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Modeling Volatility and Interdependencies of Thai Rubber Spot Price Return with Climatic Factors, Exchange Rate and Crude Oil Markets

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Abstract

Thailand is a leading producer and exporter of rubber in the world market. The interdependencies and volatility of Thai rubber price return with climatic factors (precipitation and temperature), exchange rate, and crude oil market returns are determined in this paper. Vector autoregressive moving average process with generalized autoregressive conditional heteroscedasticity (VARMA-GARCH), VARMA with generalized autoregressive conditional heteroscedasticity (VARMA-AGARCH), and copula-based GARCH models were employed for the analyses. The results demonstrated the interdependencies of Thai rubber price return with dollar and crude oil returns as well as with crude oil return and climatic factors in the VARMA-AGARCH and the copula-based GARCH models, respectively. We conclude that the volatility of Thai rubber price return is linked with volatility in the exchange rate and crude oil markets as well as climatic factors. Thus, stakeholders in the rubber industry should consider movements in those markets when forecasting Thai rubber price returns. Using a set of robust approaches is also recommended to obtain a complete picture of the volatilities and interdependencies of the asset markets.

Keywords: Thai rubber spot price return, climatic factors, crude oil index return, dollar index return, VARMA-GARCH, VARMA-AGARCH model, Copula-based GARCH model.

1. Introduction

The rubber industry is one of the most important industries in Thailand. The total area occupied by the industry devoted to rubber is 219,933 hectares; in 2007, the industry also recorded an annual output of 3.056 million tons in 2007 (Office of the Rubber Replanting Aid Fund, 2008). Apart from Thailand, Malaysia and Indonesia are also considered major producers and exporters of rubber. The total rubber output of these three countries reached 8.32 million tons in 2007, accounting for 94% of the total world market (Office of the Rubber Replanting Aid Fund, 2008).

Rubber trees thrive in tropical climates with high temperature (e.g., 26 °C to 32 °C) and rainfall with average precipitation of 2000 mm or more. In the Southeast Asian region, rubber output varies according to the season: (a) output reduction is highest during the high dry period (February to April); (b) highest output is achievable during the monsoon period (May to June), (c) output is reduced to some extent during the mild dry period (August to October), and (d) an increase in output occurs during the high monsoon period (November to January).

Recently, crude rubber output has increased due to the assistance program

launched by the Thai government, which aimed to provide better options and varieties to farmers. Heavy monsoon in Thailand normally causes an annual increase in rubber output during the third and the fourth quarters, particularly in the southern regions that comprise the largest area of domestic rubber production. During the same period, rubber prices tend to decline due to the increase in supply.

In December 2008, the domestic price of rubber fell rapidly to only 43 baht per kg in 20 days. Originally, the purchase price of fresh rubber and the production cost were 70 baht and about 27 baht per kg, respectively. Thus, the total production cost of each kilogram of processed rubber should have been almost 97 baht. These figures indicated that farmers suffered a maximum loss of about 54 baht per kg of processed rubber.

Meanwhile, due to the economic recession in the USA, the Cooperative of the Thailand Rubber Farmers urged exporters to focus on China as a potential market for exporting rubber. The Thai Ministry of Agriculture also intervened by extending the repayment duration of rubber loans. When rubber prices fall, most farmers abandon rubber planting and begin planting other crops. Thus, the Rubber Association of Thailand stopped rubber production for six months to allow rubber prices to rise again. The boom in synthetic rubber likewise caused an increasing number of rubber gardens in Thailand to disappear over the past decade.

Given the aforementioned scenario, accurately forecasting the future prices of Thai rubber can safeguard farmers and maintain the competitiveness of Thailand's important export item. Given that rubber is an important industrial product, price fluctuations may be attributable to fluctuations in its production as well as in price fluctuations in this era of globalization. Specifically, industrial commodities traded in the world market are not immune from other important market indices, particularly exchange market and crude oil market returns. Furthermore, climatic conditions in the producing country may play an important role in rubber price fluctuations. Such fluctuations cannot take place in isolation.

With this background, the current study used three robust methods to examine the relationships of Thai rubber price volatility with climatic factors (e.g., precipitation and temperature), the US dollar exchange market, and the crude oil market. The models applied included the copula-Based generalized autoregressive conditional heteroscedasticity (GARCH), vector autoregressive moving average with GARCH (VARMA-GARCH), and VARMA with asymmetric AGARCH (VARMA-AGARCH) models.

The paper is organized as follows. Section 2 reviews relevant literature on modeling volatility in markets. Section 3 presents the methodology and the data. Section 4 presents the estimated results. Section 5 presents the conclusion.

2. Review of the literature

Measuring volatility is most common in the financial market, where researchers examine interrelationships among different stock markets, because movements in prices in these markets are not immune from each other due to the globalized nature of trading. For example, Eun and Shim (1989) report that the stock market in the USA is the main source of international transmission of volatility that can, in turn, affect foreign stock markets. However, foreign stock market variations cannot explain variations within the US stock market, implying a unidirectional effect. Theodossiou and Lee (1993) prove that the US stock market has positive transmission effects on stock markets in the UK, Germany, Canada, and Japan. Kearney (2000) also notes that the variation in most stock markets in the world is derived from stock market variations in the USA and Japan, which are then transferred to Europe. Kasih (2001) argues that whether long-term or short-term, the stock markets in the USA, UK, and Japan are the leaders in the world, accounting for 75% of the total global capital traded.

With respect to volatility in the exchange rate market, Hooper and Kohangen (1978) note that changes in the margin of the exchange rate changes give way to changes in the relative price of the international product. DeGrauwe (1988), meanwhile, notes that the exchange rate risk produces substitution and income effects on the product markets, that is, exports tend to increase if the margin of exchange rate change is volatile. Doroodian (1999) concludes that fluctuation in exchange rates exert overall negative effects in international trade for developing countries.

Few studies also illustrate the importance of adaptation to climatic factors (e.g., Kaiser et al., 1993; Mendelsohn et al., 1994) to explain volatility in product markets. For example, Kaiser et al. (1993) simulate the effect of climatic factors on product market. However, their model is based on selecting an individual representative farm and simulating its returns without considering aggregation or the market-level impact of adaptation to climate change. Mendelsohn et al. (1994) examine changes in land values as well as farmers' revenues using county-level data that incorporate adaptations to climate, as reflected in current production practices. Although their study demonstrates the nature of adaptations to climatic variables, the results do not address potential changes in prices.

The aforementioned studies used simple regression frameworks to examine volatilities in the markets and/or climate change. However, they did not analyze the interdependencies of volatilities across different markets or assets nor accommodate the asymmetric behavior of these markets.

In order to incorporate interdependencies of volatilities across different markets

or assets, Ling and McAleer (2003) proposed a VARMA specification of the conditional mean and the following GARCH specification for the conditional variance:

$$(\mathrm{L})(\mathrm{Y_t} - \mu) = \Psi(\mathrm{L})\varepsilon_t \quad (1)$$

$$\varepsilon_t = D_t\eta_t \quad (2)$$

$$H_t = \omega + \sum_{l=1}^{r} A_l\vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} \beta_l H_{t-l} \quad (3)$$

where $\mathrm{H_t} = (\mathrm{h_{1t}}, \ldots, \mathrm{h_{mt}})'$, $\mathrm{D_t} = \mathrm{diag}(\mathrm{h_{i,t}^{1/2}})$, $(L) = I_m - {}_1L - \cdots - {}_pL^p$, $\Psi(L) = I_m - \Psi_1 L - \cdots - \Psi_q L^q$ are polynomials in L, $\eta_t = (\eta_{1t}, \ldots, \eta_{mt})'$, $\vec{\mathrm{e}}_t = (\mathrm{e_{1t}^2}, \ldots, \mathrm{e_{mt}^2})'$,and ω $\mathrm{A_k}$ for l =1,…,r and β_l for l =1,…,s are $\mathrm{m} \times \mathrm{m}$ matrices, and represent the ARCH and GARCH effects, respectively. Spillover effects are given in the conditional volatility for each market or asset in the portfolio, specifically where $A_l$and β_l are not diagonal matrix.

As in the univariate GARCH model, VARMA-GARCH model assumes that positive and negative shocks of equal magnitude have identical impacts on the conditional variance. In order to separate the asymmetric impacts of the positive and negative shocks, McAleer et al., (2009) proposed the VARMA-AGARCH specification for the conditional variance:

$$H_t = \omega + \sum_{l=1}^{r} A_k\vec{\varepsilon}_{t-l} + \sum_{l=1}^{r} C_l I(\eta_{t-l})\vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} \beta_l H_{t-l} \quad (4)$$

Where C_l are $m \times m$ matrices for l=1,…,r and $I_t = diag(I_{1t}, \ldots, I_{mt})$, so that

$$I = \begin{cases} 0, \varepsilon_{k,t} \geq 0 \\ 1, \varepsilon_{k,t} \leq 0 \end{cases} \quad (5)$$

where if m=1, it reduces to the asymmetric univariate GARCH or GJR. If $C_l = 0$ for all l it reduces to VARMA-GARCH. If $C_l = 0$ for all l, with $A_l$and β_l being diagonal metrices for all l and 1, then VARMA-AGARCH reduces to constant conditional correlation (CCC) model.

Nianussornkul et al. (2009a) note that the application of the VARMA-GARCH and VARMA-AGARCH models shows significant volatility spillovers from one market to another. They showed significant volatility spillover effects from the Singapore market to other markets, and demonstrated that hedging or speculation in other markets should be considered when the volatility in the Singapore bond market is changing. They also showed that as in the case of the univariate model, asymmetry in the VARMA-AGARCH model also exists for the Indonesian and Philippine bonds; thus, the asymmetric model estimation is superior to its symmetric counterpart for these two countries. Similarly, Ninanussornkul et al. (2009b) use four models to examine volatilities in the crude oil and precious metals markets (i.e., gold and silver). The results of asymmetric effects are significant in Brent and gold markets in the GJR and EGARCH (exponential GARCH) models, indicating that positive and negative shocks with equal magnitude have different impacts on conditional volatility. also use rolling windows to examine the time-varying conditional correlations of standardized shocks using VARMA-GARCH and VARMA-AGRACH models. Their results suggested that the assumption of constant conditional correlations is too restrictive and that the correlations of all pairs of assets are clearly time-varying, especially after 2002 (Ninanussornkul et al., 2009b).

Chang et al. (2009 and 2010) use constant conditional correlation (CCC), dynamic conditional correlation (DCC), VARMA-GARCH, and VARMA-AGARCH in different oil markets. Their estimates of volatility spillovers and asymmetric effects for negative and positive shocks on conditional variance suggested that VARMA-GARCH is superior to the VARMA-AGARCH model, and that VARMA-AGARCH is more suitable for examining only positive shocks on the conditional variances.

From the above literature review we can see that VARMA-AGARCH performs better than VARMA-GARCH models in forecasting volatilities across different markets or assets.

Finally, various studies apply copula methods to analyze correlations across markets and financial assets. Roncalli (2001) proposes a portfolio, which includes five financial assets in the London Metal Exchange. He used Gaussian copula and Student's copula to analyze the correlation between financial assets demonstrating significant difference in correlation coefficients. Hu (2002) uses the copula model to analyze the correlation between stock market and bond market, noting that the correlation is better in a bear market than in a bull market. Bartram et al. (2004) applies the Gaussian copula function to the GJR-GARCH-t model to estimate the correction effect of lead in Euro currency among the stock markets of 17 European countries. They proved that the correlation increased only in large-scale capital

markets, namely, those of France, Germany, Italy, the Netherlands and Spain, after a change in common customs tariff. Patton (2006), meanwhile, uses the copula function to build a bivariate copula model between the exchange rate of German mark and Japanese yen, then compared it with the Baba-Engle-Kraft-Kroner (BEKK) model. The result shows that the copula model can better explain the correlation between financial markets than the BEKK. They concluded that when the exchange rate of German mark and Japanese yen depreciates, the correlation becomes higher than when exchange rates appreciate.

Meng et al. (2004) examine the relationships of the futures markets, such as the soybean futures market in Dalian, USA and Japan, using the dollar/yen exchange rate as an example. Their results suggest that there is a strong dependence between different futures markets.

The aforementioned studies make it clear that the volatility of a specific asset in a market, in relation to other markets, must be examined because there is always evidence of dependencies in the movement of different markets affecting each other either positively or negatively. Hence, our modeling framework for the current study attempts to incorporate the interdependencies of Thai rubber price returns with other important markets (i.e., US dollar exchange rate and crude oil market) as well as climatic factors (i.e., precipitation and temperature).

3. Methodology

3.1 Data variables and selection criteria

Natural rubbers are classified into five levels (from RSS1 to RSS5). Although the highest level is RSS1, the main one is RSS3, which is traded in the spot and futures markets in the world. Thai natural rubber has been traded in the Agricultural Futures Exchange of Thailand (AFET) since May 28, 2004.

Given that Thailand trade depends highly on the USA and Japan, the exchange rate of Thai baht is a crucial factor. Other uncontrollable elements, such as tsunamis, floods and political environments, also have a direct effect on the exchange. Therefore, the US dollar/Thai baht index was chosen as the first variable.

The second variable chosen was the crude oil price. Two kinds of crude oil are traded in the futures market in Asia; these are traded exclusively by the Tokyo Commodity Exchange (TOCOM).

This study used daily data from May 28, 2004 to Dec 31, 2010, i.e., a total of 1,581 observations to match the first trading day of AFET for Thai rubber. This study aims to determine the relationships among exchange rate, crude oil, and Thai rubber. Therefore, crude oil traded in TOCOM was selected.

Finally, the growth in rubber output is closely related to seasonality. Due to the

fact that temperature and precipitation are important factors in natural rubber output (as mentioned in the introduction), the variables representing the production environment of rubber were included. Thus, climatic data from 25 locations with high rubber outputs were chosen.

The complete set of variables assumed to be related to volatility in Thai rubber prices used in the study is presented in Table 1.

Table 1. Variables used in the study

Variables	Unit	Names
Rubber price	Baht	Export Price of Thai natural rubber
US dollar	Index number	US dollar index at close – Trade weighted
Crude oil	Index number	Crude oil index in TOCOM
TempD	Celcius	Difference between todays temperature from yesterday, 1581 observations, which is made up of average temperatures by top 25 rubber producing areas in Thailand. These are: Burirum, Chanthaburi, Chon buri, Chumphon, Krabi, Nakhon Thammarat, Narathiwat, Nong Khai, Pattani, Phangnga, Phattaluang, Phetchabun, Phitsanulok, Ranong, Rayong, Sakon Nakhon, Satun, Si Sa Ket, Songkhla, Surat Thani, Trad, Trang, Udon Ratchathuni, Udon Thani and Yalain.
Rainfall	mm	Average precipitation per day, 1581 observations, where the average precipitation is from the top 25 rubber producing areas named above.

3.2 Stationarity and summary statistics of the variables

The returns of asset i, which are price, dollar and oil at time t are calculated as follows:

$$R_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{6}$$

were $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of asset i for days t and t-1, separately.

The stationarity of all data series are tested by using the Augmented Dickey-Fuller (ADF) test, which is given by:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \emptyset \Delta y_{t-1} + \varepsilon_t \tag{7}$$

For temperature, we used the difference of average temperature in this study, which is given by:

TempD= Temp – Temp(-1) (8)

The null hypothesis is $\theta = 0$ which, if not rejected, means that the series y_t is not stationary. The results shows that all series data are stationary in Table 2, as the estimated value of θ of all the returns are significantly less than zero at the 1% level.

Table 2: ADF Test of Unit Roots

Variables	Coefficient	t-statistic
Rubber price	-0.6285	-16.2503
US dollar	-1.0700	-25.7667
Crude Oil	-1.0224	-24.5450
TempD	-1.0109	-24.2884
Rainfall	-0.4068	-8.6020

Table 3 shows the descriptive statistics of the variables. The standard deviation of rubber price return is higher than those of the oil index and dollar index returns. The skewness of Price, Dollar, Oil, and TempD are negative, so they are significantly skewed to the left. For the excess kurtosis statistics, all of the variables in this study are positive, indicating that the distribution of returns has larger, thicker tails than the normal distribution. Therefore, the assumption of skewed-t is more appropriate in this study.

Table 3: Summary statistics of the volatility of the data

	Rubber price	US dollar	Crude oil	TempD	Rainfall
Mean	0.0006	-7.02E-05	0.0003	-0.0033	5.9165
SD	0.0133	0.0057	0.0251	0.6099	6.1759
Skewness	-1.0245	-0.0815	-0.1803	-0.1234	2.7080
Kurtosis	22.4839	5.1712	4.8619	7.3715	21.0084
Max	0.1238	0.0252	0.1153	3.3212	72.4000
Min	-0.1414	-0.0306	-0.1272	-2.7960	0.0000
JB	25284.2300	312.3000	236.9238	464.0900	23310.3400

Note: For Rubber price, US dollar, and Crude oil, the data type is the volatility data. It measures the differences in the indices between today and yesterday. The values for each observation could be either +ve or –ve. Overall, the mean of these variables are close to 0. The data of TempD is close to 0 because it is the difference between today's average temperature from yesterday.

3.3 Econometric models

3.3.1 VARMA-GARCH model

We apply VARMA-GARCH model to analyze the data proposed by Ling and McAleer (2003) and VARMA-AGARCH model proposed by McAleer et al., (2009). The effect of fluctuation cannot be distinguished individually very clearly in the traditional multivariate GARCH model.

The VARMA-GARCH model is expressed as:

$$Y_t = E(Y_t F_{t-1}) + \varepsilon_t \tag{9}$$

$$\varepsilon_t = D_t \eta_t \tag{10}$$

$$H_t = \omega \quad + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_{i,t-j} + \sum_{j=1}^{s} \beta_{ij} H_{i,t-j} \tag{11}$$

And VARMA-AGARCH model is in following:

$$H_t = \omega \quad + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_{i,t-j} + \sum_{j=1}^{r} C_{ij} I_{ij} \varepsilon_{i,t-j} + \sum_{j=1}^{s} \beta_{ij} H_{i,t-j} \tag{12}$$

Where $H_t = (h_{1t}, h_{2t}, \dots, h_{mt})$, $\eta_t = (\eta_{1t}, \eta_{2t}, \dots, \eta_{mt})$,

$D_t = \mathrm{diag}\left(h_{1t}^{1/2}, h_{2t}^{1/2}, \dots, h_{mt}^{1/2}\right)$

For this study, the full model is in following:

$$A_t = \gamma_{A0} + \gamma_{A1} A_{t-1} + \gamma_{A2} B_{t-1} + \gamma_{A3} C_{t-1} + \gamma_{A4} D_{t-1} + \gamma_{A5} E_{t-1} + \varepsilon_{A,t} \tag{13}$$

$$\begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{E,t} \end{bmatrix} | \Omega_{t-1} \sim N(0, H_t) \tag{14}$$

Where A is the export price of natural rubber in Thailand, B is the futures price of crude oil in TOCOM, C is the dollar index, D is the difference of average temperature with yesterday, E is the average precipitation and ε is error term.

We use normal distribution and MLE (Maximization Likelihood Estimation) procedure to estimate the parameters of this model.

$$\hat{\theta} = argmin \frac{1}{2} \sum_{t=1}^{n} (log|Q_t| + \varepsilon_t' Q_t^{-1} \varepsilon_t) \tag{15}$$

Where θ is the vector of parameters to be estimated on the conditional log-likelihood function, and $|Q_t|$ is the determinant of Q_t, the conditional

covariance matrix.

3.3.2 GARCH model

Bollerslev (1986) proposed the GARCH model which put conditional variance of lags in to ARCH model and make it general. The GARCH model is given by:

$$R_t = \mu_{t-1} + \epsilon_t \quad (16)$$

$$\epsilon_t | \Omega_{t-1} \sim N(0, h_t) \quad (17)$$

$$H_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (18)$$

When $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$, the GARCH model is stable.

GARCH (p,q) model can be describes as follows:

$$R_t = \mu_{t-1} + \epsilon_t \quad (19)$$

$$E_t | \Omega_{t-1} \sim N(0, h_t) \quad (20)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_{t-1} \quad (21)$$

Where i=1,2,…,q, J=1,2,…,p, $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ and $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$.

In this model, μ_{t-1} is the conditional mean of R_t at time t, ht is the conditional variance and Ω_{t-1} is the all useful information set at time t-1.

The GARCH (1,1) model can be described as follows:

$$r_{i,t} = c_0 + c_1 r_{i,t-1} + e_{i,t}, e_{i,t} \Psi_{t-1} = h_{i,t}, z_{i,t}, z_{i,t} \sim skewed - t(z_i \eta_i, \lambda_i) \quad (22)$$

$$e_{i,t} \sim N(0, h_{i,t}^2) \quad (23)$$

$$h_{i,t}^2 = \omega_{i,t} + \alpha e_{i,t-1}^2 + \beta h_{i,t-1} \quad (24)$$

Where $\omega_{i,t}>0$, $\alpha, \beta \geq 0$ and , $\alpha + \beta < 1$.

The error term $e_{i,t}$ is assumed to be skewed-t distribution which can be used to

describe the possibly asymmetric and heavy tail characteristics of each variable.

Following Hansen (1994), the density function is

$$skewed-t(z\eta,\lambda)=\begin{cases}BC\left(1+\frac{1}{\eta-2}\left(\frac{Bz+A}{1-\lambda}\right)^2\right)^{-(\eta+1)/2}, z<-\frac{A}{B}\\ BC\left(1+\frac{1}{\eta-2}\left(\frac{Bz+A}{1-\lambda}\right)^2\right)^{-(\eta+1)/2}, z\geq-\frac{A}{B}\end{cases} \quad (25)$$

The value of A, B and C are defined in following:

$$A\equiv 4\lambda C\frac{\eta-2}{\eta-1},\ B\equiv 1+2\lambda^2-A^2 \text{ and } C\equiv\frac{\Gamma(\eta+1/2)}{\sqrt{\pi(\eta-2)}\Gamma(\eta/2)} \quad (26)$$

Where λ and η are the asymmetry and kurtosis parameters, separately. Those are restricted to be $-1<\lambda<1$ and $2<\eta<\infty$. When $\lambda=0$, it will turn to the Student –t distribution. If $\lambda=0$ and η diverge to infinite, it will be the normal distribution.

3.3.3 Elliptical Copula

The copula function is used in discussing problems between many variables, and is also called the dependence function (Deheuvels, 1978). Sklar (1959) advances the copula theory, pointing out that one unit distribution can be analyzed to *n* marginal distribution and one copula function. Given that the number of parameters can be large, two-step methods are generally employed. Thus, in this paper, the marginal parameters were first estimated by optimizing the marginal log likelihoods independently of each other. Second, the copula parameters were estimated by optimizing the corresponding copula log likelihood at the second step.

The marginal log likelihoods function:

$$m\mathcal{L}(\theta;x)=\sum_{i=1}^{p}\sum_{j=1}^{T}\log\left(F_i\left(x_{1,t};\emptyset_i\right)\right) \quad (27)$$

The copula log-likelihood function:

$$c\mathcal{L}(\theta;u,\emptyset)=\log\left(c(F_1(x_{1,t}),\dots,F_p(x_{p,t});\theta\right) \quad (28)$$

Therefore, the log likelihoods of two elliptical copula, the Gaussian and Student-t copula are given by:

$$\mathcal{L}_G(R;u_t)=-\frac{1}{2}\sum_{t=1}^{T}(log\,R+\epsilon_t'(R^{-1}-I)\epsilon^t) \quad (29)$$

$$\mathcal{L}_{St}(R, d, u_t) =$$
$$-T\log\frac{\Gamma(\frac{d+p}{2})}{\Gamma(\frac{d}{2})} - pT log\frac{\Gamma(\frac{d+1}{2})}{\Gamma(\frac{d}{2})} - \frac{d+p}{2}\sum_{t=1}^{T}\log\left(1+\frac{\epsilon_t' R^{-1}\epsilon^t}{d}\right) - \sum_{t=1}^{T}\log R +$$
$$\frac{d+1}{2}\sum_{t=1}^{p}\sum_{t=1}^{T}\log\left(1+\frac{\epsilon_{it}^2}{d}\right)$$

(30)

where the vector ϵ_t is the vector of the transformed standardized residuals which depends on the copula specification. For the Gaussian copula, the vector $\in_t$ is defined as: $\epsilon_t = (^{-1}(u_{1,t}), \dots, ^{-1}(u_{p,t}))$, which $^{-1}$ is the inverse univariate standard normal distribution. For the Student-t copula, it defined analogously as: $\epsilon_t = (t_d^{-1}(u_{1,t}), \dots, t_d^{-1}(u_{p,t}))$, which t_d^{-1} is the inverse student's t distribution with d degrees of freedom. In both of likelihoods R denotes the correlation matrix of $\in_t$.

The DCC (1.1) model of Engle (2002) defined that the degree of freedom parameter is static for the Student-t copula and the correlation R^t evolves through time.

$$Q_t = (1-\alpha-\beta)\cdot\bar{Q} + \alpha\epsilon_{t-1}\cdot\epsilon_{t-1}' + \beta\cdot Q_{t-1} \quad (31)$$

$$R_t = \tilde{Q}_t^{-1} Q_t \tilde{Q}_t^{-1} \quad (32)$$

Where $\bar{Q}$ is sample covariance of $\in_t$, $\tilde{Q}_t$ is a square p×p matrix with zeros as off-diagonal elements and diagonal element the square root of those of Q_t. The parameter constraints for the DCC are the same as for the univariate GARCH (1,1) models.

$$\alpha + \beta < 1, \alpha, \beta \in (0,1) \quad (33)$$

4. Empirical results

The analysis of the volatility of rubber price return in relation to the volatility of oil index and dollar index returns, as well as average temperature and average precipitation, was undertaken using the VARMA-GARCH and VARMA-AGARCH models. Time-varying volatility was estimated and the asymmetric effects of positive and negative shocks of equal magnitude and volatility spillovers were tested using these models. The results of the VARMA-GARCH and VARMA-AGARCH are presented in Table 4, and the number of volatility spillovers and asymmetric effects are summarized in Table 5. Table 4 shows that three variables have spillovers to the volatility of rubber price return in the VARMA-GARCH model, including volatility of oil index return and volatility of dollar index return. For the VARMA-AGARCH model, only the volatility of dollar return has spillover effects on the volatility of rubber price. Table 5 shows that the volatility spillovers are not evident in the VARMA-AGARCH model. Therefore, we can conclude that VARMA-GARCH is superior to VARMA-AGARCH in examining the volatility of rubber price return.

Table 4: Estimates of VARMA-GARCH(1,1) and VARMA-AGARCH(1,1)

Returns of rubber price	ω	α_{price}	α_{oil}	α_{dollar}	α_{tempD}	α_{rain}	Γ
VARMA-G	0.0000***	0.1076***	0.0100**	-0.1699***	-0.0000***	0.0000	
ARCH	14.1663	4.3565	2.6135	-3.0683	-96.8093	1.1277	
VARMA-A	0.0000***	0.1847***	0.0099***	-0.1090**	-0.0000***	-0.0000	-0.1031
GARCH	6.0904	3.2536	3.1778	-2.3871	-16.9753	-0.0917	1.2004

Table 4. (Continued)

Returns of rubber price	β_{price}	β_{oil}	β_{dollar}	β_{tempD}	β_{rain}
VARMA-GARCH	0.8570***	-0.0055	0.4064***	6.88E-07	-0.0000
	39.5998	-0.7693	3.1504	0.3306	-0.0923
VARMA-AGARCH	0.8610***	-0.0122**	0.2412**	2.59E-06	-0.0000
	40.2522	-2.1605	2.3945	1.6428	-0.1999

Notes: (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge (1992) robust t-ratios.
(2) * indicates statistical significance at the 10% level; ** indicates statistical significance at the 5% level; *** indicates statistical significance at the 1% level.

Table 5: Summary of Volatility Spillovers and Asymmetric Effects

Returns	Number of volatility spillovers		Asymmetric effects
	VARMA-GARCH	VARMA-AGARCH	
Rubber price	1	2	NO

Rolling windows are also used to examine time-varying conditional correlations using the VARMA-GARCH and VARMA-AGARCH models. The rolling window size was set at 1,000 for the dollar index and oil index as shown in Figures 1 and 2, respectively. For the VARMA-GARCH model, the correlations of dollar index and oil index are not constant over time, so the assumption of constant conditional correlations may be too restrictive. However, the changes in the estimated correlations are small. Specifically, the correlation between the volatility of rubber price return and volatility of oil index return is smaller (at around 0.1) than that between volatility of rubber price return and the other three variables. The VARMA-AGARCH model shows similar results to VARMA-GARCH in that the correlations vary over time.

Figure 1: Dynamic Path of Conditional Correlations in VARMA-GARCH model

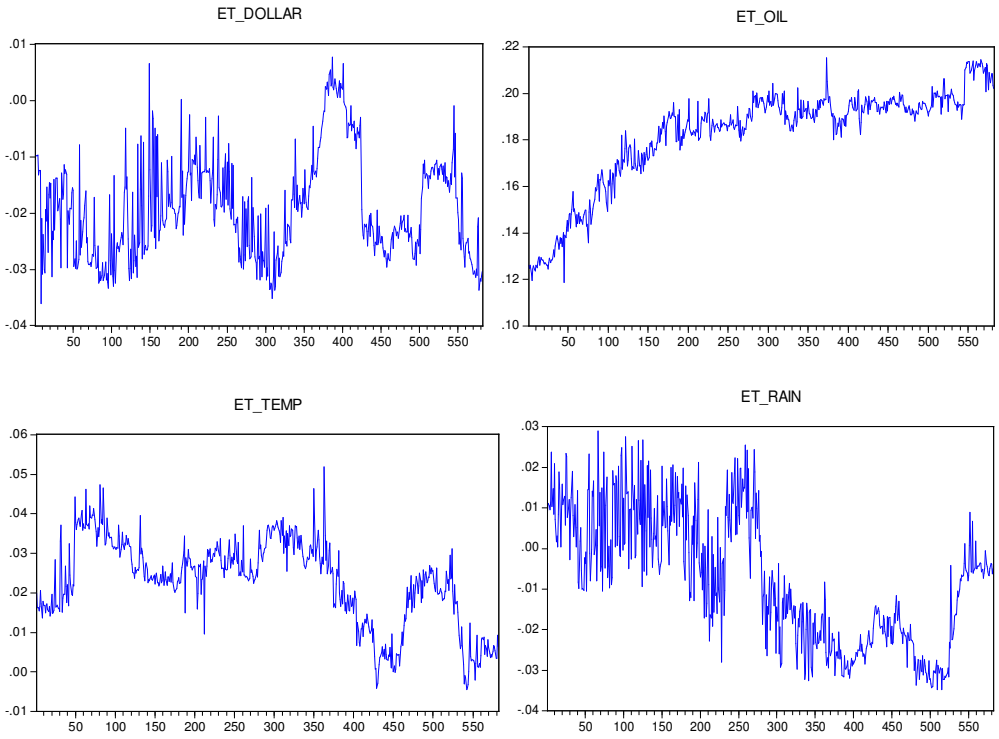

Figure 2: Dynamic Path of Conditional Correlations in VARMA-AGARCH model

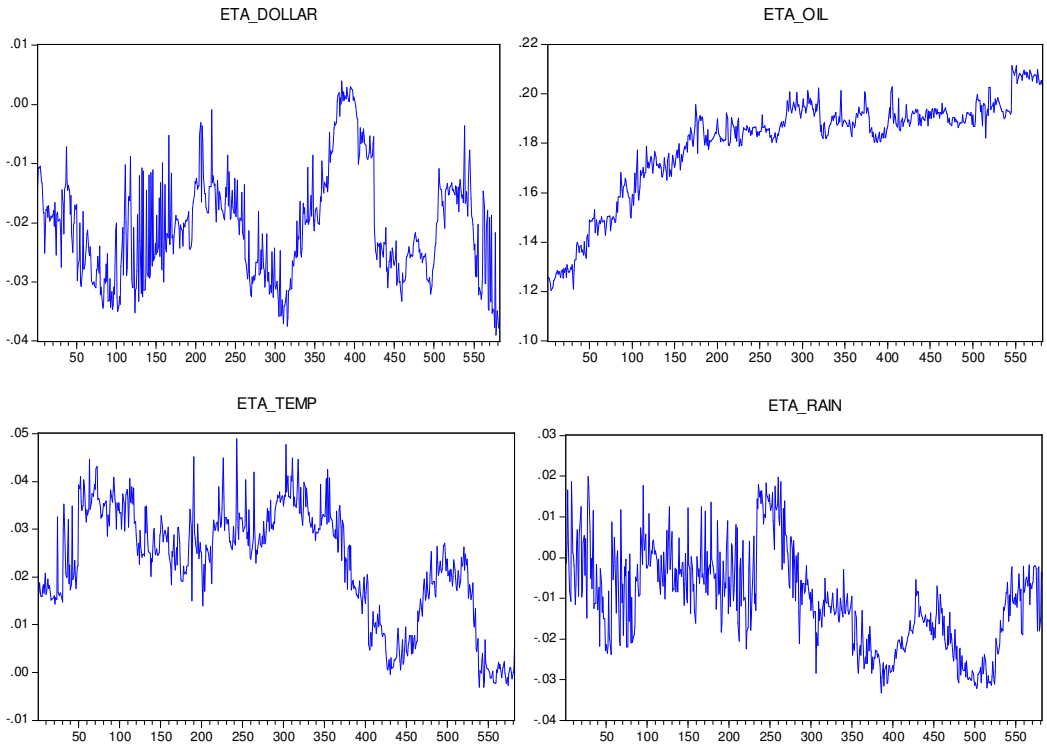

Table 6 presents the estimated result for copula-based GARCH models with feedback trading activities. Panel A shows the parameter estimates of marginal distributions with the GARCH model. The parameters of greatest interest in the mean equation are the autocorrelation of returns. The constant components of the autocorrelation ω are almost non-significant, except rubber price return. In addition, the parameter β is positive and statistically significant for all of the variables in this study. The asymmetry parameters λ is significant and negative for price, but non-significant for dollar, oil and rain, indicating that the rubber price is skewed to the left. Panels B and C present the parameter estimates for different Gaussian and Student-t copula functions. In terms of the values of AIC and BIC, the Student-t dependence structure only exhibits better explanatory power than that of Gaussian dependence between rubber price and temperature; however, Gaussian dependence shows better relation between rubber price and other variables. Moreover, the autoregressive parameter β is not significant between rubber price and dollar index, but is significant between rubber price and other variables, implying the persistence pertaining to the dependence structure between rubber price return with oil index return, temperature, and precipitation.

Table 6: Estimation result of copula based GARCH models

	Price	Dollar	Oil	TempD	Rain
Panel A: Estimation of marginal					
C_0	0.0001	-0.0002	0.0006	0.0235**	0.5000**
	(0.5450)	(-1.6246)	(1.0595)	(2.5059)	(2.1817)
C_1	0.3932***	-0.0322	-0.0302	0.3348***	0.5000***
	(11.7720)	(-1.3327)	(-1.1429)	(10.7974)	(12.0196)
ω	0.0000***	0.0000	0.0000	0.0000	0.0000
	(3.3659)	(1.3483)	(1.3981)	(0.0095)	(0.0001)
α	0.2225***	0.0336***	0.0557***	0.1659***	0.1807***
	(6.2451)	(4.3679)	(2.9826)	(5.6569)	(3.5839)
β	0.7775***	0.9664***	0.9443***	0.8341***	0.8192***
	(19.4185)	(162.7056)	(63.6227)	(23.6985)	(10.7266)
υ	2.8760***	8.4871***	8.6889***	3.2429***	3.3885***
	(21.0916)	(4.5391)	(4.1105)	(19.8588)	(5.0949)
λ	-0.0580**	-0.0276	-0.0504*	0.0408**	0.1602
	(-2.1364)	(-1.0794)	(-1.7154)	(1.9838)	(0.8989)
Panel B: Estimation of Gaussian dependence structure for Price					
α		0.0203	0.0373*	0.0644***	0.0260**
		(0.8943)	(1.6669)	(6.3721)	(2.2771)
β		0.2107	0.7153***	0.8834***	0.8937***
		(0.4645)	(3.4152)	(42.1275)	(17.8009)
ln(L)		0.705	32.052	3190.197	5.099
AIC		2.5907	-60.1044	-6376.3943	-6.1978
BIC		13.3223	-49.3728	-6365.6627	4.5339
Panel C: Estimation of student-t dependence structure for Price					
ω		35.6467	199.4353***	14.9948***	195.8707*
		(0.6129)	(57.1676)	(3.4301)	(1.6967)
α		0.0187	0.0375*	0.0531***	0.0261**
		(0.8354)	(1.6724)	(5.4367)	(2.2998)
β		0.1351	0.7139***	0.9111***	0.8937***
		(0.2289)	(3.4206)	(44.9850)	(17.8794)
ln(L)		1.517	32.021	3202.538	4.951
AIC		2.9652	-58.0420	-6399.0766	-3.9011
BIC		19.0627	-41.9446	-6382.9791	12.1963

Notes: * indicates statistical significance at the 10% level;
** indicates statistical significance at the 5% level;
*** indicates statistical significance at the 1% level.

5. Concluding Remarks

Given that Thailand is the world's top rubber producer and exporter, the sources of price changes must be identified to ensure that the country remains competitive in this market. Both changes in climatic factors as well as volatilities in the exchange rate market and crude oil market are assumed to be related to the fluctuation of Thai rubber price returns. The conditional volatility, covariance, and correlation volatility of rubber price return have been estimated using the VARMA-GARCH and copula-based GARCH models. The VARMA-GARCH model showed that volatility spillovers are evident between the volatility of rubber price return and dollar index return, while the VARMA-AGARCH model showed that the volatility spillovers are evident between the volatility of rubber price return with the volatility of dollar index and oil index returns. The coefficients of the volatility of dollar index return in both models are significant, whereas only the coefficient of the volatility of oil index return in the VARMA-AGARCH model is significant. This indicates that the volatility of dollar index return has a stronger effect on Thai rubber price returns. Furthermore, analysis of the rolling windows shows that the correlation between the volatility of rubber price and volatility of oil index return is smaller than the correlation between the volatility of rubber price and other three variables. The copula-based GARCH model shows that the Gaussian dependence has a better explanatory power than the Student-t dependence structure. Dependencies also exist between rubber price return and oil index return, rubber price return and average temperature, and rubber price return and precipitation.

Based on these results, climatic factors and fluctuations in the exchange rate market and crude oil market have significant effects on Thai rubber price returns in the world market. Therefore, the industry should consider the volatilities in these markets as well as climatic conditions when forecasting the future returns from exporting Thai rubber.

With regards the analysis methods, no single method can provide a complete picture of the dependencies and interrelatedness of the various asset markets. Therefore, a set of robust approaches, as applied here, should be used to obtain a complete picture of the complexities associated with analyses of price volatility. We hope that the results of this study can be used by government agencies, the Thai Rubber Association, farmers, as well as other key stakeholders in the rubber industry.

References

Bartram, S., S.J. Taylor and Y-H Wang, (2004), “The Euro and European Financials market dependence”, Working Paper, Lancaster University and National Central University.

Bollerslev, T., (1986), "Generalized Autoregressive Conditional Heteroskedasticity." Journal of Economics, 31, 307-327.

Chang, C.-L., M. McAleer and R. Tansuchat, (2010), "Analyzing and Forecasting Volatility Spillovers, Asymmetries and Hedging in Major Oil Markets", Energy Economics, 32, 1445-1455 (ISI).

Chang, C.-L., M. McAleer and R. Thansuchat, (2009), "Modeling Conditional Correlations for Risk Diversification in Crude Oil Markets", Journal of Energy Markets, 2(4), 1-23.

DeGrauwe, P. (1988), "Exchange Rate Variability and the Slowdown in Growth of International Trade," IMF Staff Paper, 35, 63-84.

Deheuvels, P., (1978), "Caractérisation complète des lois extrêmes multi variées ed de la convergence des type extrêmes", Publications de l'Institut de Statistique de l'Université de Paris 23, pp.1-36.

Doordian, K.(1999), "Does Exchange Rate Volatility Deter International Trade in Developing Country?" Journal of Asian Economics,10, 465-74.

Eun, C. S. and S. Shim, (1989), "International Transmission of Stock Market Movements." Journal of Financial and Quantitative Analysis, 24, 241-257.

Hansen, B., 1994. "Autoregressive conditional density estimation." International Economic Review 35, 705-730.

Hooper, P. and Kohlagen, S. W. (1978), "The Effects of Floating Exchange Rate Uncertainty on the price and Volume of International Trade." Journal of International Economics, 8, 483-511.

Hu, L. (2002), "Dependence Patterns across Financial Market: Methods and Evidence", Working paper, Yale University.

Joe, H., 1997. "Multivariate Models and Dependence Concepts." Chapman and Hall, London.

Kaiser, H. and Drennen, T. (eds.) 1993, "Agricultural Dimensions Global Climate Change." Delray Beach, FL: St. Lucie Press.

Kearney, C., (2000), "The determination and international transmission of stock market volatility." Global Finance Journal, 11(1-2), 31-66.

Ling, S. and M. McAleer, (2003)," Asymptotic Theory for a Vector ARMA-GARCH Model", Econometric Theory, 19, 278-308.

Masih, R. and A.M.M. Masih, (2001), "Long and short term dynamic causal transmission amongst international stock markets." Journal of International Money and Finance, 20, 563-587.

McAleer, M., S. Hoti and F. Chan, 2009, "Structure and asymptotic theory for multivariate asymmetric conditional volatility." Econometric Reviews 28, 422-440.

Mendelsohn, R., Nordhaus, W. and Shaw, D. (1994), "The Impact of Global Warming on Agriculture: A Ricardian Analysis." American Economic Review 84:753-71.

Meng, J.L., JiWen Si and Pu Gong (2004), "A Dependence Study for Futures Markets with Copula", Asian FA/TFA/FMA conference 2003-2004 in Taipei-2004/7/14.

Ninanussornkul, C., Chang, C.-L., M. McAleer and S. Sriboonchitta., (2009a), "Modeling the Volatility in Bond Prices in South-East Asia", International Conference on Finance and Accounting, May 2009.

Ninanussornkul, C., P. Boonyasana and T. Sriwichailanphan. 2009b, " Volatility and Volatility Spillovers in Crude Oil and Precious Metals Markets" ", International Conference on Finance and Accounting, May 2009.

Patton, A.j, (2006), "Modeling asymmetric exchange rate dependence", International Economics Review 47(2), pp. 527-556.

Roncalli, T., Bouy'e, E., Durrleman, V., Nikeghbali, A., and Riboulet, G. (2001), "Copulas: an open filed for risk management", Credit Lyonnais.

Sklar, A., (1959), "Fonctions De Répartition à n Dimensions et Leurs Marges", Publ, Inst. Statis. Univ. Paris, Vol. 8, pp.229-232.

Theodossiou, P. and U. Lee, (1993), "Mean and Volatility Spillovers across Major National Stock Market: Further Empirical Evidence." Journal of Finance Research, 16, 337-350.