Chapter 2

Literature Review

We mentioned that the factors affecting rubber prices include the exchange rate, climate, and oil prices, as well as that the VARMA-GARCH and Copula-based GARCH models are used in this research. In this chapter, we introduce previous studies that focused on these factors and methods.

2.1 Exchange Rate

Substantial research and basic theories are available on the interrelation analysis of exchange rates. The evaluation of the risks of exchange rate is critical in empirical research on rate volatility. Doroodian (1999) reported the following estimation methods for volatility of exchange rates: standard deviation; deviation from trend; difference between forward and current spot rates; Gini mean difference coefficient; coefficient of variation; as well as the ARCH or GARCH models. Several studies employed the standard deviation to evaluate the exchange rate volatility. For example, Daly (1998) applied a moving standard deviation to estimate the exchange rate; however, the method is unadvisable in cases of uncertain stability of the exchange rate volatility. Baillie et al. (1989) analyzed the exchange rate volatility by using the GARCH model. Poso (1992), Caporale et al. (1994), and Doroodian (1999) similarly applied the GARCH method in their analyses.

Hooper et al. (1978) constructed the static model of import demand and export supply. The study assumes that the exporter is prone to risk aversion in analyzing the effects of the exchange rate volatility on volume shares and trade prices. The results revealed that the uncertainty of the exchange rate negatively affects volume shares; however, the volatility of the exchange rate positively affects trade prices. Akhtar et al. (1984) utilized normal exchange rates to analyze the effects of exchange rate risk on the export and import trade in American and German manufacturing. They discovered a significant negative relationship between the export volume and import price of American manufacturing, and the import and export trade volume of German manufacturing. As exchange rate risk increases, international trade correspondingly decreases. In and Sgro (1998) tested the co-integration relationship between variables, and then used the error correction model to discuss the effects of export volume in South Korea and Singapore. The error correction model reveals that the exchange rate primarily causes the export volume variation in Singapore. Thorbecke (2006) discovered that the exchange rate variation decreases Asian exports. Currency appreciation in developed countries could affect the export and import volume among countries, but the depreciation of US dollars do not guarantee an increase in export volume. Therefore, the US government should not expect the appreciation of Asian currencies to increase the export volume to their markets. Jarita (2008) used the VECM model to test the export and import prices in relation to the exchange rate volatility of the Malaysian ringgit from January 1999 to December 2006. The results indicate significant effects of the exchange rate volatility on export and import prices.

On the other hand, several scholars believe that exchange risk positively affects exports and imports. DeGrauwe (1988) noted that the exchange risk causes a substitution and income effect. The substitution effect means that when the volatility of exchange rate increases, exporters reduce their risk export trade, thus decreasing export volume. The income effect means that when the volatility of the exchange rate increases, exporters increase their expected return of the risk export trade, thus increasing export volume. When the income effect is greater than the substitution effect, a positive relationship occurs between the exchange rate volatility and trade volume.

Giovannini (1988) discovered that when the risk of exchange rates increased, most risk-neutral traders quickly enter and slowly leave the market. The number of traders and the trade volume increases. Bailey et al. (1988) assumed that with knowledge on trade, traders could easily earn returns from the exchange rate volatility. Exchange risk and trade volume exhibit a positive relationship. Franke (1991) proved that when the volatility of exchange rate increases, the increase in cash flow from exports is significantly higher than the costs for the trader who employed disorganized policies of market entrance and exit. Broll et al. (1999) proposed that the actual options of export trade increase when the volatility of exchange rate increases. Higher exchange rate volatility raises the potential benefit, resulting in positive effects for export volume.

The above studies demonstrate that exchange risk positively affects exports and imports. However, the discussions focused on only one country. In this research, we determine the relationship between rubber prices and exchange rates in different import countries. In addition, while most studies use the exchange rate in their countries to discuss exports or imports, we use both the exchange rate of the Thai baht and that of foreign currencies to understand the effect of the factors of international product prices.

2.2 Financial Market

Measurements of volatility are most common in the financial market. Researchers examine interrelationships among different stock markets, where the nature of global trading leads to interdependent price movements. For example, Eun and Shim (1989) reported that the stock market in the US is the main source of international transmission of volatility that affects foreign stock markets. However, foreign stock market variations cannot explain variations within the US stock market, implying a unidirectional effect. Theodossiou and Lee (1993) proved that the US stock market has positive transmission effects on stock markets in the UK, Germany, Canada, and Japan. Kearney (2000) similarly noted that most of the global stock market variations are derived from those in the US and Japan, which are then transferred to Europe. Kasih (2001) argued that the stock markets in the US, UK, and Japan are the long- or short-term leaders in the world, accounting for 75% of the total global capital trade.

With respect to volatility in the futures market, Scholes (1981) reported that the differences between spread and hedge trades depend on investor demand in the spot market. He also stated that spread traders practice speculative demand, which means trading for short-term profits, and that hedge traders buy or sell futures to avoid risks. In addition, Scholes noted that traditional spread trading was applied to different products to simultaneously decrease risk and increase liquidity in the market. Peterson (1997) analyzed the advantages of spread trade, which include providing the arbitrage to test the pricing efficiency in the futures market and establishing risk transfers to spread risks by increasing the scope of investment. Therefore, speculative traders entering the futures market could increase the liquidity between products and benefit from price volatility. Bernstein (2007) proved that increasing the complexity of spread trade increases the investment benefits. When the portfolio becomes complex, the investor cannot obtain real-time information to calculate the price change. Therefore, the information asymmetry from the volatility might increase the benefits from the market. If futures price shocks exist, the pricing deviates due to different expectations. Butterworth et al. (2002) investigated spread trade using the cost of carry model as well as the variables of the Financial Times Stock Exchange (FTSE) 100 index and the FTSE Mid 250 index. They assumed that these two markets comprise over 90% of the UK stock market, which receives all types of information. Their results indicated that without consideration of transaction costs, spread trade could be beneficial. However, if the fees and Bid-Ask Spread are considered, traders would not enter the market because the benefit cannot cover the fee of all the deals. Dunis et al. (2006) similarly studied the spread trade from the West Texas Intermediate (WTI) and Brent blend (a benchmark of crude oil from the North Sea) by using the time-series model to estimate the correlations among products. Daigler (2007) discussed the relationships among the cross spread, calendar spread, and trade volume of exchange futures from four kinds of traders in the Chicago Mercantile Exchange (CME): individuals, corporations, dealers, and hedge traders.

Previous studies used the WTI and Brent blend to estimate the correlations among products. In this study, we used crude oil and gas oil prices from the Tokyo Commodity Exchange (TOCOM), which the area is the same wit Thailand in Asia, to model the volatility of rubber prices.

2.3 Climate Change

Few studies (e.g., Kaiser et al., 1993; Mendelsohn et al., 1994) illustrate the importance of adaptation to climatic factors in explaining the volatility in product markets. Kaiser et al. (1993) simulated the effect of climatic factors on the product market. However, their model is based on an individual representative farm, simulating its returns without consideration of the aggregation or the market-level impact of adaptation to climate change. Mendelsohn et al. (1994) examined changes in land values and in the revenues of farmers by using county-level data that incorporate adaptations to climate, as reflected in current production practices.

The aforementioned studies used simple regression frameworks to examine market volatilities and/or climate change. However, these studies neither analyzed the interdependencies of volatilities across different markets or assets, nor accommodated the asymmetric market behavior.

As indicated above, several studies illustrate the importance of adaptation to climatic factors. However, the results do not address potential pricing changes. In this research, we discuss how climate change affects the prices of agricultural products.

2.4 VARMA-GARCH Model

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:

$$\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t \tag{1}$$

$$\varepsilon_t = D_t \eta_t \tag{2}$$

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

where $H_t = (h_{1t}, \ldots, h_{mt})'$, $D_t = \mathrm{diag}(h_{i,t}^{1/2})$, $\Phi(L) = I_m - \Phi_1 L - \cdots - \Phi_p L^p$, $\Psi(L) = I_m - \Psi_1 L - \cdots - \Psi_q L^q$ are polynomials in L, $\eta_t = (\eta_{1t}, \ldots, \eta_{mt})'$, $\vec{\varepsilon}_t = (\varepsilon_{1t}^2, \ldots, \varepsilon_{mt}^2)'$, and ω A_k for l=1,…,r and β_l for l=1,…,s are $m \times m$ 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 $I_t = \mathrm{diag}(I_{1t}, \ldots, I_{mt})$, so that

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

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) noted that the application of the VARMA-GARCH and VARMA-AGARCH models indicates significant volatility spillovers from one market to another, as in the effect from the Singapore market to other markets. Hedging or speculation in other markets requires consideration when volatility changes in the Singapore bond market. In addition, they demonstrated that similar to the case of the univariate model, asymmetry in the VARMA-AGARCH model exists among the Indonesian and Philippine bonds; thus, the asymmetric model estimation is superior to its symmetric counterpart in these two countries. Ninanussornkul et al. (2009b) also used four models to examine volatilities in the crude oil and precious metals markets (i.e., gold and silver). The GJR and exponential GARCH (EGARCH) models demonstrated significant asymmetric effects on the Brent and gold markets, indicating that positive and negative shocks of equal magnitude produce different impacts on conditional volatility. Rolling windows were likewise employed to examine the time-varying conditional correlations of standardized shocks by using VARMA-GARCH and VARMA-AGARCH models. Their results suggested that the assumption of constant conditional correlations is too restrictive, and that the correlations of all pairs of assets clearly vary with time, especially after 2002 (Ninanussornkul et al., 2009b).

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

The above literature review indicates that compared with the VARMA-GARCH, the VARMA-AGARCH model better forecasts volatilities across diverse markets or assets. Therefore, in this research, we discuss VARMA-AGARCH and compare it with the Copula-based GARCH model.

2.5 Copula Model

Numerous studies focus on the Copula method. Roncalli (2001) built a portfolio that includes five financial assets from the London Metal Exchange (LME), and then analyzed their correlations by using Gaussian Copula and Student's Copula. A significant difference was revealed among the correlation coefficients. Hu (2002) used the Copula model to discuss the correlation between the stock and bond markets. Investigating the S&P 500 and J.P. Morgan Government Bond Indexes, the study demonstrated that the stock and bond markets had a closer correlation in the bear rather than in the bull market. Bartram et al. (2004) applied the Gaussian Copula function to the GJR-GARCH-t model to discuss the correction effect of lead on the Euro in the stock markets of each of the 17 European countries. They proved that the correlation increased only in large-scale capital markets after lead was brought to the common customs tariff, such as in the stock markets of France, Germany, Italy, Netherlands, and of Spain. Patton (2006) used the Copula function to build a bivariate Copula model between the exchange rates of German mark and Japanese yen. In comparison with the BEKK model, the Copula model better explained the correlation between the financial markets. The correlation was higher when the exchange rates of the German mark and Japanese yen depreciated rather than appreciated. JianLing, Si, and Gong (2004) studied the relationships of the futures markets, such as the soybean futures markets in Dalian, the US, and in Japan. The dollar/yen exchange rate was selected to obtain a better explanation. The results suggest a strong dependence among diverse futures markets. They studied four representative futures contracts: January soybean contract of DCE (hereafter denoted as DCE); January soybean contract of CBOT (denoted as CBOT); NSI contract of MGEX (denoted as NSI); and the IOM soybean contract of The Tokyo Grain Exchange (denoted as IOM). The dollar/yen foreign exchange rate was denoted as U.S/J. The samples were divided into four groups: DCE and CBOT; DCE and NSI; DCE and IOM; as well as DCE and U.S/J. The bivariate dependence structure of each group was then separately investigated. The estimated τ for each group was then used in estimating the copula parameters, and the optimal value was selected to characterize the dependence structures of the different futures markets. Finally, the tail dependences between different contracts and the optimal copula were investigated to obtain significant results. The drawn conclusion is of high importance to a financial risk manager.

The above studies used the bivariate Copula-based GARCH model. However, the present study uses a multivariate Copula-based GARCH model to discuss the rubber futures prices in diverse rubber and oil futures markets.