCH BEKK model, the Kalman filter AR(1) model, the Kalman filter random coefficient model, and the Kalman filter random walk model. To evaluate the forecasting accuracy of all time-varying betas, this study assessed the accuracy by using two groups of samples, in-sample forecasting and out-sample forecasting, and the measures of forecasting accuracy techniques that are normally used can be separated into two groups, relative measures and absolute measures. This study will cover both groups by including the root mean squared error (RMSE) and the mean absolute error (MAE) in the test. The MAE and the RMSE can be used together to diagnose the variation in the errors in a set of forecasts. The RMSE will always be larger or equal to the MAE; the greater difference between them, the greater will be the variance in the individual errors in the sample. If the RMSE=MAE, then all of the errors are of the same magnitude.

The root mean square error (RMSE), also named the root mean square deviation, (RMSD) is regularly used to determine the difference between the values predicted by a model and the values actually observed from the data. The RMSE of a model prediction compared to the estimated variable X_{model} is defined as the square root of the mean squared error. The formula for the RMSE calculation is shown below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

When X_{obs} is observed values at time i

X_{model} is modelled values at time i

The RMSE values can be used to differentiate and comparethe model performance of the individual model to that of other predictive models. Moreover, it can be used to evaluate the forecasting performance of one model in different periods of time as well.

The mean absolute error (MAE) calculates the average magnitude of the errors in forecasting without reflecting the direction of error. The calculation of the MAE is relatively simple. It is the summation of the magnitudes of the error divided by the number of observations, meaning the average of the magnitude ofthe error of the model. The formula for the MAE calculation is shown below.

$$MAE = \frac{\sum \left\| X_{obs,i} - X_{\mathrm{mod}el,i} \right\|}{n}$$

When $X_{obs,I}$is observed values at time i

$X_{model}$is modeled values at time i

Both the root mean square error (RMSE) and the mean absolute error (MAE) are regularly used in model evaluation studies. However, there are some studies that suggest using the MAE instead of the RMSE (Willmott and Matsuura, 2005) because the RMSE is not a good indicator of average model performance and it might be a misleading indicator of average error, and thus the MAE would be a better metric for that purpose. Nevertheless, in this study, I used both RMSE and MAE for accuracy forecasting performance purposes.

5.1.1 In-sample Forecasting

In-sample analysis means estimating the model using all of the available data, which is the same set of data that are used in beta estimation or modeling. The same set of data is used in evaluation of accuracy of forecasting and then compares the model's fitted values to the actual realizations. Nevertheless, this process is known to be excessively optimistic in terms of the model's forecasting ability since common fitting algorithms. The results of the root mean squared error (RMSE) and mean absolute error (MAE) of each method are shown in table 5.1.

As can be seen in table 5.1, the results mostly show consistency between the relative error measurement and the absolute error measurement. First, the forecasting accuracy between the two models of multivariate GARCH was compared. In most of the cases, the multivariate GARCH VECH model provided smaller or equal values of both the RMSE and MAE than the BEKK model except in the financial equity sector (FIN). This result implies that the VECH model is superior to the BEKK model in terms of in-sample forecasting. Next, the accuracy of the forecasting for the Kalman filter model was assessed. Most of all, the RMSE and MAE of the Kalman filter RC model and the RW model were quite similar and larger than the values of the Kalman filter AR(1) model. It was found that there were six of eight industries in which the Kalman filter AR(1) model had the lowest MAE, except the agriculture product equity sector (AGRO) and service

Table 5.1 In-sample RMSE and MAE

	Root Mean Squre Error (RMSE)						Mean Absolute Error (MAE)					
Index	OLS	VECH	BEKK	KF_AR	KF_RC	KF_RW	OLS	VECH	BEKK	KF_AR	KF_RC	KF_RW
AGRO	0.00815	0.00812	0.00812	0.00785	0.00816	0.00757	0.00617	0.00615	0.00615	0.00597	0.00615	0.00574
CONSUMP	0.00550	0.00540	0.00544	0.00546	0.00550	0.00552	0.00395	0.00385	0.00390	0.00388	0.00392	0.00392
FINANC	0.00643	0.00643	0.00631	0.00636	0.00634	0.00637	0.00495	0.00496	0.00488	0.00492	0.00492	0.00493
INDUS	0.00900	0.00901	0.00910	0.00914	0.00928	0.00928	0.00678	0.00680	0.00687	0.00688	0.00699	0.00699
PROPCON	0.00530	0.00527	0.00527	0.00533	0.00545	0.00546	0.00404	0.00402	0.00402	0.00405	0.00415	0.00415
RESOURCE	0.00643	0.00640	0.00658	0.00647	0.00667	0.00667	0.00483	0.00481	0.00494	0.00488	0.00496	0.00496
SERVICE	0.00600	0.00600	0.00600	0.00611	0.00606	0.00606	0.00452	0.00453	0.00453	0.00459	0.00455	0.00455
TECH	0.01044	0.01041	0.01043	0.01036	0.01049	0.01049	0.00773	0.00770	0.00770	0.00760	0.00773	0.00773

equity sector (SERVICE). Therefore, the Kalman filter AR(1) model was inferred to be the best forecasting performance model among these three models of the Kalman filter in terms of in-sample forecasting.

After that, the forecasting accuracy of two best models from the two methodologies was compared using the rolling OLS. When comparing the performance between the VECH model and Rolling OLS, it was found that the VECH model was superior to the rolling OLS for most of industries, except the industrial equity sector (INDUS), where both the RMSE and MAE obtained a slightly larger value than the value of the rolling OLS. Next, this study compared the performance of the Kalman filter AR(1) model, which is the best forecasting model among the three models of the Kalman filter, with the rolling OLS. The results did not show a significantly better performance since there were four of eight equity sectors in which the Kalman filter AR(1) model delivered a lower RMSE and MAE than the rolling OLS. However, for the equity sectors, the Kalman filter AR(1) model provided a lower RMSE and MAE, and these values of error were significantly low when compared to the rolling OLS. Next, this study compared the capability of forecasting between the multivariate GARCH VECH model and the Kalman filter, and it was shown that for five of the eight industries the multivariate GARCH VECH modelhad a lower RMSE and MAE. The exceptions were the consumer product equity sector (CONSUMP), financial equity sector (FIN) and the technology equity sector (TECH), which were the same three of four industries where the Kalman filter AR(1) model performed better than the rolling OLS model. In next section, we will try to see the pattern of systematic risk in these industries to explain why the Kalman filter AR(1) model only performed better in these groups of industries. From the overall results of in-sample forecasting, we can infer that the multivariate GARCH VECH model is superior to the rolling OLS for most of the industries. However, the Kalman filter AR(1) model showed a significantly lower error of forecasting than the rolling OLS.

5.1.2 Out-sample Forecasting

Out-sample forecasting is commonly used for examining the performance of the model in terms of being useful for forecasting a target variable. For the step of the out-sample forecasting in this study, the first 600 observations of data were placed into a group and the first beta using the various models that was mentioned was estimated to forecast the return of these industries at the 601st observation. Next, the window of 600 observations was rolled over, and the 2nd to 601st observation was selected to forecast the return at the 602nd observation and the process continued. Finally, we can compare both the RMSE and MAE of the rolling OLS, the multivariate GARCH VECH model, the multivariate GARCH BEKK model, the Kalman filter AR(1) model, the Kalman filter RC model, and the Kalman filter RW model in the same way as with in-sample forecasting, but the out-sample accuracy of the forecasting can help us compare the performance of the model and better forecast the beta. The results for the RMSE and MAE of these various models using out-sample forecasting are shown in table 5-2 below.

Table 5.2 Out-sample RMSE and MAE

	Root Mean Squre Error (RMSE)						Mean Absolute Error (MAE)					
Index	OLS	VECH	BEKK	KF_AR	KF_RC	KF_RW	OLS	VECH	BEKK	KF_AR	KF_RC	KF_RW
AGRO	0.00817	0.00822	0.00822	0.00816	0.00817	0.00817	0.00617	0.00622	0.00622	0.00617	0.00617	0.00617
CONSUMP	0.00547	0.00546	0.00547	0.00542	0.00546	0.00547	0.00390	0.00388	0.00389	0.00386	0.00390	0.00390
FINANC	0.00635	0.00643	0.00642	0.00636	0.00635	0.00638	0.00492	0.00495	0.00495	0.00493	0.00492	0.00493
INDUS	0.00929	0.00908	0.00906	0.00915	0.00928	0.00928	0.00700	0.00681	0.00681	0.00689	0.00700	0.00700
PROPCON	0.00546	0.00532	0.00533	0.00533	0.00545	0.00546	0.00415	0.00404	0.00405	0.00405	0.00415	0.00415
RESOURCE	0.00667	0.00644	0.00645	0.00647	0.00667	0.00667	0.00496	0.00484	0.00485	0.00488	0.00496	0.00496
SERVICE	0.00605	0.00599	0.00603	0.00610	0.00605	0.00605	0.00455	0.00452	0.00453	0.00458	0.00454	0.00454
TECH	0.01049	0.01046	0.01043	0.01035	0.01049	0.01049	0.00773	0.00769	0.00769	0.00758	0.00772	0.00772

Most of the results from the out-sample forecasting were consistency between the relative error measurement (RMSE) and absolute error measurement (MAE) as with the in-sample forecasting. First, the accuracy of the forecasting was compared between the VECH model and BEKK model of the multivariate GARCH method. The results showed that the MAE of VECH models were lower than the MAE of the BEKK model for all industries. However, when comparing the RMSE of these two models, not all of the cases of the RMSE of VECH models were lower than the RMSE of the BEKK model. Five of eight industries showed consistent results, except for the industrial equity sector (INDUS) and technology equity sector (TECH). The results also implied the same as with the in-sample forecasting that the VECH model was superior to the BEKK model of the multivariate GARCH. Next, the accuracy of forecasting in the Kalman filter model was compared and the results showed that most of the cases of the Kalman filter RC model and RW model contributed a similar value of the RMSE and MAE and were mostly larger than the AR(1) model. There were six of eight industries where the Kalman filter AR(1) model had the lowest RMSE and MAE, except for the financial equity sector (FIN) and service industries(SERVICE). This is the similar to the results from in-sample forecasting where the Kalman filter AR(1) model was the most accurate forecasting model among these three Kalman filter models. After that, this study compared the performance between the VECH model and rolling OLS, and it was found that the VECH model was superior to the OLS for most of the industries except for the agriculture product equity sector (AGRO) and financial equity sector (FIN), in both of which the RMSE and MAE obtained slightly larger values. Next I compared the accuracy of forecasting between the Kalman filter AR(1) model and the rolling OLS. The results were consistent with the comparisons among the Kalman filter. Only the financial equity sector (FIN) and service equity sector (SERVICE) showed that the Kalman filter AR(1) Model provided higher RMSE and MAE than the rolling OLS. Nevertheless, the RMSE and MAE from the remaining two models, which were the RC and RW, were lower than the rolling OLS for these two industries. This suggests that Kalman filter estimation was superior to the rolling OLS in terms of accuracy of return forecasting. In conclusion, the multivariate GARCH VECH model and the Kalman filter AR model were superior to the rolling OLS for most cases.

5.2 Comparison of Time-varying Beta Plot

In addition to the measurement of forecasting accuracy, we can observe the volatility of the beta by comparing the beta plotted among the three methodologies. This section will plot the time-varying beta by comparing the best beta estimated model from each methodology and the OLS by using only the out-sample forecasting beta and comparing this with the results of the accuracy forecasting in section 5.1 to see the relationship of the beta-estimated trend and performance of each model.

Overall, the beta from the out-sample estimation had a different pattern from the in-sample plot in the previous chapters. When we roll the window of observation over by removing the oldest data and adding the newer one into the sample, the result showed better performance in forecasting, as the set of data used to estimate was recent. Moreover, in terms of plotting, we can observe the smoother plot of the beta which is more useful for trend forecasting and the prediction of each equity sector systematic risk.

The plots of all eight industries had a similar pattern. The rolling OLS from the out-sample forecasting was much smoother than that of the in-sample plot. On the other hand, this was similar to the average of beta forecasting from the multivariate GARCH and Kalman filter. The time-varying beta of the Kalman filter oscillated along the beta from the rolling OLS and the highest volatile beta was from the multivariate GARCH VECH model. The pattern and trend of each equity sector are explained below.

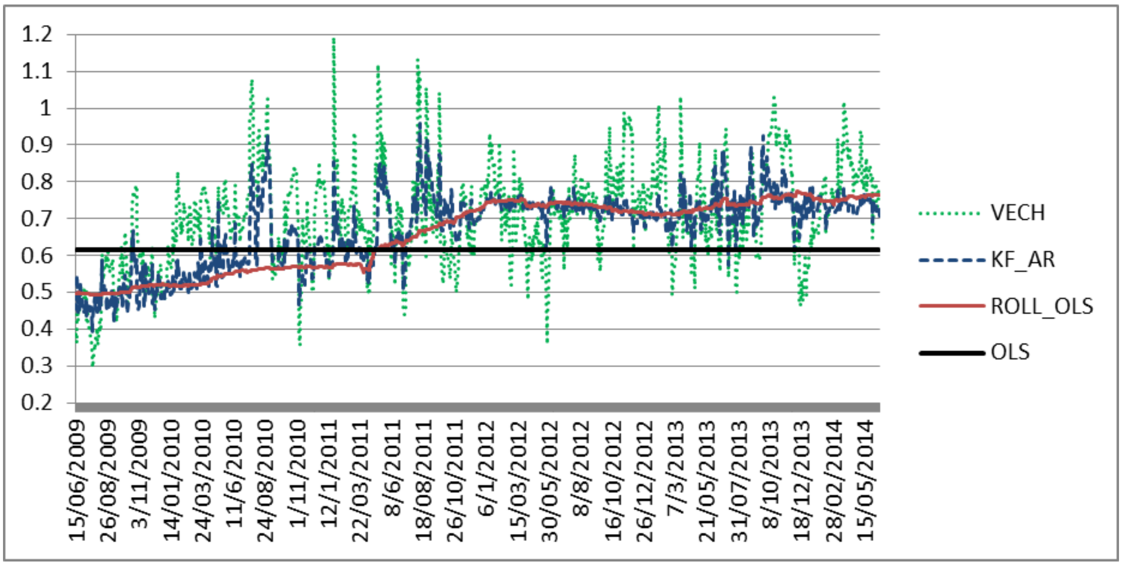

Figure 5.1 Comparison of AGRO Beta among Three Methodologies

According to the plot in figure 5.1, the time-varying beta of the agriculture product equity sector saw an obvious increasing trend from 2009 to the beginning of 2012 and remained steady around 0.75 until mid-year of 2014. This shows interesting evidence concerning the increasing trend of systematic risk for this equity sector. The time-varying beta from the multivariate GARCH VECH model was the most volatile beta when compared to the Kalman filter and rolling OLS. There were many spikes and dramatic changes of the beta in this model. Regarding the time-varying beta of the Kalman filter, the time-varying beta had a volatile pattern and quick response in the beta as well, but the range of volatility was not quite as large as with the VECH model. However, for the rolling OLS, the time-varying beta looked like a trend line—there was no response for the short-term event from this model.

The accuracy performance confirmed that both the RMSE and MAE of the multivariate GARCH VECH model provided the highest values, while the Kalman filter AR model provided the lowest values using out-sample forecasting. This implies that the quick response model but not large volatility as Kalman filter AR model was a good estimator for this equity sector.

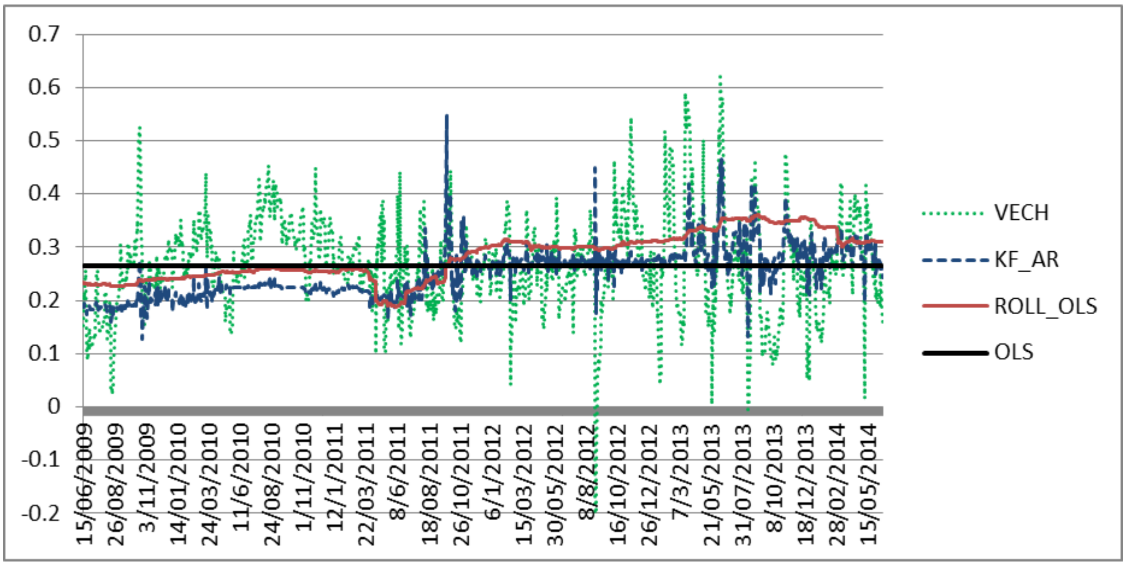

Figure 5.2 Comparison of CONSUMP Beta among Three Methodologies

There was no obvious trend of beta for this equity sector according to the nature of business in this equity sector itself. Therefore, there was a slight move up and down of the beta in a short period of time. As seen in section 5.1, the Kalman filter AR model provided the lowest RMSE and MAE for both the in-sample and out-sample forecasting. When we take a look at the beta plotting, the Kalman filter AR model had the highest volatile beta compared to the others while the beta from the multivariate GARCH VECH model and rolling OLS showed a similar pattern.

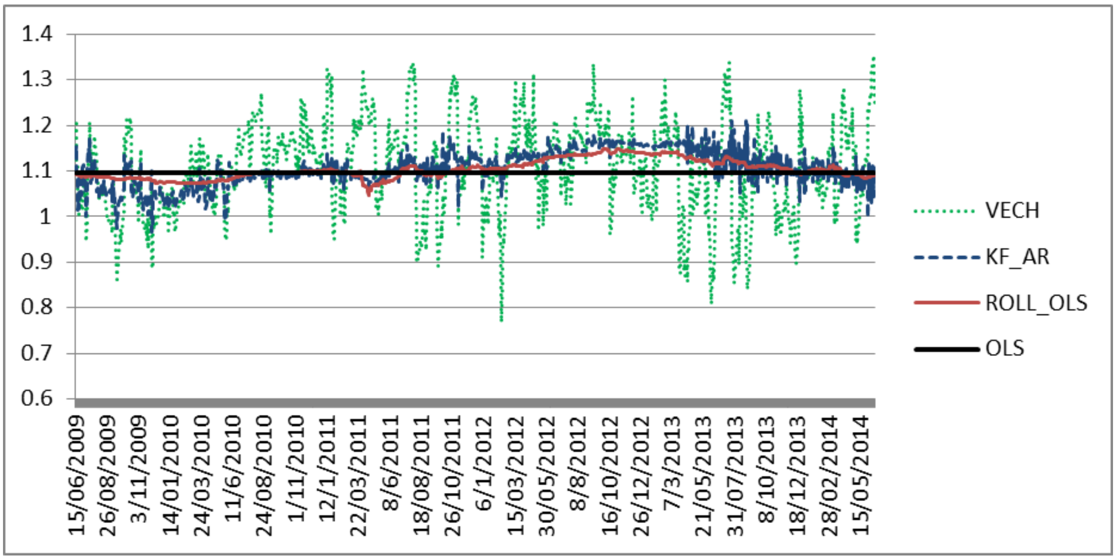

Figure 5.3 Comparison of FIN Beta among Three Methodologies

Again, from the plot, we can observe that the multivariate GARCH VECH model was the most volatile beta and not surprisingly it provided the highest RMSE and MAE using out-sample forecasting. The second volatile time-varying beta plot was the Kalman filter AR(1) model. The results from the accuracy forecasting were also consistent. Both the RMSE and MAE of this model had the second highest values among the three models. Finally, when we observe the plot of the rolling OLS, the time-varying beta of the financial equity sector was similar to the horizontal line but there existed a slight moving up at the beginning of 2010 to the first quarter of 2013. The results of the RMSE and MAE from section 5.1 show that this model was the superior model regarding the out-sample forecasting of the financial equity sector. These results are consistent with the pattern of the beta. Therefore, the lowest volatile beta suited the financial equity sector time-varying systematic risk forecasting.

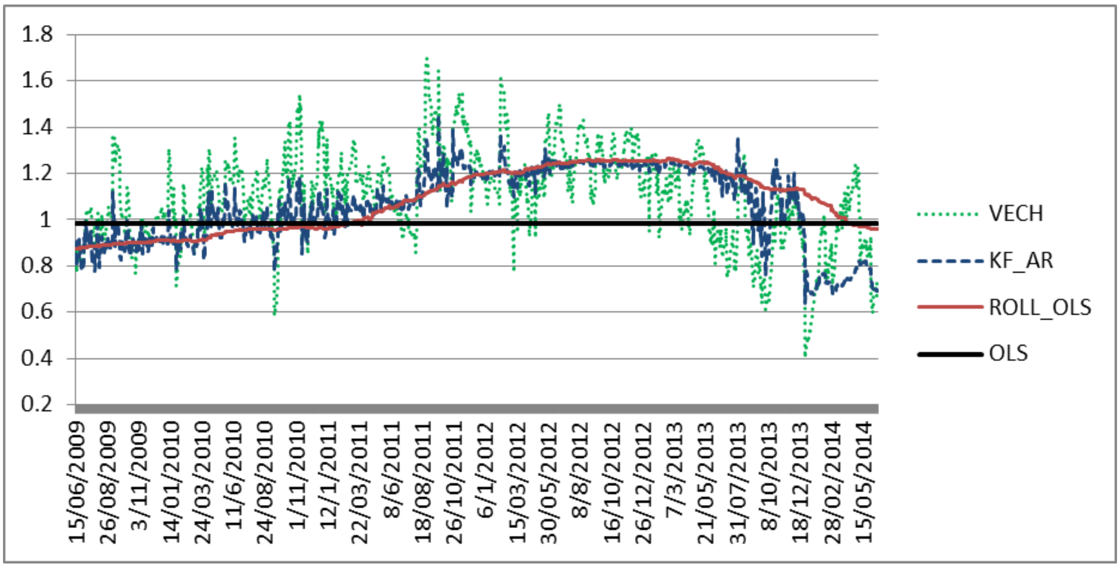

Figure 5.4 Comparison of INDUS Beta among Three Methodologies

The pattern of the beta plot of this equity sector was similar to the others. The most volatile beta was the multivariate GARCH VECH model, while the Kalman filter AR model had a smaller range of volatility and the rolling OLS provided the trend line of the beta. The best estimator considered from the lowest RMSE and MAE model was the multivariate GARCH VECH model which showed the highest swing of the beta along the period. When we take a look closely, we can observe that the multivariate GARCH VECH model RMSE and MAE were much lower than the other two models, which means that the quick response to the market sentiment model was a good model for the time-varying forecasting of this equity sector.

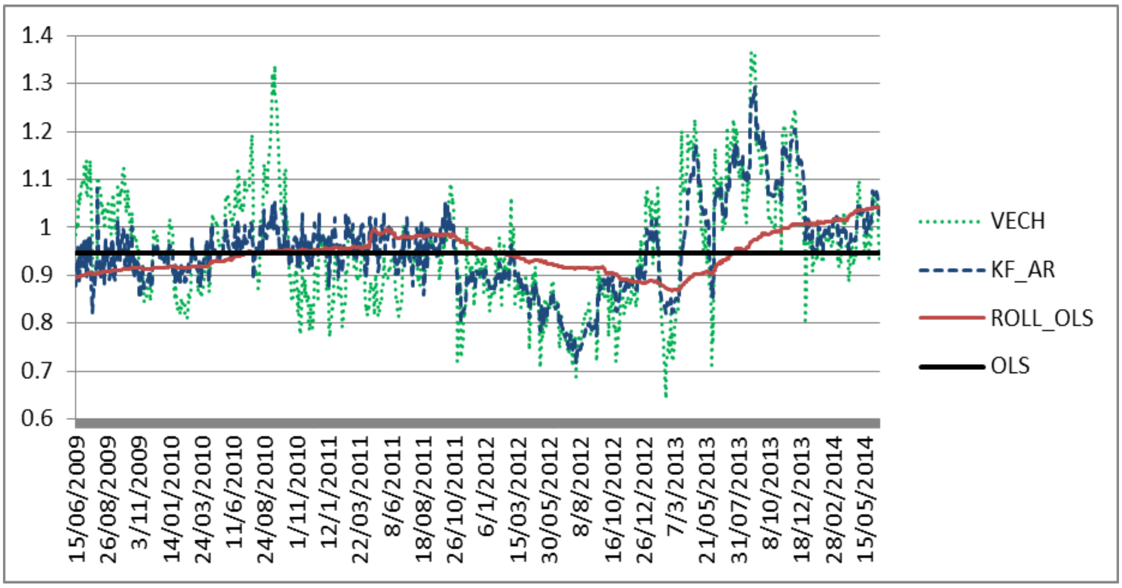

Figure 5.5 Comparison of PROPCON Beta among Three Methodologies

This equity sector presented good evidence of the time-varying beta from the multivariate GARCH and Kalman filter. According to the time-varying beta plot in figure 5.5, we can observe the obvious decreasing trend of the beta in the property and construction equity sector since the end of 2011 using the multivariate GARCH VECH model and Kalman filter AR(1) model. The beta plot also shows the recovery of this equity sector from the third quarter of 2012 until the end of 2013. However, when considering the beta from the rolling OLS, the time-varying beta of this model response was too slow for the impact of the market. The pattern of declining trend occurred in a narrow range and quite late from the real situation. When this pattern aligns with the accuracy forecasting performance from section 5.1, the RMSE and MAE values of the multivariate GARCH and Kalman filter were similar and much lower than the rolling OLS, which confirmed the superiority of these two models over the rolling OLS.

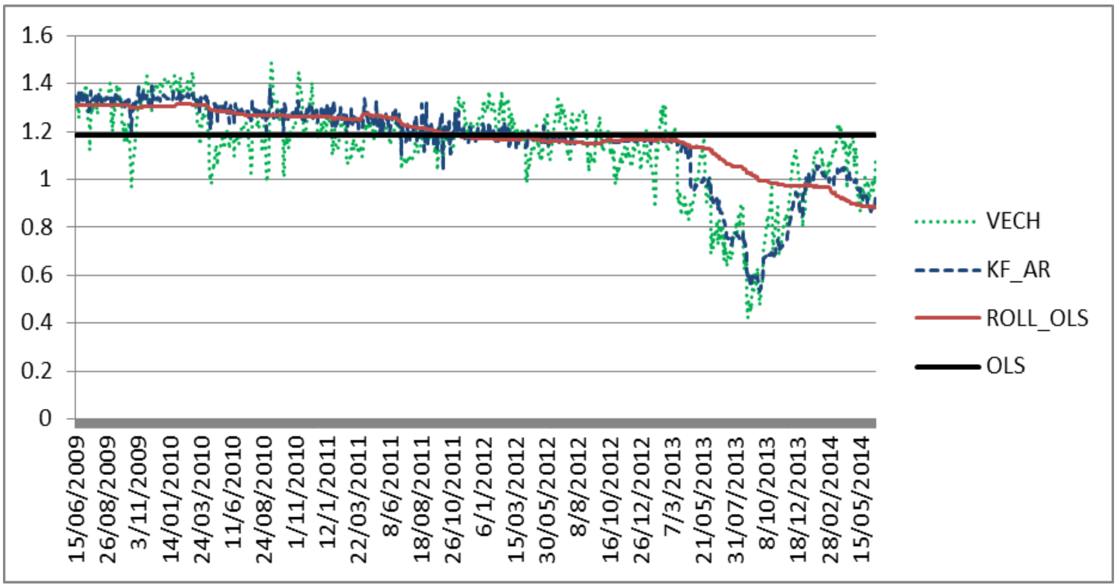

Figure 5.6 Comparison of RESOURCE Beta among Three Methodologies

The results for the time-varying beta plot and forecasting accuracy of the resource equity sector showed a similar pattern to the results from the property and construction equity sector. According to the plot of the rolling OLS, the time-varying beta showed a down trend and this continued, as there was no signal of increasing trend from the plot. However, when we take a look at the Kalman filter AR(1) model and the multivariate GARCH VECH model, it can be seen that the time-varying beta dramatically decreased from the second quarter of 2013 until recovering again in the third quarter. For the equity sector that has high impact in market movement as resource equity sector, the model that can provide the quicker response to the market, like the Kalman filter and multivariate GARCH, is more useful than the trend illustrator as the rolling OLS.

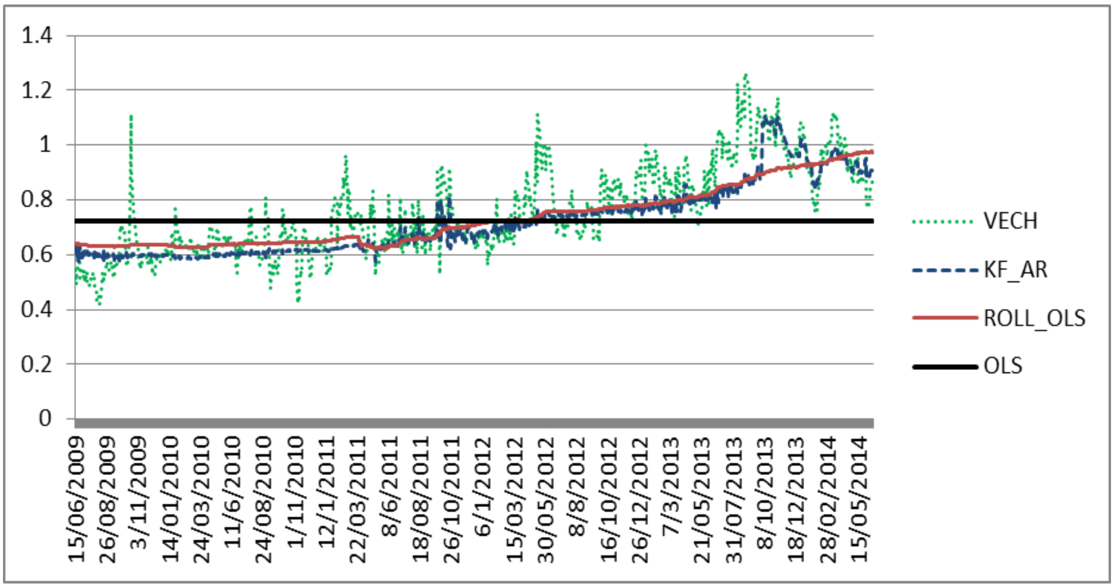

Figure 5.7 Comparison of SERVICE Beta among Three Methodologies

According to Figure 5.7, the time-varying beta of this equity sector showed an increasing trend. However, from the plot of the multivariate GARCH VECH model, there was a high jump period of the beta in the second quarter of 2012 and the third quarter of 2013. The pattern of the multivariate GARCH VECH model beta was quite volatile compared to the others and as can be seen in section 5.1, this model provided the lowest RMSE and MAE among the others using out-sample forecasting.

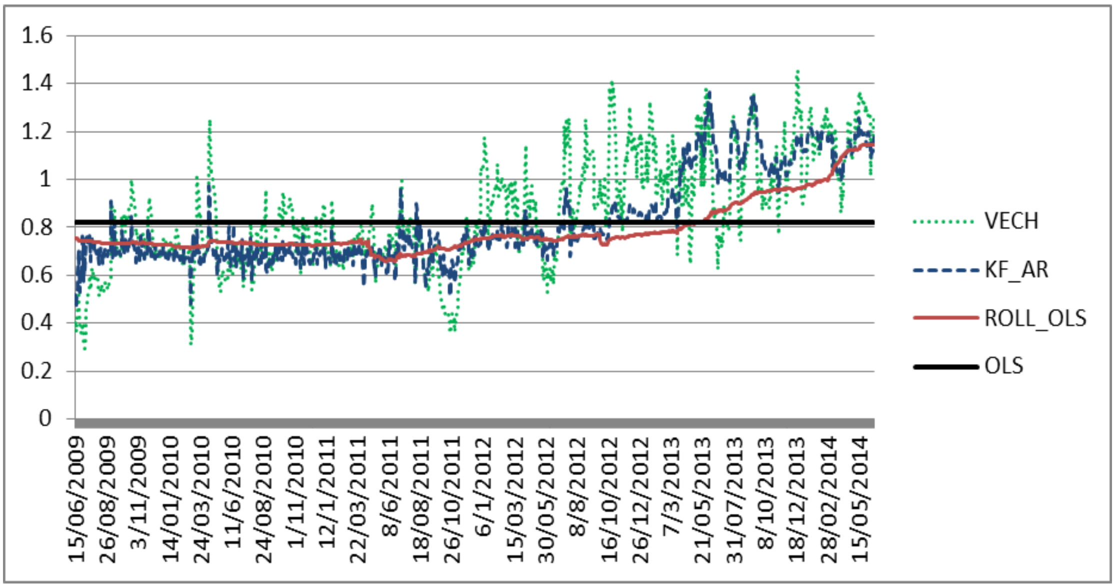

Figure 5.8 Comparison of TECH Beta among Three Methodologies

As seen in the plot, there was an increasing trend of the time-varying beta in the technology equity sector. Moreover, according to the multivariate GARCH VECH model, the systematic risk of this equity sector was quite volatile since mid-year of 2011. The time-varying beta moved up and down along the period but tended to show an increasing trend. For the Kalman filter AR(1) model, the beta was slightly going up until the second quarter of 2013. After that there was high volatility but an increasing trend as well. According to history, technology is one of the most volatile industries. Therefore, the model that can capture the movement of the market risk quickly can be a good estimator for this equity sector.

According to the pattern beta estimated for each equity sector, the financial equity sector (FINANC), the industrial equity sector (INDUS), and the resource equity sector (RESOURCE) were the industries that provided a beta above one. This means that the systematic risk of these industries was higher than the market risk. On average, the others provided a beta lower than one, which means that they provided lower systematic risk than the market. The equity sector that provided the lowest beta among the other industries was the consumer product equity sector (CONSUMP). Therefore, the time-varying betas of this equity sector were quite stable when compared to other industries. On the other hand, the highest beta was for the resource equity sector (RESOURCE), which had a beta around 1.2 using the OLS estimation. The resource equity sector contained two sectors: energy and mining. The energy sector was composed of oil companies and utility suppliers. In the past period, the oil price fluctuated all the time because of many problems, and as we know the energy sector is one of the most important sectors that drives the Thailand stock market. Therefore, it aligns with the intuitive sense that this equity sector will have higher systematic risk than the market.

In conclusion, the time-varying beta estimated by using the rolling OLS was quite smoother than both the multivariate GARCH model and the Kalman filter model. This means that the rolling OLS provided a slower response to market volatility than the others. In addition, all of the betas from the rolling OLS, multivariate GARCH, and Kalman filter AR model varied along with static beta from the OLS in all industries. However, even though the rolling OLS showed a moving up and down pattern of the systematic risk in each equity sector, and the multivariate GARCH and Kalman filter model could catch up to the volatility quicker than the rolling OLS as can be seen from the graphs—showing that the beta for the multivariate GARCH VECH model and Kalman filter AR(1) model showed a spike along the period while the rolling OLS beta did not present a large move of the beta. Moreover, according to the plots, the multivariate GARCH VECH model tended to provide the highest volatile beta. Therefore, portfolio managers that need rapid adjustment in their portfolio may consider using this beta model to vary their portfolio.

CHAPTER 6

CONCLUSION

According to modern finance theory, systematic risk, which means the risk that associate with market returns, is extremely important risk because it is the only type of risk that cannot be reduced through diversification process and it is the only type of risk that should be rewarded. Financial risk estimation methodologies have developed extensively over the last decades. In particular the evaluation and prediction of betas have become a quite important topic in financial research (Bentz and Connor, 1998; Brooks et al., 1998). Much research has attempted to find appropriate models to quantify systematic risk or beta, and the evolution of betas can follow many alternative methodologies subject to the model assumptions (Black, 1993; Bollerslev, Engle and Woolridge, 1988). The most commonly-used estimation technique is theory ordinary linear regression, which assumes parameter constancy over the historical sample period often limited by practitioners to a fixed historical window (Bramante and Gabbi, 2006). However, there is the assumption that the expected returns of investors vary through time. Therefore, the beta that varies through time is estimated through the new techniques in order to quantify the time-varying beta.

The data used in the study were the closing price of eight equity sector indexes and the SET index of Thailand’s stock market from January 2007 to June 2014. First, this study began by estimating the static beta using ordinary least squares to see the characteristics of each equity sector in Thailand’s stock market. The results of the static beta were complied with the characteristics of each equity sector. Consumer product (CONSUMP) had the lowest beta among all industries, which implies that this equity sector had the lowest systematic risk and a low correlation with the market, while the largest beta was found in the resource equity sector (RESOURCE), which is well-known as the market driver of Thailand’s stock market. The results also proved that simple ordinary least squares estimation exhibited a heteroskedasticity problem and also autocorrelation. Therefore, the model that allows for the varying of variances such as the GARCH model is a proper model for estimating the beta. After that, since the main objective of this study was finding a way to estimate time-varying systematic risk more precisely, this study improved the ordinary least squares method by using the rolling OLS, where the observations were placed in a small group or window in order to estimate the beta. Next, this window was rolling, the oldest observation was removed from the data set and replaced by the new observation. This process can produce a beta that varies through time and the trend of systematic risk for each equity sector can be observed better. However, there are two other widely accepted methodologies for estimating time-varying beta. The first methodology that properly captures the time-varying in the beta is the multivariate GARCH model. Because there are various forms of the multivariate GARCH, this study applied two models that are commonly used, the multivariate GARCH VECH model and the multivariate GARCH BEKK model, to estimate the time-varying beta. Moreover, asymmetry in covariance should also be taken into account in multivariate GARCH modeling. Both of these models were used to examine the ARCH effect and the results showed that, not surprisingly, all of the indexes showed a time-varying variance in both models. In addition, the results also followed the asymmetric responses of the market, which specify that the covariance will be higher during a market decline. Next the time-varying beta from the VECH and BEKK model was plotted to compare the patterns. The result showed that they had a similar trend of moving up or down but the VECH model tended to be more volatile than the BEKK in most of the industries. The second methodology was the Kalman filter. This study focused on three models of the Kalman filter: the Kalman filter with the random walk model, the Kalman filter with the random coefficient model, and the Kalman filter with the autoregressive model. The results showed that most of the equity sectors showed a time-varying pattern using the Kalman filter model except for the consumer product equity sector (CONSUMP). Next, this study plotted the time-varying beta estimated by these three models and found that the most volatile beta pattern was initiated by the random coefficient model.

This study also examined the forecasting accuracy for both the in-sample and out-sample of these models and compared their performance by calculating the representative and absolute error measurement which this study uses root mean square error (RMSE) and mean absolute error (MAE) as the representative. For the in-sample forecasting, the best estimator among the three methodologies, which were the rolling OLS, the multivariate GARCH, and the Kalman filter, was the multivariate GARCH VECH model according to most of the cases, this model produced the lowest RMSE and MAE. Moreover, when comparing the performance among the three models of the Kalman filter, the results showed that the Kalman filter AR(1) model performed the best. However, when comparing the RMSE and MAE of this model with the rolling OLS, the results did not show a significant finding. There were only four industries where the Kalman filter AR(1) model had a lower RMSE and MAE than the rolling OLS model. Therefore, in terms of in-sample accuracy forecasting, the multivariate GARCH VECH model performed the best among the three methodologies. Next, this study also examined the out-sample accuracy forecasting. The Multivariate GARCH VECH model also performed better than the BEKK model according to the mean absolute error (MAE). For most of the cases, the Kalman filter AR(1) model also performed better than the other two models—the random walk and random coefficient models. Moreover, when comparing the best estimator of these two methodologies with the rolling OLS, the results also confirmed that the multivariate GARCH VECH model and the Kalman filter AR(1) models were superior to the rolling OLS according to lower MAE and RMSE. However, the evidence concerning which methodology was the best estimator between the multivariate GARCH and Kalman filter was not clear. In some equity sectors, the Kalman filter obtained lower errors, while the results were opposite in some sectors as well. Next, this study also plotted the out-sample time-varying beta of the three models. The pattern for the beta plot was similar in every equity sector. The rolling OLS beta looked like the trend line. The out-sample time-varying betas were smoother than when this technique was applied to the beta estimation, as the window of data was larger. Regarding the multivariate GARCH VECH model time-varying beta plot, it was the most volatile beta of these three methodologies. It showed a pattern of high responsiveness to market impact. The last one was the plot of the

Kalman filter. This time-varying beta also showed a pattern of volatility but not as large as with the multivariate GARCH.

In conclusion, since a better understanding the market risk is an advantage for all investors and financial market participants in terms of challenging the volatility of the market time-varying betas, using the two methodologies—the multivariate GARCH and the Kalman filter—can improve the knowledge in this area. These two models performed better than the rolling OLS in terms of the accuracy of forecasting by contributing fewer errors and by showing a quicker response to market impact. This evidence can provide better tools for estimating time-varying beta. Investors can use this information in portfolio adjustment in order to improve the performance of their investments as well.

BIBLIOGRAPHY

Bekaert, Geert and Wu, Guojun. 2000. Asymmetric Volatility and Risk in Equity Markets. **The Review of Financial Study.** 13 (1): 1-42. Retrieved May 12, 2011 from http://finance.martinsewell.com/stylized-facts/volatility/ BekaertWu2000.pdf

Bey, Roger P. and Pinches, George E. 1980. Additional Evidence of Heteroscedasticity in the Market Model. **Journal of Financial and Quantitative Analysis.** 15 (2): 299-322. Retrieved Aug 30, 2012 from http://journals.cambridge.org/action/displayAbstract?fromPage= online&aid=4470872&fileId=S002210900000630X

Black, Fischer. 1972. Capital Market Equilibrium with Restricted Borrowing. **The Journal of Business.** 45 (3): 445-455. Retrieved May 12, 2011 from http://www.stat.ucla.edu/~nchristo/statistics_c183_c283/black_1972_artic le.pdf

Bollerslev, Tim; Engle, Robert F. and Wooldrige, Jeffrey M. 1988. A Capital Asset Pricing Model with Time-Varying Covariances. **Journal of Political Economy.** Retrieved May 26, 2011 from http://dukespace.lib.duke.edu:8080/dspace/ bitstream/handle/10161/1988/ Bollerslev_a_capital_asset.pdf?sequence=1

Bos, T. and Newbold, P. 1984. An Empirical Investigation of the Possibility of Stochastic Systematic Risk in the Market Model. **Journal of Business.** 57 (1): 35-41. Retrieved Aug 30, 2012 from http://www.economagic.com/UAB/vita/docs./JoB1984.pdf

Braun, Phillip A.; Nelson Daniel B. and Sunier, Alian M. 1995. Good News, Bad News, Volatility, and Betas. **The Journal of Finance.** 50 (5): 1573-1603. Retrieved Aug 30, 2012 from http://onlinelibrary.wiley.com/doi/ 10.1111/j.1540-6261.1995.tb05189.x/abstract

Choudhry, Taifoq and Wu, Hao. 2007. **Forecasting the Weekly Time-varying Beta of UK Firms: Comparison Between GARCH Models vs Kalman Filter Method.** Southampton: University of Southampton. Retrieved May 26, 2011 from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=963452

Cochrane, John H. 1999. **New Facts in Finance.** National Bureau of Economic Research Working Paper No. 7169, June 1999. Retrieved May 12, 2011 from http://faculty.chicagobooth.edu/john.cochrane/research/papers/ep3Q99_3.pdf

Ender, Walter. 2004. **Applied Econometric Time Series.** 2nd ed. Hoboken: John Wiley and Sons.

Engle, Robert F. and Kronos, Ng Victor. 1995. Multivariate Simultaneous Generalized Arch. **Econometric Theory.** 11 (1): 122-150. Retrieved May 27, 2011 from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.27.1240&rep=rep1&type=pdf

Engle, Robert F. and Ng, Victor K. 1993. Measuring and Testing the impact of News in Volatility. **The Journal of Finance.** 48 (5): 1749-1778. Retrieve Aug 30, 2012 from http://www.finance.martinsewell.com/stylized-facts/volatility/EngleNg1993.pdf

Fabozzi, Frank J. and Francis, Jack Clark. 1978. Beta as a Random Coefficient. **The Journal of Financial and Quantitative Analysis.** 13 (1): 101-116. Retrieved Aug 20, 2012 from http://www.jstor.org/stable/2330525

Fama, Eugene F. and MacBeth, James D. 1973. Risk, Return, and Equilibrium: Empirical Tests. **The Journal of Political Economy.** 81 (3): 607-636. Retrieved May 27, 2011 from http://efinance.org.cn/cn/fm/Risk,%20Return,%20and%20Equilibrium%20Empirical%20Test.pdf

Ghysels, Eric and Jacquier, Eric. 2006. **Market Beta Dynamics and Portfolio Efficiency.** University of North Carolina Kenan-Flagler Business School;Finance Department, HEC Montr´eal, CIREQ. Retrieved July 17, 2014 from http://people.bu.edu/jacquier/papers/betas.200610.pdf

Greene, William H. 2002. **Econometric Analysis.** 5th ed. Upper Saddle River, New Jersey: Pearson Education.

Grundy, Kevin and Malkiel, Burton G. 1996. Report of Beta's Death have been greatly Exaggerated. **The Journal of Portfolio Management.** 22 (3): 36–44. Retrieved May 12, 2011 from http://www.acsu.buffalo.edu ~keechung/Collection%20of%20Papers%20for%20courses/REPORTS %20OF%20BETA'S%20DEATH%20HAVE%20BEEN%20GREATLY %20EXAGGERATED.pdf

Gujarati, Damodar N. and Porter, Dawn C. 2009. **Basic Econometrics.** 5th ed. Boston: McGraw-Hill Irwin.

Hinich, Melvin and Roll, Rechard. 1981. Measuring Nonstationarity in Parameters of Market Model. **Research in Finance.** 3 (1): 1-15. Retrieved May 12, 2011 from http://hinich.webhost.utexas.edu/files/Statistics/Hinich-Roll.pdf

Ilmanen, Antti. 1995. Time-Varying Expected Returns in International Bond Markets. **The Journal of Finance**. 50 (2): 481-506. Retrieved Aug 30, 2012 from http://www.jstor.org/stable/2329416?origin=JSTOR-pdf

Koutmos, Gregory and Knif, Johan. 2002. Estimative Systematic Risk Using Time Varying Distributions. **European Financial Management.** 8 (1): 59-83. Retrieved March 31, 2011 from http://papers.ssrn.com/sol3/papers.cfm? abstract_id=308956

Lintner, John. 1965. Distribution of Incomes of Corporations Among Dividens, Retained Earnings, and Taxes. **The American Economic Review**. 46 (2): 97-113. Retrieved May 12, 2011 from http://links.jstor.org/sici?sici=0002-8282%28195605%2946%3A2%3C97%3ADOIOCA%3E2.0.CO%3B2-D

Markowitz, Harry. 1952. Portfolio Selection. **The Journal of Finance.** 7 (1): 77-91. Retrieved May 27, 2011 from https://www.math.ust.hk/~maykwok/ courses/ma362/07F/markowitz_JF.pdf

Meinhold, Richard and Singpurwalla, Nozer D. 1983. Understanding the Kalman Filter. **The American Statistician**. 37 (2): 123-127. Retrieved Jan 30, 2014 from http://www.jstor.org/stable/2685871?origin=JSTOR-pdf

Mossin, Jan. 1966. Equilibrium in a Capital Asset Market. **Econometrica.** 34, 4 (October): 768-783. Retrieved May 12, 2011 from http://www.jstor.org/stable/1910098?origin=JSTOR-pdf

Nieto, Belen; Orbe, Susan and Zarraga, Ainoha. 2014. **Time-varying Market Beta: Does the Estimation Methodology Matter?.** Retrieved Feb 13, 2013.from http://www.idescat.cat/sort/sort381/38.1.2.nieto-etal.pdf

Sharpe, William F. 1964. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. **The Journal of Finance.** 19 (3): 425-442. Retrieved May 10, 2011 from http://www.jstor.org/stable/2977928

Tse Yin Kuen and Tsui, Albert K. C. 2002. **A Multivariate GARCH Model with Time-Varying Correlations**. Retrieved May 10, 2011 from http://staff.mysmu.edu/yktse/VC_R2.pdf

Welch, Greg and Bishop, Gary. 2006. **An Introduction to the Kalman Filter.** University of North Carolina at Chapel Hill, Department of Computer Science, Retrieved Jan 30, 2014 from http://www.cs.unc.edu/~welch/media/pdf/kalman_intro.pdf

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