FORECASTING OF NATURAL RUBBER RIBBED SMOKED SHEETS NO.3 (RSS3) PRICE IN THE AGRICULTURAL FUTURES EXCHANGE OF THAILAND

Suppanunta Romprasert

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Suppanunta Romprasert

School of Development Economics

Assistant Professor ....Major Advisor

(Nada Chunsom, D.B.A.)

Assistant Professor ....Co-Advisor

(Sorasart Sukcharoensin, D.B.A.)

Assistant Professor ....Co-Advisor

(Yuthana Sethapramote, Ph.D.)

The Examining Committee Approved This Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy (Economics).

Lecturer ....Committee Chairperson

(Tanachote Boonvorachote, D.B.A.)

Assistant Professor ....Committee

(Nada Chunsom, D.B.A.)

Assistant Professor ....Committee

(Sorasart Sukcharoensin, D.B.A.)

Assistant Professor ....Committee

(Yuthana Sethapramote, Ph.D.)

Associate Professor ....Dean

(Rachain Chintayarangsan, Ph.D.)

February 19, 2010

ABSTRACT

Title of Dissertation	Forecasting of Natural Rubber Ribbed Smoked Sheets No.3 (RSS3) Price in the Agricultural Futures Exchange of Thailand
Author	Mrs. Suppanunta Romprasert
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The agricultural futures market affects the rubber price in Thailand. Rubber processors use the agricultural futures market to avoid risks associated with fluctuations in rubber price. Investors make profits from the difference between the current price and the future price. The paper presents the forecasting models for futures price of the natural rubber ribbed smoked sheets no.3 (RSS3). The results from the most efficient model can inform the decision of investors on buying and selling at the proper time. The study employs univariate criteria for the selection of the best prediction model, the market timing criteria: judging by the confusion rate (CR) values and Diebold-Mariano (DM). Paper also includes an analysis of factors affecting the RSS3 futures price in Thailand's futures market. The result indicated that daily and monthly futures prices served as unbiased estimators of future spot prices. Therefore, Thailand's RSS3 futures market was weak form efficient market. Moreover, RSS3 futures price can be predicted by net imports natural rubber China, world synthetic rubber consumption, crude oil price and futures price TOCOM. Investors can use this information with futures price prediction. Because futures price lead spot price and both futures and spot price will converse lastly. These results will make more knowledgeable in futures market expansion, so the government should support on setting up the funds to make the futures market efficiency and to develop the potential of agents in the futures market.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

In the year 2002, the supply of natural rubber in the world was reported to be approximately 5.50 to 6.10 million tons while the demand of usage was 5.45 to 6.05 million tons. Approximately 60 to 65 percent of the natural rubber were used in the tire and automobile industries. The majority of the production facilities were found to be located in the United States, Japan, France, England, and Italy. Thailand, as the top ranking natural rubber producer, has produced 2.35 million tons, or roughly 33 percent of the world's natural production in 2001. Of the amount produced in the country, 89 percent, were exported to other countries while the remaining supplies were used in the country (Office of Agricultural Economics, 2009). As shown in Figure 1.1, the top three countries that import natural rubber from Thailand include China, Japan, and the United States.

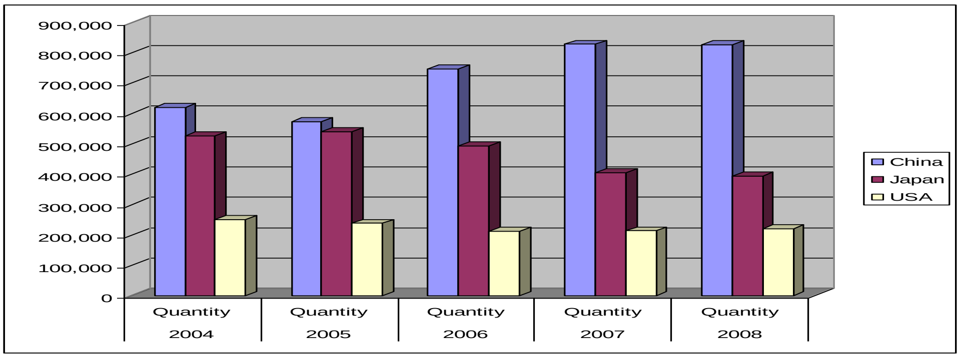

Figure 1.1 Imports of Natural Rubber from Thailand

Thailand exports approximately 41 percent of rubber in the world market and is the first ranking country. China, the United States, and Japan, on the other hand, are the top ranking importers of rubber.

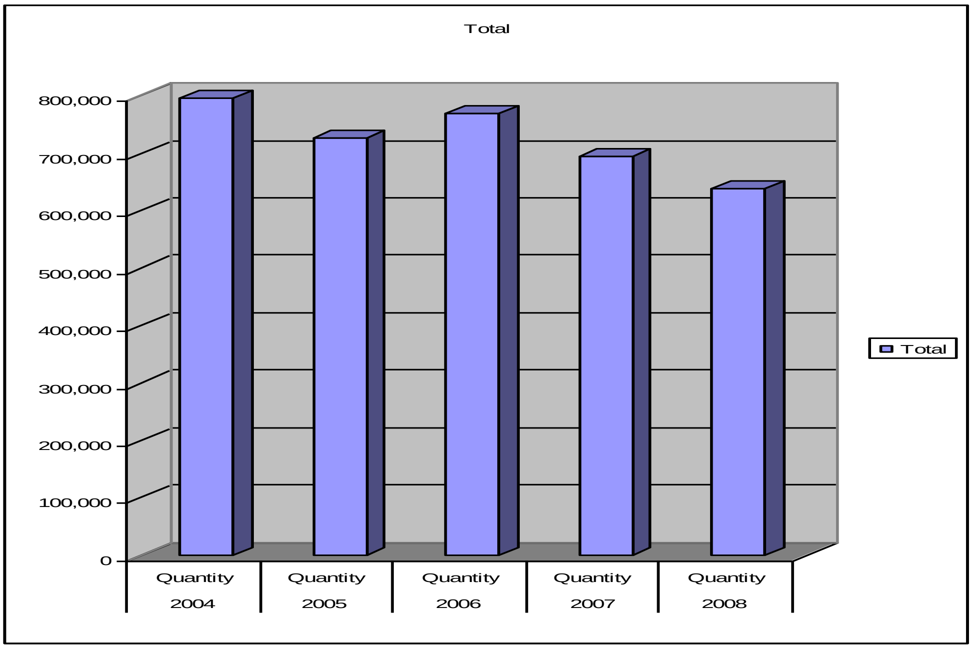

Figure 1.2 The Number of Exports from Thailand (Matrix Tons)

However, Thailand has no negotiating power in setting the price of rubber because the natural rubber market belongs to the market of buyers. The Thai government has been trying to develop the rubber market into the international level by having a role in setting the price of rubber. This will give involved parties, specifically the transforming rubber industry, rubber products industry, and exporters, better opportunities in the market. The Agricultural Futures Exchange Market in Thailand (AFET) is an alternative in solving the volatile price of agriculture which will lead to reduced risks and more guidance in market planning. The AFET was established less than 10 years ago by the Chamber of Commerce as a way to increase the market efficiency of the agriculture sector (Agricultural Futures Exchange of Thailand, 2003).

Thailand is the top ranking producer and exporter of commodities, such as rice and rubber, and has enough capacity for trading in the agriculture commodity futures market of the world. Thailand has been trading rubber using the futures contract with countries such as China, Japan, and America through brokers of each country in which agents have to be compensated for each project. Because of this, Thailand was not as competitive as other countries. The establishment of the futures market in Thailand has increased the opportunity for local traders to choose from alternative options, reduce, losses in broker fee, as well as the ability to plan on buying, selling and stocking of rubber in the country.

The study aims to find the proper forecasting model, identify the appropriate time period applicable in estimating rubber prices in both the daily and monthly. To achieve these aims the paper focuses on the objectives considerations, as follows: 1) to discover the proper forecasting model and 2) to identify the appropriate fundamental factors affecting the changes in the daily and monthly time period which are important in estimating rubber prices, particularly on demand-supply factors. To achieve these objectives, the paper focuses on a number of key considerations,

First, the agricultural futures exchange market in Thailand (AFET). Second, rubber prices, which refer to the natural rubber ribbed smoked sheets no. 3. Third, the forecasting model used in the study of the rubber price in the futures market are classified into short time prediction, targeted at finding a forecasting model that is most suitable period using daily rubber prices and long time prediction which uses monthly forecasting. Prior to make the final decision, the paper considers and examines external factors that may affect the rubber futures prices. To consider the period that rubber price tends to move up or down in the future, we build graph-leading indicators. Fourth, the time period used in short time prediction are classified as follows a) using 310 days data starting from 1st August 2007 to 31st October 2008. Fifth, the time period used in a monthly basis from May 2004 to May 2009 comprising of 61 months and both daily and monthly are using 2/3 as an estimator and 1/3 as a forecasting. Sixth, for both short and long time prediction, the paper observes the variables that affect rubber prices by using multiple regressions of daily data that was gathered during 1st August 2007 to 31st October 2008 while the monthly data were gathered during May 2004 through May 2009. The variables comprise of Exchange Rate (baht/$), Exchange Rate (yen/$), Crude oil price, TOCOM, Net imports natural rubber in Japan, Net imports natural rubber in China, Net imports synthetic rubber in Japan, Net imports synthetic rubber in China, World natural rubber consumption and World synthetic rubber consumption. Lastly, the periods when rubber prices expand or shrink are examined by graphical analysis between monthly rubber prices. Constructing the model of monthly rubber price is derived from indicated variables with the monthly natural rubber ribbed smoked sheets no. 3 price as the reference line.

The structure of this paper starts from the general concept of the study followed by the review of literature, the concept of futures market efficiency, general knowledge of forecasting method and the methods and data used in the study. The last two sections discuss the results of the analysis and the implications of the forecasting model.

1.2 Rationale of the Study

The forecasting logic of rubber prices in the futures market is similar to the price movement in the stock market. Moreover, it can provide an estimate, taking into consideration the effects of external factors. This is because adjustment in the rubber price in the long term may be affected by the law of supply and demand. However, the purpose of futures market is to serve as an instrument for agricultural rubber groups, producers, agricultural suppliers and investors to manage risks associated with the fluctuations in commodity prices. This involves buffering of risks related to efficiency, transparency and fairness. Hence, the study will focus on the methods of forecasting by using two cases. The first case, uses the technical analysis and focuses only on the duration of rubber prices without considering exogenous variables. The second, which is a fundamental analysis, accounts for the effects of exogenous variables.

Since each analysis has its strong and weak points, the paper integrates technical and fundamental analyses as the approach for investigating the probability of the output produced by the fundamental analysis. The result is expected to test the extent to which the fundamental analysis can be trusted and serves as a way to double check the results. The fundamental analysis in current year has many forecasting methods, but the most well-known and frequently used analytical programs include the Naïve or Random Walk (RW), Random Walk with Drift (RWD), Vector Auto

Regressive (VAR), Autoregressive (AR), Simple Moving Average (MA), Simple Exponential Smoothing (SES), Trend (T), Random Walk with Drift and Trend (RWDT) and Box-Jenkins (ARIMA). According to the analytical programs, paper chooses the suitable and reliable one and takes into consideration various factors such as the period of forecasting, the amount of data, and the level of prediction validity. Additionally, this study highlights the proper method for the movement of the rubber price data in the futures market and finds the proper period of time and appropriate number of data used in the forecasting. The paper uses the line graph in considering the trend of rubber prices that occur in the future periods. Fundamental analysis is used to examine the factors that influence rubber prices and search the model of rubber price when the factors that influence rubber price are dynamic. However, only the market price mechanism is considered in this paper.

This paper employs the use of two main techniques for conducting price analysis, mainly fundamental and technical analyses. For the fundamental analysis, the analyst uses future projected demand and supply. This is in contrast with the technical analysis in which the analyst makes use of past information, such as past commodity prices, volumes, and open interests to predict the futures price. The fundamental analysis is comparatively more complicated and is relatively more time consuming compared to the technical analysis. In addition, the fundamental analysts needs to have a strong knowledge on the current situation of the commodity market, economics, and statistics while the technical analyst focuses more on graphical analysis on the past price data without taking much time to forecast the immediate futures price. Taking into consideration the strengths and weaknesses of each technique, the study of the RSS3 futures market efficiency in this paper uses both techniques in order to compensate for the pros and cons of each method. The paper is also aimed at studying the factors that affect the rubber futures price in the futures market. The emphasis of this paper is in evaluation of mathematical forecasting models which is similar to previous studies of Kellard, Newbold, Rayner and Ennew, 1999; Bowman and Husain, 2004; Milunovich and Joyeux, 2007).

1.3 Objectives of the Study

Based on the statements above, the objectives of the study are as follows:

1) To examine the efficiency of the price discovery process in RSS3 futures market.

2) To examine the forecasting models using the daily futures price for RSS3.

3) To determine the variables those affect the RSS3 futures price in the futures market.

1.4 Contributions of the Study

The model will be used to estimate the trend of rubber futures prices in the futures market effectively. Furthermore, the forecasting model may be applied to facilitate decision making for traders in their daily market transactions and exposures. The results from this research will also be used as a guideline in developing forecasting models for other commodities prices in the futures market. It will also help the government to plan the purchase, sale and production of rubber in the near future.

1.5 Structure of the Study

The study is divided into five chapters as follows:

Chapter 1: the introduction background, rationale, objectives, research framework, beneficial expectations, and structure of this study.

Chapter 2: the literature review is divided into four sections, which covers a review on the forecasting method and the research framework. Various literatures are reviewed extensively in the fields of efficiency in price discovery, evaluation of econometric forecasting model and the determinants created in the prediction model. The research framework covers the relationship between the market price mechanisms and the rubber futures price proposed in this section. The period of study and the performance measurement effect are also proposed.

Chapter 3: the research methodology in which secondary data collection is carried out. Most of the secondary data are collected from the AFET database, The Thai Rubber Association database, The Bank of Thailand database, and The Rubber Thai Research Center Database.

Chapter 4: the analysis and findings of this research. Separate regression tests are used to investigate the relationship between the market price mechanism and the rubber futures price. For the models' performance analysis, all criterions are used to find the differences in selecting models' performances. In addition, multiple regressions are used to determine the factors that explain rubber futures price. Discussions of the findings are also included in this chapter.

Chapter 5: the conclusions, contribution, recommendations, limitation and proposal for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter presents literary works, particularly the literatures on efficiency in price discovery, evaluation of the econometric forecasting model and the determinants. The chapter is divided into three main sections: 1) price information and efficiency literature; 2) literature on the factors affecting the rubber futures price; 3) methodology literatures

2.1 Price Information and Efficiency

Some of the literature reviews on a comprehensive test of the efficiency rubber futures on the futures markets have emphasized the informational role that the markets perform. The price information they yield facilitates both production and storage decisions. For example, assuming the futures market is efficient, Cox finds empirical evidence to indicate that the futures trading increased the information incorporated in a commodity's spot prices more fully reflect available market information when there is futures trading. Cox (1976: 1215-1237); Peck (1976: 407-423); Turnovsky (1979: 301-327); and Grossman (1989: 218). Cox argues that futures trading can alter the amount of information reflected in expected prices because speculators aided by futures trading may be more informed about future conditions and because the information incorporated in a futures price can be acquired cheaply by individuals who do not trade in the futures markets. Cox's empirical results are drawn from the onion, potato, pork belly, cattle, and frozen orange juice markets.

The forward pricing role of the futures markets became important when trading in contracts for non-storable commodities was initiated. Peck (1976: 407-423) revives the notion of the forward pricing role and argues that the futures markets provide forward prices that could be used by a producer in formulating the production decision. Her paper consists of an examination of the effects a forward price might have on the stability of commodity prices. The conclusions are that the futures markets dampen price fluctuations by facilitating the storage decision and that the producer use of the futures price in production decisions creates converging price fluctuations. These results are similar to those given in a much earlier discussion by Johnson (1947) who argues that if producers made their production decisions in relation to forward prices, greater individual and industry stability could be achieved.

Turnovsky (1979: 301-327) suggests that Peck’s paper suffers from several limitations. Turnovsky considers the implications of an efficient futures market for commodity price stabilization. Theoretically, he shows the introduction of an efficient futures market will tend to stabilize spot prices. This result is similar to Samuelson’s (1971: 335-337) demonstration that competitive speculation stabilizes prices to the optimal extent - speculators buy low and sell high. The allocation of welfare gains or losses from the introduction of a commodity futures market is also considered by Turnovsky. It is found in general that the allocation of the benefits from a futures market to the various groups in the economy tends to be an intractable exercise. However, in the case where no private storage exists, it is found that the futures market yields net gains to producers and losses to consumers. McKinnon (1967: 844-861) and Turnovsky (1979: 301-327) both conclude that the introduction of an efficient futures market will almost certainly stabilize spot prices and that its main benefits occur through its effects on production decisions. It is also suggested that the introduction of the futures markets may be an effective and cheaper alternative to buffer stock stabilization.

These results may suffer from the fact that the price information provided by the futures markets does not have a large enough time horizon to yield all of the benefits alluded to by McKinnon and Turnovsky. Grossman (1989: 218) argues that the private and social incentives for the operation of a futures market are a function of how much information spot prices alone can convey from ‘informed’ to ‘uninformed’ traders in the market. He reasons that the trading activity of informed firms in the present spot market makes the spot price a function of their information, and uninformed traders can use the spot price as a statistic which reveals all of the informed traders’ information. However, he argues that the spot price will not reveal all of the informed traders’ information because there are many other random factors that determine the price. With the introduction of a futures market, the uninformed firms will have the futures price as well as the spot price transmitting the informed firms' information to them, and this is the informational role of the futures markets. He seems to ignore the influence of random factors in determining the futures price and the fact that spot and futures prices are likely to be determined simultaneously.

Stein (1987: 1123-1145) shows that it is the theoretically possible for the price destabilization to arise with the introduction of more speculators. The new speculators change the informational content of prices and affect the reaction of incumbent traders. The entry of new speculators lowers the informational content of prices to existing traders. Crain and Lee (1996: 325-343) found a high degree of correlation between changing U.S. farm programs and changing spot and futures price variability. Some farm programs raise price volatility while other programs tend to lower volatility. The effect is so strong that they find the seasonality effects of volatility to not be as important as the impact of farm programs.

2.1.1 Commodity Price Developments

The researchers have come to varying conclusions regarding efficiency of the commodity futures markets and whether futures prices are unbiased predictors of future spot prices. For example, Moosa and Al-Loughani (1994: 99-105) found evidence of a risk premium in the crude oil futures markets and conclude that futures prices are not efficient forecasters of future spot prices. On the other hand, Kumar (1992: 432-461) presented evidence to support market efficiency and found in favor of futures prices as unbiased forecasters of crude oil prices. Brenner and Kroner (1995: 23-42) suggested that the inconsistencies observed between futures and spot prices may be the result of carrying costs rather than a failing of the efficient market hypothesis. Avsar and Goss (2001: 479-499) observed that inefficiencies are likely to be exacerbated in relatively young and shallow futures markets, such as the electricity market, where forecast errors may indicate a market still coming to terms with the true market model. Inefficiencies could also be exacerbated in markets with thin trading issues or at time-to-maturity horizons that are relatively long as market liquidity is also likely to affect risk premia (Kaminsky and Kumar, 1990b).

In finance aspect, the efficient-market hypothesis (EMH) asserts that financial markets are “informationally efficient”. The EMH claims one cannot consistently achieve returns in excess of average market returns on a risk-adjusted basis. There are three majors versions of the hypothesis: weak, semi-strong and strong. Rather than test for market efficiency directly particular on the three hypotheses, the objective of this paper is to simply investigate whether the futures prices can help predict developments of the spot prices in the future. If spot and futures prices of a commodity are found to be nonstationary and if there is evidence to suggest a cointegrating relationship between the series, it would be expected that the addition of futures prices to a forecasting model will improve the performance of the model forecasts. A related exercise was conducted by Kaminsky and Kumar (1990a: 671-699), who looked into the power of the futures prices to forecast the future spot prices for seven commodities at horizons of up to nine months, although they did not exploit potential cointegrating relatonships between the spot and futures prices. Beck (1994: 249-257), on the other hand, used cointegration techniques to test for market efficiency and the presence of risk premia in five commodity markets at the 8- and 24-week horizons. McKenzie and Holt (2002: 1519-1532) employed the cointegration and error correction models to test the market efficiency and unbiasedness in four agricultural commodity markets. It was found that out of two of the four commodities in their sample, the statistical model-based forecasts outperformed futures in a statistical sense.

Previous studies examining the performance of forecasts implied by the futures prices versus those generated by models or expert opinion came to mixed conclusions about the performance of futures-based forecasts relative to judgmental or models-based forecasts. For example, Bessler and Brandt (1992: 249-2630) found that their expert opinion livestock forecaster performed significantly better in a statistical sense at the one-quarter horizon than the futures market for cattle but not for hogs. On the other hand, Irwin, Gerlow and Liu (1994) concluded that their expert opinion forecaster failed to perform significantly better than the futures market at the one-and two-quarter horizons, both for cattle and for hogs. It should be noted, however, that because of the time-restricted nature of the futures contracts, the futures prices were not used to generate longer-term forecasts (one-five years). Hence, the performance of such forecasts, especially in relation to judgmental forecasts, were not consistently examined at the longer horizons for a reasonably wide set of commodities. Moreover, these studies did not assess directional performance, the ability to predict turning points across different types of forecasts.

Commodity prices have generally been found to be nonstationary, although the precise nature of the trend (deterministic, stochastic, or containing structural breaks) is open to debate (Cashin, Liang and McDermott, 2000: 177-217). The Prebisch-Singer hypothesis posits that there is a general downward trend in the primary commodity prices which is a thesis supported by many subsequent researchers. For example, a small but long-term negative deterministic trend in the commodity price series was found by Cuddington (1992: 207-227); Lutz (1999: 44-57), with the important exception of Cashin, Liang and McDermott (2000: 175-199); while Helg (1991); Leon and Soto (1997: 347-366); Cashin, Liang and McDermott (2000: 175-199) included some cyclical movement. This trend is typically augmented by long-lasting price shocks, for example, Helg (1991), Cuddington (1992: 207-227), Leon and Soto (1997: 347-366), and Cashin, Liang and McDermott (2000: 177-217); also, there is a significant degree of variability in the commodity prices that has increased over time (Cashin, Liang and McDermott, 2000: 177-217).

The necessary condition for the futures market efficiency has been tested in the grain by Rausser and Carter (1983: 469-478), in livestock by Garcia, Leuthold, Fortenbery and Sarassoro (1988: 162-169) including with Martin and Garcia (1981: 209-215), in energy by Ma (1989: 393-419) and in financial by Hafer and Hein (1989:33-42) and Leitch and Tanner (1991: 580-590) futures markets. In this context, the futures forecasts have been compared to those produced by time series and econometric models used by Leuthold, Garica, Adam and Park (1989: 193-204). The overall results of these studies are mixed, depending on the markets examined and alternative forecasting methods (Garcia, Hudson and Waller, 1988: 119-130). Generally speaking, the futures pricing efficiency has been rejected most often using ex post forecasts generated by the researchers’ own models and in the livestock markets (Irwin, Gerlow and Liu, 1994: 861-875). For example, Irwin, Gerlow and Liu (1994) indicated that there was evidence of forecast inefficiency in the livestock markets, especially at longer forecast horizons, when the futures forecasts were compared to out-of-sample forecasts generated ex post by the econometric or time series methods (Leuthold and Hartmann, 1979: 482-489; Leuthold, Garcia, Adam and Park, 1989: 193-204).

In contrast, studies that examined ex ante forecasts produced by experts in real-time generally did not reject the forecast efficiency (Bessler and Brandt, 1992: 249-263). In either case, the statistical criteria for forecast efficiency rests on the futures market producing a mean squared error smaller than those of competing forecasts (Leuthold, Garcia, Adam and Park, 1989: 193-204). However, as stated by Harvey, Leybourne, and Newbold (1998). However, as stated by Harvey, Leybourne and Newbold (1998: 254-259), finding forecasts, such as futures forecasts, are significantly better than those of a competitor should not "induce complacency". It is entirely possible that a forecast can have a mean squared error smaller than a competitor but if that forecast does not "encompass" all the information in the competing forecast, then it is not conditionally efficient. In this light, the traditional necessary condition for having the smallest mean squared error is not stringent enough. A higher hurdle, forecast encompassing, should be cleared in order to make any definitive arguments concerning the efficiency of the futures market.

Given the arguments of Harvey, Leybourne and Newbold (1998: 254-259), the overall objective of this research is to illustrate that the accepted mean square error necessary condition is not stringent enough and may lead to low power against the null hypothesis of forecast efficiency. As suggested in the opening quote, a smaller mean squared error is akin the trader needing to "know everything" that the market knows "something better than others". This practical observation suggests that an efficient futures market must do more than produce the smallest mean squared forecast error. Instead, a futures forecast must meet a more exacting criterion – it must encompass all competing forecasts. Thus, this research introduces forecasts encompassing as a more exacting necessary condition for the futures market efficiency. In doing this, a direct application of the encompassing principle is provided using ex ante forecasts produced by market experts, as well as out-of-sample forecasts produced by univariate time series models over alternative forecast horizons.

2.1.2 Efficiency of Futures Market

A very broad definition of an efficient futures market is one in which the prices fully reflect available information at any point in time (Fama, 1970: 383-417). Alternatively, if information is costly, an efficient market is one which reflects information up to the point where the marginal benefits from trading or futures contracts based on this information do not exceed the marginal costs of collecting the information (Fama, 1991: 1575-1617). Th empirical testing for efficiency is difficult because these definitions are so general.

The empirical work on the efficiency of the futures markets typically measures the adjustments of the futures prices to a particular information set. In his early review of this work in security markets, Fama (1970: 383-417) classified efficient market tests into three groups: weak, semi-strong, and strong forms. Fama's concept of efficient markets is different from (but not necessarily inconsistent with) the traditional welfare concept of efficiency in economic theory. Fama measures market efficiency by the speed at which prices reflect changes in supply and demand information, whereas the welfare concept of efficiency is concerned with maximizing the size of the economic pie. The information set for weak-form tests is confined to historical market prices. The semi-strong form tests measure the market's adjustments to historical prices plus all other relevant public information while the strong-form tests measure its adjustment to 'inside' information not available to the public. However, any test of market efficiency is necessarily a joint test of efficiency and a model of asset pricing, which means that market efficiency per se is not strictly testable (Fama, 1991: 1575-1617). Figlewski (1978: 581-597) has questioned the efficiency assumption in its most general form. He developed a model of a speculative market in which the redistribution of wealth among traders with different information is studied and theoretically demonstrates that in neither the short nor the long run is full efficiency (in Fama's stron-form sense) likely in a financial market if the participants are risk-averse. Structured as Fama weak-form tests, the early studies of efficiency applied mechanical filters to futures prices to determine the success profit-wise of various trading systems. For instance, see Stevenson and Bear (1970: 65-81); Leuthold (1972: 879-889) and Praetz (1975: 240-249). Furthermore, Cargill and Rausser (1975: 1043-1053) compare and contrast the use of mechanical filters to determine whether profits can be generated and the use of statistical tests to determine whether systematic price behavior is present. They found that filter tests were not a substitute for statistical analysis. Using statistical analysis, they rejected the simple random walk model as an explanation of commodity market behavior.

Tomek and Gray (1970: 372-380), and later Kofi (1973: 584-594), were the first to test the forecasting ability of the futures market within the context of market efficiency. They challenged Working's reluctance to view the futures price quotations for storable commodities as forecasts, and they argued that inventories of storable commodities provide a link between the springtime prices of the post-harvest futures and the subsequent harvest-time prices, which helps to make the futures price a self-fulfilling forecast. Using OLS, they estimated the coefficients of the linear regression. A 'perfect forecast' was one for which alpha and beta were estimated to be zero and unity, respectively. Both studies found that the forward pricing function of the futures markets was more reliable for continuous than for discontinuous inventory markets. For potatoes, coffee, wheat, corn, soybeans, and cocoa, Kofi's (1973: 584-594) results from the 1953-1969 data clearly showed that the further away from the contract expiration date, the worse the futures market performed as a predictor of spot prices. Leuthold (1972: 878-889) estimated the OLS equation like Tomek and Gray, including Kofi for corn and cattle, and found similar results that the futures market was an efficient predictor of the spot prices for only near maturity dates. His results for cattle showed that, up until the 15th week prior to delivery, the cash price was a more accurate indicator of realized cash prices than was the futures price. This phenomenon was also confirmed for Maine potatoes by Gray (1972: 337-365), and for live beef cattle, corn and Maine potatoes by Stein (1987: 223-232). The estimated coefficients of the equivalent of the same equation similar to Tomek and Gray, including Kofi, led Stein to conclude that the futures price, earlier than four months to delivery, was a biased and useless forecast of the closing price.

Kenyon, Jones and McGuirk (1993: 399-407) examined the forward pricing performance of soybeans and corn, and how this may have changed over time. For the 1952-1972 period, they found both soybeans and corn futures to be unbiased forecasts of forthcoming spot prices. However, for the more recent 1974-1991 period, they found both soybeans and corn futures to be biased estimates of forthcoming spot prices. Maberly (1985: 425-432) and Elam and Dixon (1988: 365-372) argued that running OLS on equation like Tomek and Gray including Kofi could give misleading results with regards to pricing efficiency. They have different reasons for making the same claim. Maberly argued that the studies may have erroneously found inefficiency due to biased OLS estimates resulting from ex-post ‘censored’ data. The spot price is censored from above by the value of the futures price and the futures price is censored from below by the value of the spot price. This means that the forecast error and the forecast futures price are negatively correlated in that OLS equation. Elam and Dixon agree with Maberly’s conclusion but they argued that his reasoning was flawed. Elam and Dixon suggested the OLS bias was due to the fact that the regressor in equation of Tomek and Gray including Kofi was the lagged value of the dependent variable. More recently, Brenner and Kroner (1995: 23-42) took a different tack and argued that the test for price bias with equation of Tomek and Gray including Kofi was inappropriate for commodity markets because the spot and futures prices may have not been cointegrated because the cost of carrying had a stochastic trend.

Tomek (1997: 23-44) stressed that the futures prices could provide poor price forecasts but still be efficient, as long as their forecasts were better than any alternative, such as econometric model. If the futures market is efficient, then it should be able to out-forecast an econometric model.

Just and Rausser (1981: 197-208) found that the futures market did just as well as publicly available econometric models in terms of forecasting commodity prices. Roll (1984a: 861-880) found that price movements in the orange juice futures market could predict freezing temperatures in Florida better that the US national weather service could. In other words, the futures market was found to be efficient in terms of incorporating available weather information. However, Roll indicated that a ‘puzzle’ remains in the orange juice futures market because there was a large amount of inexplicable price volatility. Fama and French (1987: 55-73) tested for evidence of whether or not commodity futures prices provided forecast information superior to the information contained in the spot prices. They found that the futures markets for seasonal commodities contained superior forecast power relative to spot prices. However, this was not the case for nonseasonal commodities.

The event studies and efficiency implications: papers by Miller (1979: 67-70); Hoffman (1980: 145-150); Gorham (1987: 30-38); Sumner and Mueller (1989: 1-8) including Colling and Irwin (1990: 84-94) have demonstrated that the futures prices reacted quickly to the release of USDA livestock and crop reports. Sumner and Mueller (1989: 1-8) investigated the informational content of USDA corn and soybean harvest forecasts. They developed a statistical test to determine whether the mean and variance of day-to-day futures price changes were influenced by releases of corn and soybean crop reports. They found that USDA harvest forecasts affected market price movements but concluded that significant information content did not mean that crop reports were worth the price to taxpayers. In a follow-up study, Fortenbery and Sumner (1993: 157-173) found that after 1984, the corn and soybean futures prices did not react to the release of USDA reports. Garcia, Irwin, Leuthold and Yang (1997: 559-570) found that the unanticipated component of USDA corn and soybean reports affected the futures prices but the informational value of the reports had decline since the mid-1980s.

2.2 Factors Affecting the Rubber Futures Price

There is a relationship between the physicals and futures prices. Not only does the operation of hedging link physical and futures prices, but also futures prices are determined by factors influencing physical prices. In addition, the futures prices are widely used in physical trading around the world. Since there are many similar factors influencing demand and supply of the futures and physicals, the movements in the two prices are generally the same. Prices are likely to increase when demand is greater than supply and vice versa. In fact, movement in the same direction is the rationale behind hedging in the first place. However, even when they move in the same direction, they may not move at the same rate. The difference of the two prices, i.e. the basis, can be widening or narrowing whether price are rising or falling. For example, a rise in interest, with everything else constant, will result in lower physical prices but higher futures prices. The point is that even though prices may not move in the same direction, they are interrelated. In general, the futures prices lead physicals prices rather than the other way around.

Whether the distant futures should be higher or lower than the spot prices depends on the physicals relative to the futures markets. In general, when the physicals market is in surplus, the prices of spot and/or nearby futures are lower than the prices of distant futures. This is called a normal, contango, or forwardation market. The opposite situation, sometimes referred to as a backwardation or inverted market, is when the prices of spot and nearby futures are higher than those of distant futures and generally occurs when there is a shortage of physical commodity. The reason that contango or forwardation is called a normal market is that in the reverse situation, when the spot price is higher than the future prices, there would be a tendency for stockholders to sell stock now to reduce their inventory and possibly gain profit. At the same time they will buy forwards at a relatively low price to increase stock. This is likely to depress spot and stimulate futures prices. However, when the futures are higher than the spot, it may not be beneficial to buy at the lower spot price unless the premium on the futures is greater than the carrying cost.

The question of premium or discount on the futures depends on the supply and demand situation and seasonal factors. For agricultural commodities, one can expect that during the harvest period when supply is generally high, there is likely to be a discount on spot supplies. The possibility of a premium will occur when available supply is tight in relation to current demand. The limit of a premium on spot depends on the extent of the shortage of the commodity at the time. However, a discount on spot over futures is usually limited to carrying charges, warehousing, insurance and interests. Extra profit can be made if this is not the case. In a normal situation, when supply is sufficient to meet expected demand, the premium on futures would be approximately equal to carrying charges. Hence, as the delivery date draws nearer and carrying charges decrease, the premium narrows. It can be proven that the basis is more likely to approach full carrying charges in time of surplus and prices are declining. On the other hand, there is no limit to the premium in the inverted markets when there is a shortage of physical commodity.

Because spot price is lower than the futures price and the delivery date is close by in a normal market, there will be a tendency for the increase in demand for spot and supply of the futures. People who are short in futures or those who are starting transactions by selling futures contract will buy spot and make delivery. One the other hand, those who are long or starting transactions by the purchase of a futures contract will liquidate. As a result, the forward price will tend to either fall faster or rise slower, while the opposite is true for the spot price. In the end, the price of spot and the natured futures must be equal. The opposite case is for inverted markets, where the futures will be bought and longs will be willing to wait until delivery, whereas shorts will try to cover by buying back contracts. The tendency is for the futures prices to rise relatively fast compared to the spot prices, and become approximately equal at maturity.

So, in theory, it can be said that the spot and distant prices do not necessarily move in the same direction and the basis can either increase or decrease.

What dominates and play roles in rubber price determination each day are some general factors that support the uptrend of rubber prices. The downtrend would happen when it comes to the reverse effect at the same.

1) Oil price change by all means affects nearly everything in the world. Its by-product is also used as one of the main content to produce Synthetic Rubber (SR). As SR is a perfect substitute goods of Natural Rubber (NR) so when oil price increase, SR price increases, and then NR price also increases.

2) Rubber stock at sellers may mean the current seasonal index in annual round. By nature, rubber trees stop yielding latex produce around the end of February until early June. It causes the aggregate rubber volume in the central market to be fewer. This situation tends to push the rubber market price to be in upward trend during the end of rubber season. The expectation of sellers is also set as a condition where the sellers hold the last stock for expectant high price to sell during the closing of the season.

3) Rubber stock at buyers; when the big buyers like China keep collecting rubber stock with the expectation of future price buffer, it may control the price at the low level for some period of time. The big buyers are China, Japan and the U.S. The special demand for rubber usage from big buyers also counts. The Olympic Games 2008 in Beijing, China led to an outburst of economic boost which results in high level production of goods. Tires and rubber-related goods are heavily produced to respond to this occurrence of economic boom.

The signs that convey price significance: rubber price will be higher, when Yen depreciates, Baht depreciates, higher oil price, higher gold price, floods and heavy rains in growing areas, stock markets boom, big three buyers; interest rate down, big three buyers; economic growth, less rubber stock, hedge Funds price support. Rubber price will be lower, when Yen appreciates, Baht appreciates, lower oil price, lower gold price, big three buyers slow down the purchase, hedge Funds move to invest in gold and oil, big stock markets fall.

2.3 Methodology Review

The macroeconomic stability is an external, yet critical factor in the operations of the futures markets. Commodity price risk is merely one of the diverse risks that users of futures contracts try to hedge against. Thus, it is imperative that a country maintains a sound macroeconomic environment for a local exchange and contract to succeed.

2.3.1 Methodology in Price Efficiency

This methodology primarily focuses on the use of the time series technique in understanding time related properties of RSS3 spot and futures market prices in Thailand, and to compare it with the naïve model. Traditional econometric techniques are found to be inadequate when trying to make inferences with time ordered observational data. Prior theory traditionally suggests the explanatory variables that should go into a model. However, the theory was developed using the ceteris-paribus assumption. When “all other things” are not fixed, as is the case with experimental data, researchers must rely on less “structured” models. The paper used prior theory to suggest variables to be studied.

2.3.1.1 Univariate Time Series Model

The Time series analysis studies data observed over a period of time. Each observation is indexed by ‘t’ in order to keep track of the order of its observation. A key idea behind all time series models is that the order of observation matters. As an example, if a person says that he is observing futures prices of RSS3 over a period of time. When a new piece of information hits the market in the current time, it moves the price away from the most recent price value. This new piece of information is not well defined as a random draw from the historical mean price. Therefore, the historical mean is not a good measure of forecasting the effect of the shock. The analysis of a single series of data and its movement through time is called univariate analysis.

Let X_t be a random variable whose value only depends on the past lag values of itself, and values of an error term. This is known as the innovation term in the time series literature. A simple univariate model can be defined as follows: $X_t = \alpha + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \beta_p X_{t-p} + e_t$ 1) where α is the intercept term and the β s are unknown parameters. The term e is the uncorrelated error term. This is assumed to have a zero mean and a variance of σ_e^2. We just defined in equation (1) an autoregressive model of order p, where p is the number of lags in the model. Stationarity is an important property in the time series processes. In general, a time series process is stationary if the mean, variance and co-variance of the series are finite and constant. But if we consider a random walk model: $Y_t = Y_{t-1} + e_t$, the variance of the series is infinite and the series is not stationary, say Y_t is today's futures price and Y_{t-1} is yesterday's futures price in the futures market and the e_t is the white noise term. Such series can be differenced once or many times to make them stationary. If the series is differenced once, it is said to be integrated to order one. That means, $\Delta Y_t = (Y_t - Y_{t-1})$ is a stationary series and integrated of order one; here Y_t is an I(1) series.

Table 2.1 Summary of Literature on Univariate

Author	**Findings**	**Context of the study**	**Measuring Method**
Baghestani, Jung and Daniel (2000)	The futures market data outperform both the univariate and professional survey forecasts.	Treasury bill rates	Univariate
Abosedra (2006)	The univariate forecast suggests that the futures price of crude oil tends to be semi-strongly efficient.	Crude oil	Univariate

2.3.1.2 Vector Autoregressive Model (Multivariate Time Series Model)

Constraining oneself to univariate models is generally overly restrictive, as the real world is oftentimes viewed or theoretically as a set of interacting variables. This leads to the use of multivariate models, where many variables and their interactions are considered. Thus the Vector Auto Regression (VAR) models have become popular. The VAR model is a theoretical analysis or non-structural analysis that summarizes the regularities in a set of variables which the theory suggests as important (Bessler, 1984: 25-30). These models are useful in the analysis of observational data, for example, data that are collected without experimental controls. In structural modeling, a pre-determined model is suggested through the knowledge of the prior theory and structure. In VAR modeling the choice of variables studied does not depend on the pre-determined structure, rather on the problem under study and theory, which will be used to study regularities of data.

2.3.1.3 Test of Non-Stationarity

A series is said to be mean non-stationary if the data points are moving away from its historical mean for a long periods of time. In other words, the data are non-mean reverting. Granger and Newbold (1974: 111-120) used the Monte Carlo simulations to show that results from regressions that use such data could be spurious. Non-stationary data may have an infinite variance. This may lead to improper inferences based on the t-statistic in estimation and hypothesis testing. Further studies have proved that other traditional statistics such as F distribution and R^2 statistic do not have the correct properties in the presence of non-stationary data (Phillips, 1986: 311-340).

A formal test on non-stationarity is the Dickey-Fuller test (DF). The t-statistic, calculated as the ratio between estimated coefficient and standard error of the estimated coefficient, is the test statistic used in the DF test. The approximate 5 percent critical value estimated using the Monte Carlo simulation is -2.89 (say one calculates and gets a critical value of -4.85, then one rejects the null and conclude that the series is stationary in levels). But sometimes the DF test may suffer from problems of autocorrelation problem in the residuals estimated (Granger and Newbold, 1986). Then one can use an augmented DF test (ADF) to sufficiently whiten the residuals.

2.3.1.4 Computation of the Theil's U-Statistic

By calculating the Theil U-statistic, one compares the VAR model forecasts against the forecasts generated assuming a random walk model. Efficient markets are assumed to have a random walk type of behavior. The statistics in excess of one means that the model did not forecast well compared to the random walk model.

Given the importance of and interest in the pricing efficiency of futures markets as a topic of inquiry, numerous studies have examined the efficiency of agricultural futures markets. Nearly every agricultural futures contract listed by an exchange today has been examined in some context (Garcia, Hudson, and Waller, 1988). In examining the necessary conditions for futures market efficiency, three sets of forecasts are use in predicting the USDA's announced Class III price: futures forecasts, forecasts generated from simple time series models, and expert opinion forecasts. These forecasts are first evaluated using the traditional forecast accuracy measure of root mean squared error. In addition to casual comparisons of mean squared error, the multiple data model (MDM) procedure tests for statistical differences in forecast accuracy (Harvey, Leybourne and Newbold, 1998) are used. The more stringent test of pricing efficiency, which is forecast encompassing, is then tested in a multiple encompassing framework using the MS test statistic put forth by Hervey and Newbold which they suggest as a test statistic MS based on Hotelling's generalized T2-statistic. Intuitively, futures market efficiency should be intimately linked to the ability of that market to forecast. Nevertheless, Working (1985) was reluctant to call futures prices forecasts.

In addition, Tomek and Gray (1970) suggested that cash prices of non-storable commodities may be able to forecast deferred prices better than futures prices can. The futures market will not forecast if doing so elicits behavior that will prove the forecast wrong (Koontz et al., 1992). Yet, poor forecasting does not necessarily make a market inefficient. The futures market may still be the best forecast available. Thus, the mere existence of poor forecasts is not sufficient to contradict efficiency. Fama (1970) suggested that a futures market is efficient if the prices contain all relevant information. He also described efficiency in terms of whether abnormal trading profits can be earned conditional upon three possible sets of information, namely, weak form, semi-strong form, and strong form. Grossman and Stiglitz (1980) extended Fama's definition by noting that where information has a cost, informational efficient markets will be impossible. Essentially, their work adds that for perceived inefficiencies to be real inefficiencies, they must be large enough to merit the cost of trading them out. Fama (1970) acknowledged this as well. In addition, profit comparisons for efficiency testing should account for risk. In recently, the long-run equilibrium condition shows the main role on efficiency and unbiasness on measuring method called cointegration.

Cointegration is an econometric property of time series variables. If two or more series are themselves non-stationary, but a linear combination of them is stationary, then the series are said to be cointegrated. For instance, a stock market index and the price of its associated futures contract move through time, each roughly following a random walk. Testing the hypothesis that there is a statistically significant connection between the futures price and the spot price could now be done by testing for a cointegrating vector. Before the 1980s many economists used linear regressions on non-stationary time series data, which Clive Granger used the Engle-Granger two-step method (null hypothesis: no cointegration, so residual is a random walk) and others showed to be a dangerous approach, that could produce spurious correlation. His 1987 paper with Robert Engle used the Johansen procedure formalized the cointegrating vector approach and coined the term. It is often said that cointegration is a means for correctly testing hypotheses concerning the relationship between two variables having unit roots. The summary of literature shows in Table 2.2.

Table 2.2 Summary of Literature on Cointegration

Author	**Findings**	**Context of the study**	**Measuring Method**
Kellard et al. (1999)	The long-run equilibrium condition holds, but there was evidence of short-run inefficiency by cointegration	Soybeans on the CBOT, live hogs and live cattle	Cointegration

Table 2.2 **(Continued)**

Author	Findings	Context of the study	Measuring Method
Ke and Wang (2002)	The existence of a long-term equilibrium relation between the futures price and cash price	Soybean futures market	Cointegration
Mckenzie and Holt (2002)	Futures markets for all the commodities except broiler were efficient and unbiased in the long-run	USA futures markets for cattle, hogs, corn, soybean meal and broiler	Cointegration
Zapata et al. (2005)	Futures market for sugar leads the cash market in price discovery	Sugar futures prices traded in New York and the world cash prices for exported sugar	Cointegration
Hourvouliades (2006)	Offered evidence for the EMH, with the series following a random walk, having a long-term equilibrium	Stock index futures market	Cointegration
Aulton et al. (2008)	Efficiency and unbiasedness in relation to wheat, only efficiency in relation to potatoes and pig meat.	UK agricultural commodites	Cointegration

2.3.2 Methodology in Forecasting Model

2.3.2.1 Forecasting Models

The simplest form of a forecasting model is the unit root model with trend and drift. If the commodity price series contains a unit root, then a different stationary model or cointegration should be used to model prices, otherwise the basic trend stationary model is appropriate. This simple model can serve as a useful benchmark for comparison with other more sophisticated models.

An alternative forecasting model could be one that allows for an autoregressive process and a moving average model for the errors. Such a model may be particularly appropriate for commodities where prices are mean reverting (Irwin, Zulauf and Jackson, 1996: 397-399).

If markets are efficient, the futures prices should be unbiased predictors of future spot prices and a simple prediction model should give superior results to those using alternative variables. Efficiency tests would require careful matching of futures contract horizons and expiry dates with actual spot prices. As described, the averaging of futures and spot price data in our dataset does not permit such tests with reasonable accuracy. To that end, the futures prices can be added to the unit root model and ARMA specifications in an effort to obtain more accurate forecasts.

Finally, if the commodity spot and the futures prices are co integrated, an error-correction model (ECM) can be used to capitalize on this relationship. Engle and Granger (1987: 251-276) show that a system of two co integrated series implies an error-correcting equation. Assuming that the futures prices are weakly exogenous, this was verified during the co integration testing. The ECM is used in the study as a contrast to the best forecast obtained from the simple unit root and ARMA models with and without futures, as well as judgmental forecasts.

More complex models may, of course, be developed, such as that of Heaney (2002: 45-65) which incorporates cost-of-carry into a forecasting model for lead prices and hence contains an interest rate component, or Generalized AutoRegressive Conditional Heteroskedastics (GARCH) models (Morana, 2001: 325-338) and probability-based forecast models. However, for the purposes of Morana's paper, where the objective is to gauge whether the incorporation of the futures prices potentially yields superior forecast performance, the forecasts use only historical spot prices and futures prices in an effort to identify simple models which may be successfully applied to a wide range of commodities, rather than to specific commodities.

In the first forecast model, a simple random walk without drift is considered. The second model considered is also a random walk, but with a drift term. Random walk models explicitly impose a unit root on the system, and often well relative to a wide class of more complex models in practice, and are thus useful benchmarks. The third model examined is a linear vector autoregressive model (VAR) Notice that the forecasts are based on price levels rather than differences. Level VARs may outperform differenced VAR empirically, even though the variables are nonstationary. The reason why this may be the case is that the differences could result in a loss of information. The excellent discussions on applying VAR models can be found in Sim (1980: 1-49), Enders (1995), Clements and Hendry (1995: 127-146) including Hoffman and Rasche (1996: 495-517). Nothing can justify that by using levels VARs instead of differenced VARs might lead to a loss of information with respect to co-movements among variables. The advantage of applying levels VARs is that one may better mimic the true data generating process. Finally, one estimates the parameters of all regressions at each point of time using a fixed sample size and then forecast prices based on these estimated parameters. On each day, all the estimators and models are updated as a fixed 207-day sample moves forward one period. The forecasting horizon examined is one step ahead.

2.3.2.2 Type on Selection Criteria

Most of the researches employ a number of out-of-sample model selection criteria to evaluate the predictive performance of the models considered. These criteria can be classified into two categories: criteria for multi-equation system, and criteria for univariate forecast. All criteria are calculated using forecast errors based on the samples and forecast horizons. Some research also constructs on the Diebold and Mariano predictive accuracy tests for pair wise model comparison, as well as profitability test based on a maximum-spread trading strategy, market timing test based on confusion matrices, and associated Chi-squared tests of independence.

1) The Evaluation Criteria for Full System

(1) Trace of Mean Square Error Matrix (TMSE)

(2) Trace of Mean Absolute Percentage Error Matrix (TMAPE)

(3) Mean Schwarz Information Criterion (MSIC)

SIC is a complexity penalized likelihood measure (Rissanen, 1978: 465-471; Schwarz, 1978: 461-464;). It is the only in sample model selection criterion used in the paper. The in sample SIC may not offer a convenient shortcut to true out-of-sample performance, as was shown in Swanson and White (1995: 265-275). However, the in-sample SIC can be very useful to other contexts, such as for selecting candidate forecasts in forecast combination (Swanson and Zeng, 1996).

(4) Trading-Rule Profitability Criterion (TPC)

The final system measure is a trading-rule based profitability criterion. As was suggested by Leitch and Tanner (1991: 580-590), conventional selection statistics like mean square errors may not be closely related to economic profits. This implies that a profit measure may be more appropriate to evaluate the forecasts from the different models. This paper examines comparable spreads of contracts maturing at different dates for the same commodity. If one spread is anticipated to fluctuate most, then no matter if the spread today is long or short, which depends on the direction of the forecasts, the opposite position in the same spread will occur in the next period. Note that this rule is a buy-hold strategy, where the arbitrageurs during each day enter into offsetting positions against the spread taken h-days ago. This may not be the best strategy though since the position taken based on forecasts h days ago will not be updated as extra data becomes available. One reason one did not use a more sophisticated strategy is that one is more interested in the forecasting accuracy of the different models for the given forecast horizon where the transaction costs are not considered. However, one expects that the evaluation of the relative performance of different models should not be affected by this omission since one’s strategy restricts trading volume to one unit per day and more importantly, all models involve the same trading frequency. Also, the capital requirement for market-to-market should not be a problem as the holding periods are short and the offsetting position will always be taken cyclically. Overall, the capital availability is not a trivial question in a spread-based trading strategy. A more detailed discussion can be found in Abken (1989: 77-86). Other questions affecting the implementation of a trading strategy involve the potential illiquidity issues and problems associated with the delivery periods of the futures contracts which are ignored in the study. An overview of similar issues can be found in Ma, Mercer and Walker (1992: 203-217). Finally, one possible reason why a spread-based trading strategy could result in a positive profit is mean reversion. A partial list of relevant literature where the issue is discussed includes Fama and French (1988: 1075-1093); Cecchetti, Lam and Mark (1990: 399-418); Kim, Nelson and Startz (1991: 515-528); Miller, Muthuswamy and Whaley (1994: 479-513); as well as Bessembinder, Coughenour, Seguin and Smoller (1995: 361-375) including Swanson, Zeng and Kocagil (1996).

2) Evaluation Criteria for Univariate Forecasts

When evaluating the ex-post effectiveness of forecasts, standard statistical measures are commonly used. Mean pricing error, mean absolute pricing error, mean absolute relative pricing error (MARPE), median absolute relative pricing error and root mean squared error (RMSE) are typically calculated. The results are used to generate conclusions about the accuracy of forecasts, for example, Just and Rausser (1981: 197-208); Leitch and Tanner (1991: 580-590); Bessler and Brandt (1992: 249-263) including Gerlow, Irwin and Liu (1993: 387-397). This research will focus primarily on RMSE, which gives a measure of the magnitude of the average forecast error, as an effective measure. It may be noted, however, that the RMSE is a measure that is commodity specific and cannot be readily used for comparing across commodities. Mean squared error (MSE) is used extensively to evaluate the forecasting performance of the futures markets. Early studies relied on casual comparisons of MSE (Leuthold, 1974: 271-279) while more recent studies have examined the statistical difference in forecast error (Irwin, Gerlow and Liu, 1994: 861-875. As previously stated, the standard necessary condition for futures market efficiency is that no competing forecast such as a time series, econometric, or expert opinion forecast provides a smaller MSE than the futures market forecast. However, differences in MSE among competing forecasts are often subtle, thus leading the researcher to wonder if differences in MSE are due only to chance. Although significant advances have been made in evaluating the statistical difference in prediction errors (Diebold and Mariano, 1995: 253-263; Harvey, Leybourne and Newbold, 1998: 281-291), stating the necessary condition for the futures market inefficiency strictly in a comparative MSE framework is potentially misleading. The following intuitive example illustrates how the MSE is a necessary condition if flawed. Therefore, a trader armed with the alternative model could conceivably use it to extract trading profits from the futures market. Given this counter example, the traditional MSE necessary condition for futures market efficiency is incomplete, and forecast encompassing is proposed as a more exacting necessary condition.

(1) Root Mean Square Error (RMSE)

The RMSE is one of the most widely used measures of forecast accuracy. While simple and intuitive, MSE is not without potential drawbacks. First, MSE may be inconsistent with profit measures, as was pointed out in Leitch and Tanner (1991: 580-590); Stekler (1991: 375-384) and Swanson and White (1995: 265-257). Furthermore, MSE is not invariant to non-singular, scale preserving linear transformations. This problem is discussed in Clements and Hendry (1995: 127-146).

As the magnitude of the RMSE is specific to each price series, it can be difficult to quickly assess the performance of a model from this statistic. Hence in this application, the RMSE result is displayed relative to the RMSE of either the random walk model or the others, to facilitate comparison between models. The base model will have a value of unity. If a comparison model has a relative RMSE value greater than unity, it may be considered to underperform the base model in terms of statistical accuracy. On the other hand, a relative RMSE value less than unity would indicate superior RMSE performance in relation to the base model.

Directional accuracy is also relevant to commodity forecasts, where the ability to identify future turning points is of particular importance. When assessing forecast performance, the identification of directional changes may indeed be more important than the actual magnitude of error. Two methods are used to assess directional accuracy in this study. The first is the Harding and Pagan (2002) test of concordance, which seeks to identify synchronicity in the turning points of two series. The Harding-Pagan test is a statistical measure that casts no preference on the ability of the model to predict important changes as opposed to small but directionally accurate changes. This measure is augmented by the Cumby and Modest (1987: 169-189) test, which weighs the prediction of significant turning points more highly and hence is often used as a measure of the profitability of a prediction.

A rough measure of directional accuracy can be obtained by simply counting the number of times the forecast and actual prices move in the same direction. From this, a percentage of accurate directional forecasts may be calculated for each model. On average, a random walk model should pick the direction successfully around 50 percent of the time, and that more accurate forecast models should improve on this. Harding and Pagan (2002) extend this concept of directional accuracy, creating a measure of synchronicity that may be used to determine whether forecasts are in sync with actual price movements, or whether the confluence of prediction and reality is simply luck.

Hence, this statistic measures how closely, in directional terms, prices implied by futures move with actual spot prices. As noted above, forecasts form a random walk model would be expected, on average, to yield Concordance statistic of about 0.5.

Another test of the directional performance of forecast models is the Cumby and Modest (1987: 169-189) test for market timing ability, which is an extension of the Merton (1981: 363-406) market timing test. It was designed to use information about the magnitude of change, as well as the direction of change to generate a performance statistic. The estimates are applied with the White (1980: 817-835) adjustment for heteroskedasticity. In essence, this differs from the Harding-Pagan statistic in that the dependent variable incorporates both the magnitude as well as the direction of the change. Hence, the Cumby-Modest statistic gives extra weight to situations under which the forecast would have correctly predicted the direction of large actual changes in spot prices. When a forecast misses a directional change in prices that is small in magnitude, it is not penalized as heavily by the Cumby-Modest statistic as it is by the Harding-Pagan statistic.

(2) Mean Absolute Percentage Error (MAPE)

(3) Diebold-Mariano Predictive Accuracy Test (DM Test)

Harvey, Leybourne and Newbold (1998: 281-291) originally proposed a modification of the Diebold-Mariano test for differences in MSE to account for non-normal distributions of the forecast error series. The paper also constructs the asymptotic loss differential test proposed in Diebold and Mariano (1995: 253-263). Using only the loss differential series and the assumption that the loss differential series is covariant stationary and has short memory, the DM test has a null hypothesis that both forecasting models are equally accurate. Following the suggestion of Diebold and Mariano (1995: 253-263), the paper uses rectangular lag window defined by $L[\tau / S(T) = 1$ for $|\tau / S(T)| < 1$, =0 otherwise. Note that assuming (h-1)-dependence of loss differentials for h-step ahead forecasts implies only (h-1) sample autocovariances needed in the eatimation of f(0), so that S(T)=h-1.

(4) Confusing Matrix (CM) and Confusion Rate (CR)

An alternative model selection criterion is the market timing criterion suggested by Henriksson and Merton (1981: 513-533); Schnader and Stekler (1990: 99-107); Pesaran and Timmermann (1994: 1-7); and Stekler (1994: 495-505), which can be used to forecast economic turning point. The confusion rate calculated in the paper is retrieved from a two by two contingency table, called Confusion Matrix (CM). The best model according to CR is the least confusing one (the one is with the smallest value of CR). Pesaran and Timmermann (1994: 1-7) showed that the test of market timing in the context of forecasting the direction of assert price movements proposed by Henriksson and Merton is asymptotically equivalent to the standard chi-squared test of independence in a confusion matrix, when the column and row sums are not a priori fixed, which is the case in this analysis. One examines the standard chi-squared test of independence. The null hypothesis is the independence between the actual and the predicted directions. Thus, rejecting the null hypothesis provides direct evidence that the model is useful as a predictor of the sign of change in the prices. The chi-squared is therefore used to test statistics. In the recently period, some researches already provide the standard statistical measurement in Table 2.3.

Table 2.3 Summary of Literature on Evaluation of Econometric Forecasting

Author	Findings	Context of the study	Statistical Measurement
Liew et al. (2000)	ARMA models fit the price series well	Salawak black pepper price	RMSE, MAE and MAPE
Du and Wang (2004)	ARIMA models are fitted to the data resulting in the selection	CZCE Wheat futures price	RMSE
Hossain et al. (2006)	Using Box-Jenkins on the basis of forecasting	Commodities in Bangladesh	AIC, BIC, RMSE, MAE, MAPE and THEIL'S
Badr and Moghaddasi (2009)	ARIMA outperformed in predicting the price	Wheat	RMSE, MAE and MAPE

2.3.3 Variables Measurement

The study is made on the variables' effects on the price of rubber by regression for monthly time-series that are mentioned as follows:

1) RSS3 futures price at time t-1
2) Oil price
3) Exchange rate (Baht per Dollar US.)
4) Exchange rate (Yen per Dollar US.)
5) Quantity of consuming synthetic rubber in the world
6) Quantity of imports of synthetic rubber (Japan)
7) Quantity of imports of synthetic rubber (China)
8) Quantity of consuming natural rubber in the world
9) Quantity of imports of natural rubber (Japan)
10) Quantity of imports of natural rubber (China)

The method of constructing model is as follows:

1) Normalisation: it is used to adjust each variable using the same measuring unit.

2) Creating the reference graph by using monthly RSS3 is the reference graph on rubber price.

3) Plotting a histogram between price and independent variables.

4) Considering the leading variable.

When all the variables' graphs are gathered, visual examination is used to select the graph that is similar to the reference graph. Some variables used within this century show in Table 2.4.

Table 2.4 Summary of Literature on Determinants Used

Author	Findings	Context of the study	Variable Measure
Jumah and Kunst (1999)	Exchange rate posed as a main source of risk for commodity futures price	Coffee and cocoa futures	Dollar / Sterling exchange rate
De Roon et al. (2002)	Hedging pressure effects remain significant after controlling the price	Agricultural, mineral, and exchange futures markets	Price
Meulenberg and Pennings (2005)	Latent variables are important in discriminating variables	Dutch Hog	Farmers' perceived performance, reference price
Luo (2007)	Market expectation has fundamental significant effect	Crude oil	Supply and demand, geopolitical factors
Khin et al. (2008)	The fundamental variables were significant to the price of natural rubber	Natural rubber	Demand, total production, commercial vehicle cars' tires, total production of natural rubber product, lagged price

CHAPTER 3

METHODOLOGY

3.1 Research Methodology

The paper aims at suggesting a set of test through the number of time series data of RSS3 futures market in Thailand. Thereafter, the paper continues to focus on the usage of time-series techniques to understand the time related properties of RSS3 and to compare each model with the naïve model. Findings reveal that traditional mathematic techniques, such as mean squared error and root mean squared error, are found to be inadequate when trying to make inferences with time ordered observational data. Prior theory suggests the explanatory variables that should go into a model. However, the theory is developed using the ceteris-paribus assumption. When "all other things" are not fixed, as is the case with experimental data, researchers must rely on less "structured" models. Here, the paper uses prior theory to suggest variables to be studied, but relies on empirical patterns in the time sequence to specify explicit relationships among each variable.

3.1.1 Unit Root Test

A unit root test tests whether a time series variable is non-stationary using an autoregressive model. The most famous test is the Augmented Dickey-Fuller test. Another test is the Phillips-Perron test. Both these tests use the existence of a unit root as the null hypothesis.

3.1.1.1 Test of Non-Stationary

Non-stationary data may have an infinite variance. This may lead to improper inferences based on the t-statistic in estimation and hypothesis testing. Further studies have proved that other traditional statistics such as F distribution and

R^2 statistic do not have the correct properties in the presence of non-stationary data (Phillips, 1986).

Autocorrelation is the cross-correlation of a signal with itself it is used frequently in signal processing for analyzing functions or series of values, such as time domain signals. It further implies that the autocorrelation can be expressed as a function of the time-lag. When the autocorrelation function is normalized by mean and variance, it is sometimes referred to as the autocorrelation coefficient (Loeve, 1977). In regression analysis using time series data, autocorrelation of the residuals ("error terms", in econometrics) is a problem. Autocorrelation violates the ordinary least squares (OLS) assumption that the error terms are uncorrelated. While it does not bias the OLS coefficient estimates, the standard errors tend to be underestimated (and the t-scores overestimated) when the autocorrelations of the errors at low lags are positive. The traditional test for the presence of first-order autocorrelation is the Durbin–Watson statistic or, if the explanatory variables include a lagged dependent variable, Durbin's h statistic. A more flexible test, covering autocorrelation of higher orders and applicable whether or not the regressors include lags of the dependent variable, is the Breusch–Godfrey test. This involves an auxiliary regression, wherein the residuals obtained from estimating the model of interest are regressed on 1) the original regressors and 2) k lags of the residuals, where k is the order of the test. The simplest version of the test statistic from this auxiliary regression is TR^2, where T is the sample size and R^2 is the coefficient of determination. Under the null hypothesis of no autocorrelation, this statistic is asymptotically distributed as χ^2 with k degrees of freedom. Responses to nonzero autocorrelation include generalized least squares and the Newey–West HAC estimator (Heteroskedasticity and Autocorrelation Consistent).

A formal test on non-stationary is the **Dickey-Fuller test (DF)**. The null hypothesis is that the series is non-stationary. It rejects the null of series non-stationery. This means the series is stationary in levels. The t-statistic, it is calculated as the ratio between estimated coefficient and standard error of the estimated coefficient, is the test statistic used in the DF test. The approximate 5 percent critical value estimated using Monte Carlo simulation is -2.89 (say one gets a critical value calculate as -4.85, then one rejects the null and conclude that the series is stationary in levels). But sometimes the DF test may suffer from problems of autocorrelation in the estimated residuals (Granger and Newbold, 1986).

KPSS test, under the null hypothesis of level stationary, KPSS $\rightarrow \int V_1(r)^2 dr$, where V1(r) is a standard Brownian bridge: $V_1(r) = B(r) - rB(1)$ and B(r) is a Brownian motion process on $r \in [0, 1]$. Under the null hypothesis of trend stationary, KPSS $\rightarrow \int V_2(r)^2 dr$, where $V_2(r)$ is the second level Brownian bridge, given by $V_2(r) = B(r) + (2r - 3r^2)\, B(1) + (-6r + 6r^2) \int B(s)ds$. The upper tail critical values of the asymptotic distribution of the KPSS statistic are listed in Table 3.1, given by Kwiatkowski, Phillips, Schmidt and Shin (1992).

Table 3.1 Upper Tail Critical Values for the KPSS Test Statistic Asymptotic Distribution

Distribution	**Upper tail percentiles**			
	0.1	**0.05**	**0.025**	**0.01**
$\int_0^1 V_1(r)^2 dr$	0.347	0.463	0.574	0.739
$\int_0^1 V_2(r)^2 dr$	0.119	0.146	0.176	0.216

Run test, test on the stationary of a time series. A "run" is defined as a sequence of identical observations that is followed or preceded by a different observation or no observation at all. First, the median MD of the observations x(i) is evaluated, and the series y(i) is derived from x(i) as: y(i)=0 if x(i)<MD; y(i)=1 if x(i)>MD or =MD. Then the number of runs in y(i) is computed. If x(i) is a stationary random process, the number of runs is a random variable with mean=N/2+1 and variance=(N(N-2))/(4(N-1)). An observed number of runs significantly different from N/2+1 indicates non-stationary because of the possible presence of a trend in x(i). A table of runs distribution can be found in (Bendat and Piersol, 1986).

First-Order Autoregressive Scheme or AR (1), the assumption $E(U_iU_j) \neq 0; j \neq i$ is too general to deal with as it stands and we need to have a more precise model of the form that the autocorrelation takes. Specifically, we consider the hypothesis that the errors follow a first-order autoregressive or AR(1) scheme:

$u_t = \rho u_{t-1} + \varepsilon_t$, $t = 1, \ldots, T$; $-1<\rho<1$ where u_t and ε_t are assumed to be independent error processes and ε_t has the standard properties: $E(\varepsilon_t) = 0$, $E(\varepsilon^2{}_t) = \sigma^2{}_\varepsilon = 1, \ldots, T$ and $E(\varepsilon_t\varepsilon_s) = 0$; $t, s = 1, \ldots, T$; $s \neq t$.

Variance Ratio Tests, the variance ratio test developed by Lo and MacKinlay (1988) is based on the fact that the variance of q-differences of an uncorrelated series is q-times the variance of its first difference. If the estimated variance ratio is statistically different from one, then the uncorrelated hypothesis would be rejected. Lo and MacKinlay (1988) suggested that it is necessary to examine the variance ratio tests for several selected of q and the random walk hypothesis can be rejected when the test statistics are rejected for all q.

Two important reasons need to test for random walk or unit root test of stationary:

1) If a variable follows a random-walk: A regression of one variable against another can lead to a “spurious” result. (The Gauss-Markov Theorem would not hold, because a random walk does not have a finite variance, and the OLS would not yield a consistent estimator.). Detrend before running the regression will not help, because the detrended series will still be non-stationary. First-difference will yield stationary series if a series has stochastic trend.

2) If a variable follow a random walk, the effect of a temporary shock will not dissipate after several time periods but instead will be permanent. It has implications to understanding of the economy. If the process is non-stationary, it will often be difficult to represent the time series over past and future intervals of time by a simple algebraic model. If the process is stationary, then one can model the process via an equation with fixed coefficients that can be estimated from past data.

Regarding on the previous information, each of the tool analysis can be pick to use as its strong and weak points provided as:

ACF: **Strong point** is used frequently in signal processing for analyzing functions or series of values.

Weak point is often used without the normalization.

Unit Root:

ADF: **Strong point** is the tests are run with and without a linear time trend.

Weak point is the normal test significance level is not reliable when the error terms are autocorrelated. The larger the autocorrelation of error terms, the larger the distortion in general will be of the test significance.

KPSS: **Strong point** is easily to decompose the series into the sum of a deterministic trend, a random walk, and a stationary error with the linear regression model.

Weak point is difficult to determine the reference point: for the reference point that are too small the test is biased when there is autocorrelation, for the reference point that is too large it loses power.

Run Tests: **Strong point** is this test can detect a monotonic trend in a time series and simply that if the subgroups are truly from the stated distribution, and independent of one another, then there will not be any pattern to the points. The tests are applied without regard to the selected control limit ordinates.

Weak point is the run tests do, however, increase the power of the control chart, but also providing an increased false alarm rate.

AR(1): **Strong point** is AR(1) ignored the structural factors assuming that the causal factors will continue to interact as they have in the past.

Weak point is in economics, it is considered dangerous to rely on an autoregressive model in a time of structural change. Many economists prefer structural models that specify the forces driving a system such as prices along with supply and demand responses.

VRT: **Strong point** is if one wants to test whether a time series follows a random walk, one can take advantage of the fact that the variance of a random walk increases linearly with time.

Weak point is the random walk hypothesis can be rejected when the varience ratio tests statistics are rejected for all q (period return).

3.1.1.2 Cointegration

In the present paper, the Johansen approach is used to test the efficiency of RSS3 Thai agricultural commodity futures. A non-stationary time series is said to be integrated in order 1, often denoted by I(1), if the series is stationary after first-order differencing. An (n*1) vector time series Y_t is said to be co integrated if each of the n series taken individually is I(1), while some linear combination of the series AY_t is stationary for some non-zero vector A (Hamilton, 1994).

The theory of cointegration relates to the study of the efficiency of a futures market in the following way. Let S_t be the cash price at time t and F_{t-i} be the futures price I periods before th contract matures at time t. If the futures price can provide a predictive signal for the cash price I periods ahead, then some linear combination of S_t and F_{t-i} is expected to be stationary. That is, there exists a and b such that, Zt = St – a – bFt-i is stationary with mean zero. If both S_t and F_{t-i} are I(1), a condition that usually holds for prices, the vector S_t, F_{t-i} is then co integrated. This co integration between S_t and F_{t-i} is a necessary condition for market efficiency (Lai and Lai, 1991). This is because cointegration ensures that there exists a long-run equilibrium relationship.

Cointegration tests: Before testing for cointegration, each individual price series should be examined to determine whether they are I(1). Augmented Dickey (ADF) and the Phillips-Perron unit root tests are the common methods (Lai and Lai, 1991; McKenzie and Holt, 2002) are used here. If both the futures price and cash price are I(1), Johansen's cointegration tests can then be conducted through a k^{th}-order vector error correction (VEC) model of form: $\Delta Y_t = \Phi D_t + \Pi Y_{t-1} + \sum_{t=1}^{k-1} \Gamma_t \Delta Y_{t-i} + \varepsilon_t$

where Y_t is an (n*1) vector to be tested for cointegration; $\Delta Y_t = Y_t - Y_{t-1}$; D_1 is a deterministic term consisting of a vector of seasonal dummy variables; Φ, Π, Γ are coefficient matrices; and k is chosen such that ε_t is a multivariate normal white noise process with mean zero and finite covariance matrix.

3.1.1.3 Error Correction

The simplest form of a forecasting model is the unit root model with trend and drift, which may be written as: $S_t = \alpha + \beta S_{t-1} + §T + e_t$ where S_t is the natural logarithm of the commodity spot price at time t and T is a time trend variable. The error term, e_t , is assumed to be white noise. This simple model can serve as a useful benchmark for comparison with other, more sophisticated models.

An alternative forecasting model could be one that allows for an autoregressive process in the first difference of S_t and a moving average model for the errors. A suitable time series model of this form, the ARMA model, may be written as:

$\Delta S_t = \alpha + \sum_{j=1}^{p} \beta_j \Delta S_{t-j} + e_t$ with errors given by $e_t = \sum_{t=1}^{q} \gamma_i u_{t-i} + u_t$ and where u_t is white noise. Such a model may be particularly appropriate for commodities where prices are mean reverting (Irwin, Zulauf and Jackson, 1996).

If markets are efficient, futures prices should be unbiased predictors of future spot prices and a simple prediction model should give superior results to those using alternative variables. The general futures forecast model is: $S_t = \alpha + \beta F_{t|t-k} + e_t$ where $F_{t|t-i}$ is the price for period t implied by futures markets in period t-k. Rather than testing market efficiency, which would imply $\alpha = 0$ and $\beta = 1$ the aim here is to examine whether futures prices can enhance the forecasting ability of simple models. Efficiency tests would require careful matching of futures contract horizons and expiry dates with actual spot prices.

Finally, if commodity spot and futures prices are cointegrated, an error-correction model (ECM) can be used to capitalize on this relationship. Engle and Granger (1987: 251-276) show that a system of two cointegrated series implies an error-correcting equation. This was verified during cointegration testing, the general form of the ECM is: $\Delta S_t = \alpha + \beta_0 \varepsilon_{t-1} + \sum_{i=1}^{m} \beta_i \Delta F_{t-i|t-k} + \sum_{j=1}^{n} \gamma_j \Delta S_{t-j} + u_t$ where ε_t is the lagged residual of the cointegrating equation.

However, for the purposes of this study, where the objective is to gauge whether the incorporation of futures prices potentially yields superior forecast performance, forecasts use only historical spot prices and futures prices in an effort to identify simple models which may be successfully applied to a wide range of RSS3 commodities, rather than to specific commodities.

3.1.2 Forecasting Methodology

Makridakis (1983), one of the gurus of quantitative forecasting, correctly points out that judgmental forecasting is superior to mathematical models; however, there are many forecasting applications where computer generated forecasts are more feasible following in Table 3.2.

Table 3.2 To Select the Forecasting Method

			FORECASTING METHOD				
	NAÏVE	**MA**	**C**	**EX**	**B-J**	**REG**	**ECONO**
TIME PERIOD							
NEAR	X		X	X	X		
SHORT		X	X	X	X	X	X
MEDIUM		X	X	X		X	X
LONG			X	X		X	X
DATA'S CHARACTERISTIC							
STABLE	X	X	X	X	X		
SEASONAL			X	X	X	X	X
CYCLE			X			X	X
TREND			X	X	X	X	X
SIZE OF DATA	LESS	10	30	10	50	30	LESS
(S-SEASONAL)			6(S)	2(S)	6(S)	6(S)	
EXPENSES							
LOW	X	X		X			
MEDIUM			X			X	
HIGH					X		X

Source: Makridakis, 1983.
Note: MA is Moving Average model. C is composition model. EX is exponential model. B-J is Box's Jenkins model. REG is regression model. ECONO is econometric model.

The usefulness of a forecast is an application sensitive construct. Each forecasting situation must be evaluated individually regarding its usefulness. One of the ideas on doing this paper is to consider how the results will be used. It is important to consider who the readers of the final report will be during the initial planning stages of a project. It is wasteful to expend resources on research that has little or no use. So, the paper must strive to develop forecasts that are of maximum usefulness to planners.

This means that each situation must be evaluated individually as to the methodology and type of forecasts that are most appropriate to the particular application. Dublin (1989) has expressed the idea that the way we contemplate the future is an expression of our desires to create that future. Forecasting can, and often does, contribute to the creation of the future, but it is clear that other factors are also operating. The forecast is a way to control today's decisions. Dublin is correct. The purpose of forecasting is to control the present. In fact, one of the assumptions of forecasting is that the forecasts will be used by policy-makers to make decisions.

3.1.2.1 Estimated Models

Time series forecasting here is the use of a model to forecast future events based on known past events: to forecast future data points before they are measured. However, it is also possible to use econometric models that are not tied to any specific economic theory (Sim, 1980). The nine models are:

1) Random walk without drift (RW)

The forecasting model suggested is $\hat{Y}(t) - Y(t\text{-}1) = \alpha$ where alpha is the mean of the first difference, i.e., the average change one period to the next. If paper rearranges this equation to put Y(t) by itself on the left, paper gets: $Y(t) = Y(t\text{-}1) + \alpha$. In other words, paper predicts that this period's value will equal last period's value plus a constant representing the average change between periods. This is the so-called "random walk" model: it assumes that, from one period to the next, the original time series merely takes a random "step" away from its last recorded position. If the constant term (alpha) in the random walk model is zero, it is a random walk without drift.

2) Random walk with drift (RWD)

Now let the change in y_t be partially deterministic and partially stochastic. The random walk plus drift model augments the random walk model by adding a constant term a_0, so that $y_t = y_{t-1} + a_0 + \varepsilon_t$. Given the initial condition y_0, the general solution for y_t is given by $y_t = y_0 + a_0 t + \sum\varepsilon_i$. Hence, the behavior of y_t is governed by two non-stationary components: a linear deterministic trend and the stochastic trend $\sum\varepsilon_i$. To explain, the deterministic change in each realization of $\{y_t\}$is a_0; after t periods the cumulated change is $a_0{}^t$. In addition, there is the stochastic trend $\sum\varepsilon_i$; each ε_i shock has a permanent effect on the mean of y_t. Notice that the first difference of the series is stationary; taking the first difference yields the stationary sequence $\Delta y_t = a_0 + \varepsilon_t$.

3) Autoregressive (AR)

In the autoregressive process of order p the current observation y_T is generated by a weighted average of past observations going back p periods, together with a random disturbance in the current period. We denote this process as AR (p) and write its equation as $y_t = \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-p} + \delta + \varepsilon_t$. Here δ is a constant term which relates to the mean of the stochastic process.

4) Vector autoregressive model with time trend (VAR)

VARs were introduced as an alternative approach to multi-equation modeling through the work of Sim (1980). In VARs as formulated by Sim (1980), all the variables are assumed to be endogenous. The equations of the model are constrained to be linear, and so we need not worry about functional forms. Letting x_1, x_2, …, x_n be the endogenous variables and Z_1, …, Z_m be the exogenous variables, a VAR is given by the following set of n linear equations: $x_{1,t} = a_{10} + \sum_{j=1}^{p} a_{11j} x_{1,t-j} + \sum_{j=1}^{p} a_{12j} x_{2,t-j} + \ldots + \sum_{j=1}^{p} a_{1nj} x_{n,t-j} + \sum_{j=0}^{r} b_{11j} z_{1,t-1} + \ldots + \sum_{j=0}^{r} b_{1mj} z_{m,t-j} + \varepsilon_{1t}$. The VAR is a theoretic analysis or non-structural analysis that summarizes the regularities in a set of variables which theory suggests as important (Bessler, 1984). These models are useful in the analysis of observational data. In structural modeling, a pre-determined model is suggested through the knowledge of the prior theory and structure. But in VAR modeling the choice of variables studied does not depend on the pre-determined structure, rather on the problem under study and theory, which will be used to study regularities of data.

5) Moving average (MA)

Now let us examine the simple first-order moving average process, MA (1): $y_t = \delta + \varepsilon_t - \theta_1 \varepsilon_{t-1}$. The one-period forecast for this process is

$\hat{y}_T(1) = E(y_{T+1}|y_T, \ldots, y_1) = \delta - \theta_1 \varepsilon_{t-1}$ where $\hat{\varepsilon}_T$ is the actual residual from the current and most recent observation.

6) Simple exponential smoothing (SES)

ARIMA (0,1,1) without constant = simple exponential smoothing: The prediction equation for the simple exponential smoothing model can be written in a number of mathematically equivalent ways, one of which is:

$\hat{Y}(t) = Y(t-1) - \theta e(t-1)$ where $e(t-1)$ denotes the error at period t-1. The simple exponential smoothing model is therefore a first-order moving average ("MA (1)") model with one order of non-seasonal differencing and no constant term --i.e., an "ARIMA (0,1,1) model without constant." This forecasting method is most widely used of all forecasting techniques (Attaran, 1992). It requires little computation and is used when data pattern is horizontal.

7) Deterministic trend (T)

The forecasting equation for the linear trend model is:

$Y(t) = \alpha + \beta t$ where t is the time index. The parameters alpha and beta (the "intercept" and a "slope" of the trend line) are usually estimated via a simple regression in which Y is the dependent variable and the time index t is the independent variable. Although linear trend models have their uses, they are often inappropriate for business and economic data. Most naturally occurring business time series do not behave as though there are straight lines fixed in space that they are trying to follow: real trends change their slopes and/or their intercepts over time. The linear trend model tries to find the slope and intercept that give the best average fit to all the past data, and unfortunately its deviation from the data is often greatest near the end of the time series, where the forecasting action is.

8) Random walk with drift and trend (RWDT)

$y_t = y_{t-1} + a_0 + \varepsilon_t$ where a_0 is the constant "drift". Solving the difference equation $y_t = y_0 + a_0 t + \Sigma\varepsilon_i$ where, again, the summation is over t. The terms $a_0 t + \Sigma\varepsilon_i$ are both non-stationary. Now, we have a deterministic plus a stochastic trend. By the way, $y_t - y_{t-1} = \Delta y_t = a_0 + \varepsilon_t$ is stationary. The unconditional expectation is $E_t(y_{t+s}) = y_0 + a_0(t+s)$. The forecast function which is conditional on past y_t is:

$$y_{t+s} = y_0 + a_0(t+s) + \sum_{i=1}^{t+s} \varepsilon_i = y_t + a_0 s + \sum_{i=1}^{s} \varepsilon_{t+i}.$$

9) Autoregressive integrated moving average (ARIMA)

ARIMA as an acronym for Autoregressive Integrated Moving Average Model, it is also known as Box-Jenkins model. It is a class of models of random processes in discrete time or time series. ARIMA model is widely used in time series analysis. ARIMA model extends the autoregressive moving average (ARMA) model. In contrast to the ARMA model, which is adequate only for stationary time series, ARIMA model may be an adequate model for nonstationary time series.

3.1.2.2 Three Criteria

The paper employs a number of out-of-sample model selection criteria to evaluate the predictive performance of the nine models considered. These criteria can be classified into three criteria: univariate criteria, market timing criteria and Diebold-Mariano. All criteria are calculated using forecast errors based on the samples and forecast horizons. Since paper constructs one step-ahead forecast, each model generates nine error series, and three system-wide model selection criteria are calculated for each of nine forecasting models examined. As a result, 9*3*9 = 243 system statistics are computed. Diebold and Mariano predictive accuracy tests is used for pair wise model comparison, as well as market timing test based on confusion matrices, and associated Chi-squared tests of independence.

1) Univariate criteria

For example, Just and Rausser (1981); Bessler and Brandt (1992); and Gerlow, Irwin and Liu (1993), these researches will focus primarily on RMSE, which gives a measure of the magnitude of the average forecast error, as an effectiveness measure. However, there are still some other squared errors mentioned below:

(1) Root Mean Square Error (RMSE)

The RMSE is one of the most widely used measures of forecast accuracy.

(2) Mean Absolute Percentage Error (MAPE)

The MAPE are closely related to MSE, $MAPE = 1/T\sum_{t=1}^{T}\left|\frac{fe_{i,t}}{FT_t}\right|$

where FE_t is the actual price series to be predicted.

(3) Mean Absolute Error (MAE)

The mean absolute error is a common measure of forecast error in time series analysis.

(4) Thiel's U-statistic

If U-statistic = 1, the naïve method is as good as the forecasting technique being evaluated. If U-statistic < 1, the forecasting technique being used is better than the naïve method, the smaller the U-statistic, the better the forecasting technique relative to the naïve method. If U-statistic > 1, there is no point in using a formal forecasting method, since using a naïve method will produce better results.

2) Market timing criteria

An alternative model selection criterion is the market timing criterion suggested by Henriksson and Merton (1981); Schnader and Stekler (1990); Pesaran and Timmermann (1994); and Stekler (1994), which can be used to forecast economic turning point. The confusion rate calculated in the paper is retrieved from a 2*2 contingency table, called confusion matrix (CM). The following is the definition of a CM.

$$\begin{array}{lll} & & \text{Actual Price Movement} \\ & & \begin{array}{cc} \text{up} & \text{down} \end{array} \\ \text{Predicted Price Movement} & \begin{array}{l} \text{up} \\ \text{down} \end{array} & \begin{bmatrix} n_{11} & n_{12} \\ n_{21} & n_{22} \end{bmatrix} \end{array}$$

where n_{11} = number of cases correctly predicted up;

n_{21} = number of cases wrongly predicted down;

n_{12} = number of cases wrongly predicted up;

n_{22} = number of cases correctly predicted down.

The confusion rate is then computed as the frequency of off-diagonal elements, or $CR = (n_{12} + n_{21}) / T$ where $T = n_{11} + n_{12} + n_{21} + n_{22}$. The best model according to CR is the least confused one (the one is with the smallest value of CR). Pesaran and Timmermann (1994) showed that the test of market timing in the context of forecasting the direction of assert price movements proposed by Henriksson and Merton is asymptotically equivalent to the standard chi-squared test of independence in a confusion matrix. Paper examines the standard chi-squared test of independence. The null hypothesis is independence between the actual and the predicted directions. Thus, rejecting the null hypothesis provide direct evidence that the model is useful as a predictor of the sign of change in the prices.

3) Diebold-Mariano test

Harvey, Leybourne and Newbold (1998) originally proposed a modification of the Diebold-Mariano test for differences in MSE to account for non-normal distributions of the forecast error series. Paper also constructs the asymptotic loss differential test proposed in Diebold and Mariano (1995). Diebold and Mariano (1995) used only the loss differential series and the assumption that the loss differential series is covariance stationary and short memory, the DM test has a null hypothesis that both forecasting models are equally accurate. The loss differential series used in the analyses are $d_t = (fe_{i,t})^2 - (fe_{i,t})^2$, for the test based on MSE; $d_t = |fe_{i,t}| - |fe_{i,t}|$, for the test based on MAD; and $d_t = \left|\frac{fe_{i,t} - fe_{j,t}}{FE_t}\right|$ for the MAPE test, where $fe_{i,t}$ and $fe_{j,t}$ correspond to the forecast error sequences from two forecast models i and j, which are being compared.

3.1.3 Determinants

Studying the variables affect on rubber price by regression for daily and monthly time-series. The daily data start from 1st August 2007 to 31st October 2008 and the monthly data start from May 2004 to May 2009. Those variables are: exchange rate (Yen per Dollar US.), crude oil price, exchange rate (Baht per Dollar US.), TOCOM, quantity of consuming natural rubber in the world, quantity of consuming synthetic rubber in the world, quantity of imports natural rubber (Japan), quantity of imports synthetic rubber (Japan), quantity of imports synthetic rubber (China) and quantity of imports natural rubber (China). Moreover, the method of constructing model is as: creating the reference graph by using monthly RSS3 is the reference graph on rubber price; plotting histogram between price and independent variables; considering the leading variable. When paper gets all variables' graphs, paper will select the graph that is similar to the reference graph by using visual examination.

3.2 Scope of the Study

The paper scopes the study as follows:

1) For rubber prices benchmark, the paper uses the natural rubber ribbed smoked sheets no.3. This is because it makes up majority of the exports based on observing the level of exports Free On Board (FOB) (the term of commonly used when shipping goods to indicate who pays loading and transportation cost), that is applied as the selling price in futures market.

2) Nine models are used to estimate and to evaluate the forecasting model. These are random walk, random walk with drift, VAR, AR, MA, simple exponential smoothing, time trend, random walk with drift and trend, and ARIMA.

3) To conduct a search for selecting appropriate models, the paper used univariate criterion, market timing criterion and DM test.

4) To examine the model for rubber futures price, the paper searches on determinants that affect on rubber futures price by accounting on multiple regression models, but only considers some factors on market price mechanism. Those variables are TOCOM, exchange rate (Yen per Dollar US.), crude oil price, exchange rate (Baht per Dollar US.), quantity of consumption of natural rubber in the world, quantity of consumption of synthetic rubber in the world, quantity of imports synthetic rubber (Japan), quantity of imports natural rubber (Japan), quantity of imports synthetic rubber (China) and quantity of imports natural rubber (China).

3.3 Research Design Data Collection

Daily and monthly settlement prices for ribbed smoked rubber sheet No.3 (RSS3) futures markets are employed. All price data are obtained from Agricultural Futures Exchange of Thailand (AFET), Rubber Research Institute of Thailand (RRIT), and The Thai Rubber Association (TTRA) database. The sample period on daily starts on 1st August 2007 and ends on 31st October 2008. The out-of-sample period used is 4th June 2008 to 31st October 2008. Thus, the first forecast for 4th June 2008 is constructed based on in-sample estimation using the period 1st August 2007 to 3rd June 2008. Also, the sample period on monthly starts on May 2004 to May 2009, the out-of-sample period used is June 2007 to May 2009. So, the first forecast for June 2007 is constructed based on in-sample estimation using the period May 2004 to May 2007. However, the paper does not expect that the results will be affected. In Swanson, Zeng and Kocagil (1996), they used the data with 3-month, 6-month and one-year in sample sizes and did not find any effects from choosing different in-sample sizes. The advantage of using futures prices is that the paper avoids problems that arise when overlapping contracts are used, as well as problems associated with the volatility near the delivery periods.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Efficiency in Price

This chapter focuses on RSS3 futures because we cannot obtain sufficient daily data observations for other futures products from AFET such as BHMR, BWR5, and TC. So, we collect data on RSS3 futures price for the period 1st August 2007 to 31st October 2008. The daily closing price series are obtained from the Agricultural Futures Exchange in Thailand (AFET) database. The nearby futures contract is selected because it is the most active and has high liquidity. We also use the futures closing price of delivery contracts on delivery date as a proxy for the daily spot price and construct 1 through 6-month-ahead RSS3 futures price based on the delivery date to investigate the relationship between daily spot and futures prices.

The study investigates the statistical properties of RSS3 futures price from 2007 to 2008. In particular, the objectives are as: 1) Examining whether there is any dependence in daily RSS3 futures price changes 2) Examining whether RSS3 futures prices are unbiased predictors of future spot prices on the delivery dates.

4.1.1 Empirical Evidence for Random Walk Hypothesis

To investigate the dependence in prices we use a variety of tests. Early research used serial correlation coefficients and runs test to investigate whether price series follow a random walk (Fama, 1965). More explicit tests of random walk examine whether unit roots exist in price series. Dickey and Fuller (1979, 1981) proposed unit root test and their procedure Augmented Dickey-Fuller or ADF has the null hypothesis that a series has a unit root. A complementary testdeveloped by Kwiatkowski, Phillips, Schmidt, and Shin (1992): KPSS uses the null hypothesis that the time series of prices is stationary. The study uses ADF measures because the ADF test is based on the assumption of a normal distribution, but this might not be strictly valid for many financial time series. An alternative procedure to test the random walk hypothesis is the variance ratio test developed by Lo and MacKinlay (1988, 1989). This test allows for heteroskedasticity in the data and does not require the assumption of normality.

In this part of chapter, the results and discussions for efficiency in price discovery include with Autocorrelation Function (ACF), Unit Root Tests by Augmented Dickey-Fuller (ADF) test and The KPSS test, Run Test, First-Order Autoregressive Scheme or AR(1), and Variance Ratio Tests to show the movement on RSS3 price will follow the Random Walk Theory whether. To estimate the basic characteristic such as trend and season; also, the relationship on the movement behavior of time series data, we will show the figures on spot and futures in each contract for 1to 6-month.

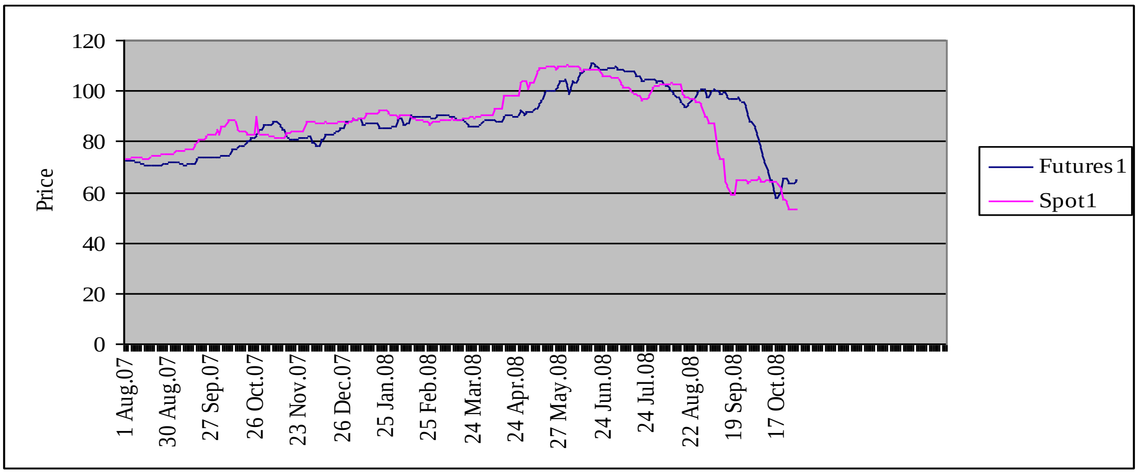

Figure 4.1 Price on Spot and Futures Contract 1-Month Ahead

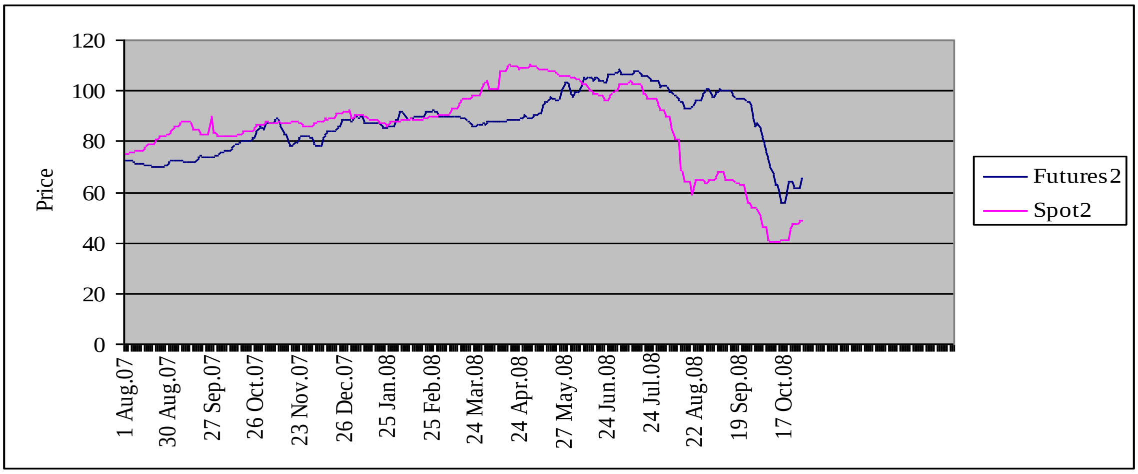

Figure 4.2 Price on Spot and Futures Contract 2-Month Ahead

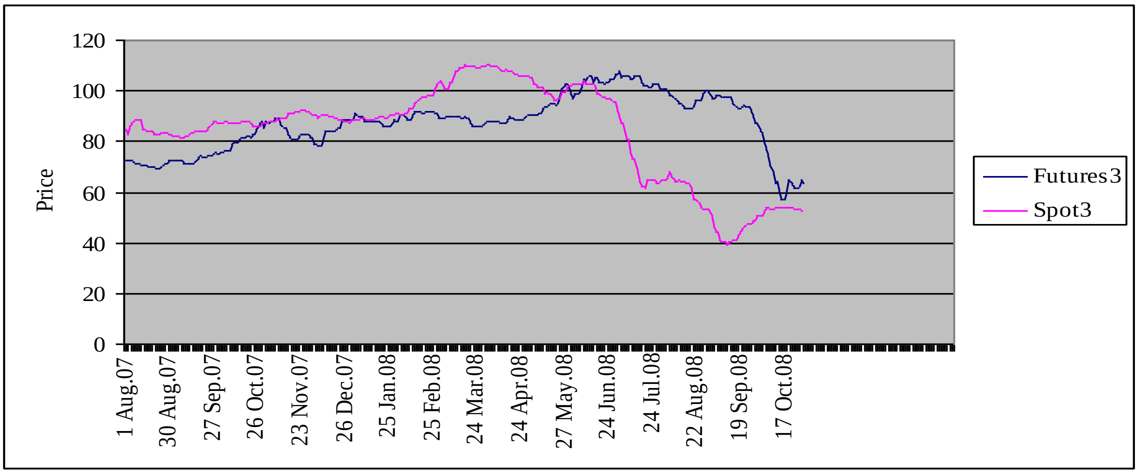

Figure 4.3 Price on Spot and Futures Contract 3-Month Ahead

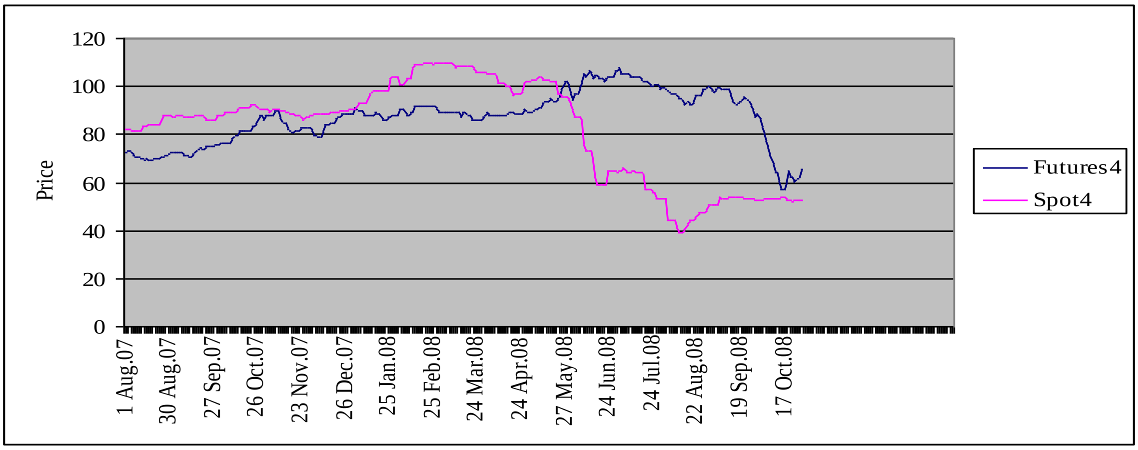

Figure 4.4 Price on Spot and Futures Contract 4-Month Ahead

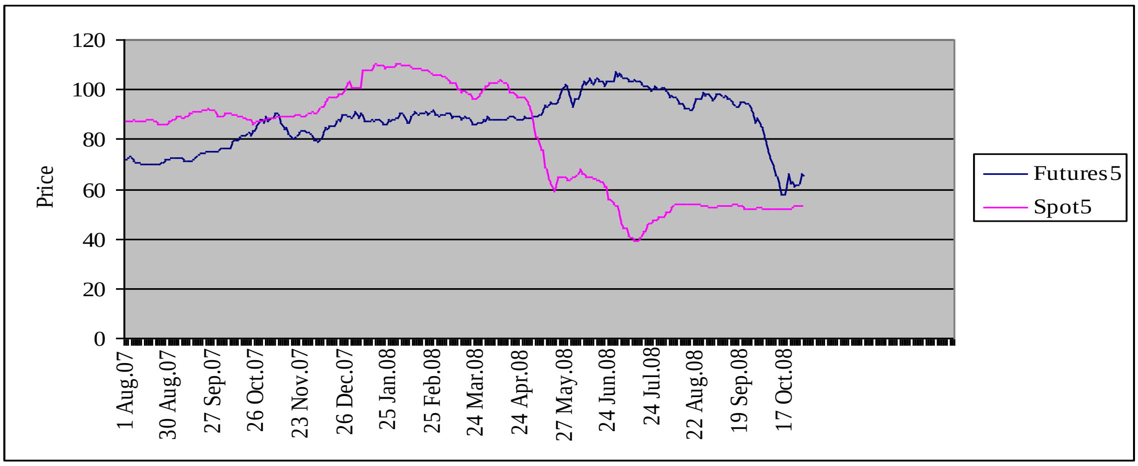

Figure 4.5 Price on Spot and Futures Contract 5-Month Ahead

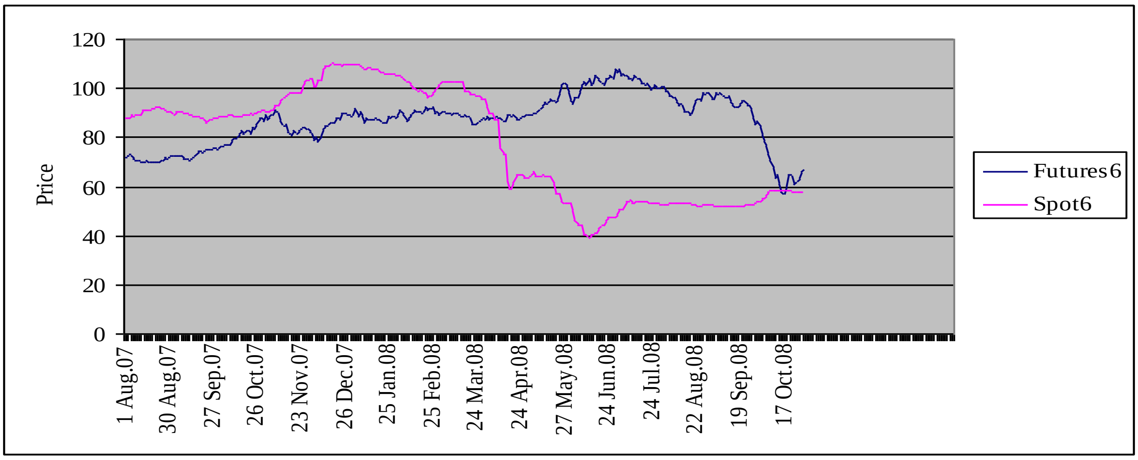

Figure 4.6 Price on Spot and Futures Contract 6-Month Ahead

Figure 4.1 to 4.6 shows the price in each contract month. It consists of future spot price and futures price. The figures show that RSS3 in AFET and future spot price are highly volatile because of the reason relating from main characteristics of rubber such as supply and demand between buyer and seller, quantity of rubber during harvest time or out of harvest time, changing in environments, and world price. Moreover, analytical on the volatile on RSS3 in November 26th 2007 (contract 6-month ahead) shows that spot price is increasing from 90.75 Baht per kilogram to be 103.65 Baht per kilogram. But futures price is around 82.00 Baht per kilogram because this month is in rainy season creating the shortage in supply of rubber to the market. This reason causes the lower futures price comparing to the spot price and is called “Backwardation”.

Continuing to consider on the figures finds that at the same period contract 1-month ahead to contract 6-month ahead, the future spot price and futures price have cointegration. However, noticeable that the further contract-month ahead is used, the cointegration between future spot price and futures price is less because of higher volatile but the trends still move in the same direction. It implies that the further contract-month ahead can be less representative for predicting on future spot price.

Studying on weak form efficient market on RSS3 futures to explain the form of price's movement and the return on investment of RSS3 futures, we provide into two parts. First part, we test the independent with futures itself and the second part; we test the independent between futures and spot. First part, we analyze by using tools, i.e, autocorrelation function test, run test and autoregressive model to show the return on RSS3 futures price whether independent. Also, using the variance ratio tests and unit root tests to show the return on RSS3 futures price whether follows by the random walk theory. Now, we use time series on RSS3 futures comparing on past and present by considering on Q Statistic and using the significant at 0.05 followed by Table 4.1:

Table 4.1 Correlogram of Return on RSS3 Futures Contract 1 through 6-Month Ahead

Contract	**1-month**	**2-month**	**3-month**	**4-month**	**5-month**	**6-month**
Q(1)	45.923	48.373	36.775	28.394	10.317	10.371
Q(2)	57.940	57.856	43.201	35.986	18.363	16.074
Q(3)	62.161	60.053	44.407	37.259	18.463	16.120
Q(4)	67.010	63.014	47.776	39.990	20.271	17.008
Q(5)	75.836	66.929	49.846	42.006	20.765	18.565
Q(6)	85.016	73.734	56.127	46.634	27.844	26.827
Q(7)	89.318	76.648	56.764	47.917	28.837	27.371
Q(8)	90.347	77.958	57.242	48.458	29.510	27.374
Q(9)	96.925	82.428	62.116	54.349	33.543	33.309
Q(10)	97.018	82.442	62.639	54.358	33.543	33.320

Note: p-value < 0.05 at every lag

Table 4.1 shows that the return on RSS3 futures price is independence because when we consider on p-value finding that the calculated value is less than critical value in all contracts-month at 0.05 significant level. So, it rejects the null hypothesis that the return on RSS3 futures price is independence correlation over time period.

Next, analyzing on Run Test to study the return on RSS3 futures whether independent following in Table 4.2:

The condition to accept the null hypothesis that the return of RSS3 futures is independent: $E(R) - 1.96\sigma_R \leq R \leq E(R) + 1.96\sigma_R$ where R is total actual number of runs; E(R) is total expected number of runs; σ_R is standard error of R. So, if it cannot reject the null hypothesis, it will imply that the return of RSS3 futures is independent.

Table 4.2 Results on Run Test

	1-month	2-month	3-month	4-month	5-month	6-month
Total Residuals	309	309	309	309	309	309
Plus Residuals	160	228	216	206	185	160
Negative Residuals	149	81	93	103	124	149
Total Actual Number of Runs	163	115	103	116	156	163
E(R)	155.30	120.53	131.02	138.33	149.48	155.30
σ_R	8.76	6.78	7.38	7.80	8.43	8.76
$1.96*\sigma_R$	76.80	46	54.46	60.79	71.10	76.80
$E(R) + 1.96*\sigma_R$	172.48	133.83	145.48	153.61	166.01	172.48
$E(R) - 1.96*\sigma_R$	138.13	107.24	116.55	123.05	132.95	138.13

Run Test results show that the contract 2, 5 and 6 month ahead cannot reject the null hypothesis on “the different return is independent”. So, it implies that the different returns are independent.

On First-Order Autoregressive Scheme or AR(1) shows in Table 4.3, AR(1) uses autoregressive coefficient (ρ) to test the independence between the return on RSS3 futures price at time t and the return on RSS3 futures price at time t-1 with null hypothesis: $\rho = 0$ (coefficient of autocorrelation = 0). If it cannot reject the null hypothesis, it will conclude that the return on RSS3 futures price at time t has no relationship with the return on RSS3 futures price at time t-1.

Table 4.3 Results on AR(1)

	Variable	t-statistic	p-value	R^2
μ_1	0.5003	11.6938	0.0000	0.4020
μ_2	0.5000	11.5519	0.0000	0.3031
μ_3	0.5047	12.3317	0.0000	0.3314
μ_4	0.5000	12.8280	0.0000	0.3491
μ_5	0.5002	14.5735	0.0000	0.4090
μ_6	0.5009	14.5856	0.0000	0.1094

Considering on p-value of all contracts-month for RSS3 futures price finds that all p-value is less than significant level of 0.01, so we rejects the null hypothesis meaning that the return on RSS3 futures price at time t has the relationship with the return on RSS3 futures price at time t-1.

Variance Ratio Tests (VRT) in Table 4.4, the tests checks the RSS3 futures' characteristic whether followed by random walk theory using Z-statistic. So, VRT should be 1 to show that it follows random walk meaning that the RSS3 futures market is weak form efficient market. The null hypothesis: VRT(d) = 1; the alternative hypothesis: VRT(d) $\neq 1$. If Z computed is less than Z critical (0.4750), then it cannot reject the null hypothesis meaning that the order changing in price of RSS3 futures follows random walk theory.

Table 4.4 Results on Variance Ratio Tests

First different RSS3 futures	Value	Prob.
Contract 1-month	0.0624	0.0000
Contract 2-month	0.0741	0.0000
Contract 3-month	0.0714	0.0000
Contract 4-month	0.0774	0.0000
Contract 5-month	0.0844	0.0000
Contract 6-month	0.0928	0.0000

All contracts-month from VRT show that it rejects the null hypothesis meaning that RSS3 futures market does not follow random walk theory.

Another test on efficiency is unit root tests. We need to test the data on stationary because if the data is non-stationary, it will make the problem on spurious regression and the value will deviate from the true. So, we need to test the unit root by Augmented Dickey-Fuller test (ADF) and Kwiatkowski-Phillips-Schmidt-shin test (KPSS- test) following as in Table 4.5 and Table 4.6:

Table 4.5 ADF on Each Price from lnSpot and lnRSS3 Futures Markets, 1st August 2007 through 31st October 2008

	Level		1st Difference		Basis	
Variable	**ADF-statistic**		**ADF-statistic**		**ADF-statistic**	
Spot	-1.3663	(0.81074)	-9.8905	(0.0001***)		
Future 1	-0.8519	(0.92535)	-11.6648	(0.0001***)	-3.6921	(0.02040**)
Future 2	-1.0713	(0.88797)	-11.5371	(0.0001***)	-3.6491	(0.02303**)
Future 3	-0.6756	(0.94673)	-12.0897	(0.0001***)	-3.4304	(0.04142**)
Future 4	-0.8980	(0.91861)	-12.8119	(0.0001***)	-3.4117	(0.04345**)
Future 5	-1.0779	(0.88661)	-14.5423	(0.0001***)	-3.4798	(0.03644**)
Future 6	-1.0982	(0.88234)	-14.5148	(0.0001***)	-3.4427	(0.04012**)

Note: - ADF is the Augmented Dickey-Fuller Test using intercept.

- All data is used in Natural logarithm form.
- ( ) is p-value.
- *** significant at 0.01
- ** significant at 0.05

In the logarithm converted analysis, Table 4.5 reports the ADF test; the null hypothesis of a unit root (non-stationary, random walk) cannot be rejected at 0.05 level. It implies that all variables are non-stationary. After that test at first difference, it uses for solving non-stationary problem finding that all variables are stationary significant at 0.01 and continues testing stationary for basis (futures – spot), it shows that all basis values of every contracts-month are stationary significant at 0.05.

The ADF shows that market again is mean non-stationary in the level. As residuals from these markets are better behaved under the ADF; we make the residuals "white" by augmenting the DF test with lags of the dependent variable. The empirical suggests the use of results from augmented tests; the tests suggest that price in the markets behave as a random walk: $P_t = P_{t-1} + e_t$, where e_t is a white noise or uncorrelated innovation.

On the studying in each price as each evolves in the market through time, we fully expects that each will individually look much like a random walk (Samuelson, 1965). That is, from the results on the Table 4.5, each market behaves such that new information perturbs price away from the most recent value and not as a perturbation from the historical mean. Each market is mean non-stationary according to the unit root tests as price from each market is efficient or weak-form efficient. The word "efficient" is used to suggest that the best prediction of price in each spot and RSS3 Thailand in period t+1 is something different from the price in period t. Its historical mean price is a useful statistic for next period's price. This result appears to hold for the RSS3 futures and spot markets. Here paper cannot reject the random-walk hypothesis. Following Fama (1970), the study says spot and RSS3 futures in Thailand markets are efficient in terms of price discovery because the random walk hypothesis is consistently supported by the ADF for RSS3 daily nearby futures closing price series. Then, this fact means that there is no dependence in daily price changes for

RSS3 futures, and weak form efficiency has been achieved. However, this is only one aspect from ADF test.

So, we need to test on the other methods of unit root test besides ADF test to find the suitable conclusion as in Table 4.6.

Table 4.6 KPSS on Each Price from lnSpot and lnRSS3 Futures Markets, 1st August 2007 through 31st October 2008

Variable	Level LM-statistic	1st Difference LM-statistic	Basis LM-statistic
Spot	0.9401	0.2612	
Future 1	0.8338	0.4615	0.2626
Future 2	0.7350	0.4060	0.5719
Future 3	0.7011	0.5111	0.6881
Future 4	0.6893	0.4281	0.7234
Future 5	0.6970	0.4817	0.7489
Future 6	0.6651	0.3972	0.7894

Note: - KPSS is the Kwiatkowski-Phillips-Schmidt-shin Test using intercept.
- All data is used in Natural logarithm form.

KPSS-test results show that most of LM-Stat value is greater than critical value at 0.01 and 0.05, respectively. So, it rejects hypothesis “no unit root”, meaning that time series of future spot price and futures price is non-stationary in the period studied. It follows the random walk theory.

From the results of the ADF and KPSS tests in Table 4.5 and Table 4.6 conclude that RSS3 futures and spot markets are individually non-stationary in logarithm analysis at level. However, this study uses time series data, so it might meet the problem on non-stationary. Therefore, to avoid this problem, we will work on first difference as: $S_{t+n} – S_t = \beta_0 + \beta_1(F_{t,n} – St) + e_t$ where S_{t+n} = natural logarithm of spot price at time t+n or future spot price, S_t = natural logarithm of spot price at time t, $F_{t,n}$ = natural logarithm of futures price at time t for delivery in time t+n, β_0 = constant risk premium, β_1= basis, and e_t = residual. $(S_{t+n} – S_t)$ is spot difference which it is the value different of price in the spot market and $(F_{t,n} – S_t)$ is basis which it is the different of price in two markets at particular time because spot diff and basis are stationary as result in Table 4.5 and Table 4.6. We can use OLS showing the equation on spot difference to mention on constant risk premium (β_0) and the basis (β_1) to analyze the market efficiency in Tale 4.7:

Table 4.7 OLS Results from Each Contract-Month

Contract	**Equation**	**CRP t-stat**	**Basis t-stat**	R^2
1-month	$(S_{t+n}-S_t)=-0.0034+1.2235(F_{t,n}-S_t)$	-0.5103	10.8303***	0.2758
2-month	$(S_{t+n}-S_t)=-0.0342+0.1322(F_{t,n}-S_t)$	-4.3778***	5.6705***	0.0945
3-month	$(S_{t+n}-S_t)=-0.0259+0.6015(F_{t,n}-S_t)$	-2.8944***	4.3166***	0.0570
4-month	$(S_{t+n}-S_t)=-0.0291+0.3802(F_{t,n}-S_t)$	-3.3384***	2.8484***	0.0257
5-month	$(S_{t+n}-S_t)=-0.0285+0.3985(F_{t,n}-S_t)$	-3.3467***	3.1085***	0.0304
6-month	$(S_{t+n}-S_t)=-0.0240+0.4632(F_{t,n}-S_t)$	-2.7775***	3.6792**	0.0421

Note: - CRP is Constant Risk Premium
- t-stat is t-statistic value
- *** significant at 0.01
- ** significant at 0.05

The basic information from analyzing on market efficiency finds that β_0 and β_1 of all contracts are significant at 0.01 and 0.05 excepting the constant risk premium of contract 1-month ahead; also, all of R^2 are very low. However, we can explain the relationship between basis and spot difference in positively relationship.

However, we need to continue testing the long range relationship by using cointegration and error correction model (ECM) in the next topic because it can use to solve the problem on non-stationary that can explain by long run equilibrium relationship on the direction for movement of future spot price and futures price. Also, it can show the speed of short run adjustment that explains by ECM model.

Furthermore, the study offers the tests on unit root behavior for the market in the following. However, before using the time series data, we adjusted the data by using Natural Logarithm (ln) for both futures price and future spot price for easily on interpretation. The unit root test on spot and RSS3 futures price in the market has so many reasons of testing such as time series data always are non-stationary; Bring the data that are non-stationary to analyze in regression will create the spurious regression; and R^2, t-statistic, and F-statistic from the spurious regression are not correct and do not use because of unreliability and because the distribution is not normal and the estimators are inconsistent. The variables that are stationary and non-stationary have three characteristics as: For stationary, Y_t will be as: Mean: $E(Y_t) = \mu$; Variance: $Var(Yt) = E(Y_t - \mu)^2 = \sigma^2$; Covariance: $E[(Y_t – \mu) (Y_{t+k} – \mu)] = \gamma_k$. For nonstationary, Y_t will be as: Mean: $E(Y_t) = t\mu$; Variance: $Var(Y_t) = E(Y_t – \mu)^2 = t\sigma^2$; Covariance: $E[(Y_t – \mu) (Y_{t+k} – \mu)] = t\gamma_k$.

Moreover, the regression that expects to be spurious regression is as: R-Squared and t-statistic values are very high, but the Durbin-Watson (DW) is very low. Granger and Newbold (1974) suggested that if R^2 > DW, it will show that regression equation might be problem called spurious regression because if the time series data has the relationship with time, the $\sum_t (y_t – ybar)^2$ will increase when time passes. However, if the error has very high relationship, ρ value will high and DW value will low.

4.1.2 Empirical Evidence for Unbiasedness Hypothesis

Samuelson (1965) claimed that “futures prices in an efficient market follow a martingale process, which implies that the futures price is unbiased predictor of the future spot prices. If the market is efficient, then the futures price is an unbiased predictor of the future spot price, which is called the “unbiasedness” hypothesis”. In this study we use cointegration test and Wald test to check for evident of unbiasness hypothesis. The cointegration test is to find long run relationship between futures and spot. The unbiasness is to show that constant risk premium equal zero and bata equal one assumption by the hypothesis. The cointegration test, time series data that uses in regression even though is nonstationary, but if the variables have the qualification on “cointegration”, the result will not meet spurious regression problem. This concept was developed by Engle and Granger (1987: 251-276) concluding that “The two time series data might have the simultaneous relationship which it is called cointegration even though the data is nonstationary”.

Before testing on cointegration, it should check the relationship of variables from the graph showing as Figure 4.1 through Figure 4.6. All figures show that spot and futures price tend to move together in the long run. Therefore, now we will test cointegration following Engle and Granger methodology. In previous information, the unit root test finds that lnSpot and lnRSS3 have stationary at 1st difference or I(1). Then, if the error term value from equation $S_{t+n} = \beta_0 + \beta_0 F_{t,n} + e_t$ where S_{t+n} is natural logarithm of spot price at time t+n or future spot price; $F_{t,n}$ is natural logarithm of futures price at time t for delivery in time t+n; and e_t is residual. The stationary of the estimated error terms will show that this equation has cointegration or the long run relationship.

Referring to Engle-Granger Two Step Procedure (Engle and Granger, 1987), by testing the qualification unit root of variable residual without trend and intercept to test stationary, the residual is stationary means spot price and futures price having long run relationship or cointegration. After that test hypothesis: H_0: $\beta_0 = 0$ and $\beta_1 = 1$; H_1: $\beta_0 \neq 0$ or $\beta_1 \neq 1$ on unbiasness in Table 4.8. If we cannot reject H_0, it will show that the market is efficient in long run where as $\beta_0 = 0$ means that the investors in the market are risk nature and if $\beta_1 = 1$ means that investors in the market use all market’s information making decisions.

Table 4.8 OLS Results from Each Contract-Month on Unbiasness

Contract	Equation	Wald Test	P-Value	R^2
1-month	$\hat{S}_{t+n} = -0.045923 + 1.009714 F_{t,n}$	0.373517	0.6886	0.857713
2-month	$\hat{S}_{t+n} = -0.191718 + 1.043244 F_{t,n}$	1.585307	0.2066	0.852254
3-month	$\hat{S}_{t+n} = -0.321655 + 1.072455 F_{t,n}$	3.169698	0.0434**	0.815252
4-month	$\hat{S}_{t+n} = -0.337270 + 1.076032 F_{t,n}$	2.985500	0.0520**	0.790256
5-month	$\hat{S}_{t+n} = -0.445661 + 1.100360 F_{t,n}$	4.128831	0.0170**	0.760169
6-month	$\hat{S}_{t+n} = -0.338880 + 1.076537 F_{t,n}$	2.291173	0.1029*	0.734414

Note: - ** significant at 0.05
- * significant at 0.10

From OLS results, The Wald Test finds that the results cannot reject the joint null hypothesis of forward unbiasness H_0: $\beta_0 = 0$and $\beta_1 = 1$. Then, it can conclude that futures price can be the representative for future spot price. For contract 1and 2-month, we cannot reject the null hypothesis of forward rate unbiasness. We consider that forward rate can be unbiased predict of the future spot price coefficient on bias coefficient is close to one as c(2) be 1.009714 and 1.043244 for contract 1 and 2-month, respectively including the constant risk premium is closed to zero. But for the contract 3 to 6 month, we reject the null hypothesis. This result provides evident that forward cannot be unbiased prediction of the spot rate even though we can find cointegration, but the unbiasness is not found.

When we continue to consider Table 4.8 on contract 2-month, we found that it can be the representative of forecasting future spot price in the ratio 1.043244. The ratio on the rate of increasing in future spot price on contract 2-month and of decreasing in contract 6-month finding that the futures price can be the representative of future spot price in the ratio of 1.043244, 1.072455, 1.076032, 1.100360 and 1.076537 respectively. It shows that the capacity being the representative for predicting future spot price will decrease starting on 3-month contract ahead. Also, it can imply that after contract 5-month the investors cannot have much effective response to the information in AFET causing the market is not efficient. Because it might have less liquidity on buying-selling RSS3 or none of volume occurs on that particular further contract 5-month or the investors and agents have problem on predicting the future spot price or the investors might not have enough understanding on products in AFET. For speculators who are typically sophisticated, risk-taking investors with expertise in the market in which they are trading and will usually use highly leveraged investments such as futures, they should use the contract 1 or 2-month ahead to make the profits. Besides, the other point should be concerned is about "spread trading" because most of futures market is in contango style meaning that the contract near-month price is cheaper than contract far-month price which this concept can be explained by "Cost of Carry". But in some period, the futures market is in backwardation style meaning that the contract near-month price is expensive than contract far-month price which this event can be occurred from the urgent needs on products in the present period. Let's check from the figure 4.7:

Now, we need to continue testing the cointegration on unit root test of residual in Table 4.9. If the residual is stationary, it will explain that spot price and futures price have cointegration.

Table 4.9 Tests Stationary of Residual on Each Price from lnSpot and lnRSS3 Futures Markets, 1st August 2007 through 31st October 2008

Variable	**Augmented Dickey-Fuller Test Level**	
	Mackinnon t-Statistic	**p-value**
Residual 1-month	-3.615106	0.02532**
Residual 2-month	-3.794369	0.01516***
Residual 3-month	-3.638018	0.02376**
Residual 4-month	-3.473208	0.03707**
Residual 5-month	-3.577940	0.02803**
Residual 6-month	-4.213114	0.00403***

Note: - *** significant at 0.01
- ** significant at 0.05

According to Table 4.9 finds that "reject null hypothesis" (Mackinnon Test) at 1% significant in all contracts-month ahead and shows the residual value has no unit root being as stationary. We conclude that futures price and future spot price have long range equilibrium relationship.

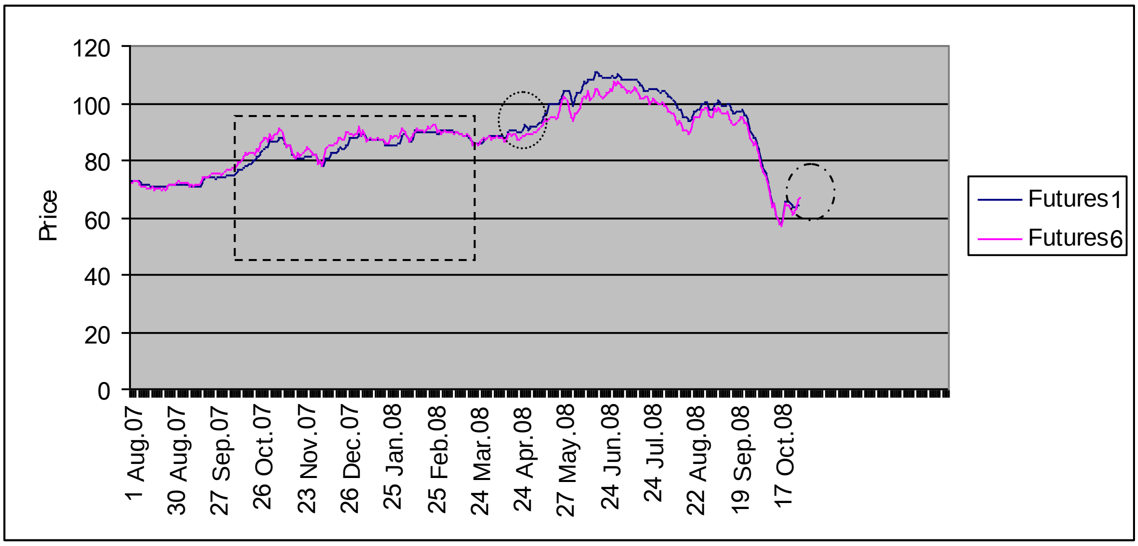

Figure 4.7 Spread Trading in Futures Contract 1 and 6-Month

Figure 4.7, is contango market, is entry market and is exit market. Then, during 27th September 2007 to 24th March 2008 is contango market because the contract far-month (Futures6) is higher than the contract near-month (Futures1) until 24th April 2008 the contract far-month price drop below the contract near-month price showing the unusual market situation called Backwardation Market. In this situation if the investors believe that in the future, the market will be back at Contango Market again. The investors can earn the profit from spread trading which it is called "Short Calendar Spread" open short near-month and in the same time open long far-month. And then when the market goes back to the contango market which it is on 18th October 2008, the investors can go out from the market by closing all both contracts and receive the profits. This real example we believe that it can be an optional choice for investors searching the profits broader than specific only on outright trading. Moreover, we believe that this technique can be an instrument creating the confident for the investors' portfolios.

In summary, RSS3 in AFET has cointegration in all contract-month but it will reject the unbiasness hypothesis after the contract 2-month ahead. Furthermore, if we use the tool analyzing on the weak form efficiency, it found that each of the tools can explain along with its objective.

Autocorrelation Function (ACF): testing the relationship on the return in time t and time t-1. It considers on Q statistic. The result showed “not followed the random walk theory; the market is inefficient”.

Unit Root Tests: using Augmented Dickey-Fuller (ADF) test on the null hypothesis is Unit Root and using KPSS test of stationary on the alternative hypothesis is Unit Root. The result from ADF test and KPSS test showed “followed the random walk theory; the market is weak form efficiency”.

Run Test or Geary Test: using for study the movement behavior on the return of RSS3 futures by considering on the sign of RSS3 futures. The result showed “followed the random walk theory; market is weak form efficiency”.

First-Order Autoregressive Scheme or AR(1): testing the relationship of the return on RSS3 futures at time t and time t-1 by considering on coefficient of autocorrelation. The result showed “not followed the random walk theory; the market is inefficient”.

Variance Ratio Tests: testing the movement of time-series followed by random walk whether. Concentration is on each period should have the linear relationship in the difference interval. That implies there is the qualification followed by the random walk theory. The result showed “followed the random walk theory; market is weak form efficiency”.

Also, the variables used in cointegration model are non-stationary from testing on Unit Root Test; therefore, we cannot explain the statistical values because of Spurious Equation. However, we can solve the problem by doing the First difference and Error Correction Model (ECM) along with an increasing the lag term into the equation for describing the relationship and the speed on adjustment of future spot price.

The coming up process is on estimating error-correction model in daily data. When the equation $\ln Spot_t = \alpha + \beta_t \ln RSS3_{t-1}$ has cointegration, when the variable on time series that has cointegrating relationship we can use “Error-Correction Model: ECM” which links between short and long run as following:

$\Delta S_{t+n} = \alpha + \phi \hat{e}_{t-1} + \sum_{i=1}^{n} \delta \Delta S_{(t+n)-i} + \sum_{j=0}^{m} \gamma \Delta F_{t-j} + \mu_t$ where ΔS_{t+n} is first difference at natural logarithm of spot future price; $\Delta F_{t,n}$ is first difference at natural logarithm of futures price; ϕ is speed of adjustment of spot future price; $\hat{e}_{t-1}$ is residual of cointegration coming from $S_{t+n} - \hat{S}_{t+n}$; μ_t is residual of error correction model (ECM).

To find out the suitable ECM, we can consider from t-statistic of δ (coefficient on the first difference at natural logarithm of spot future price at time (t+n)-1) by putting many lag term of both variables and gradually cutting down lag term that has not significant till reaching the proper model. This process should consider to significant tell for lag include in the model. We solve k equal five for maximum lag included in the model.

Contract 1-month ahead

$$\Delta\hat{S}_{t+n} = -0.080458\hat{e}_{t-1} + 0.181461\Delta S_{(t+n)-2} + 0.006389\Delta F_t$$

t-Stat (-3.675889)*** (3.378841)*** (5.759639)***

R^2 = 0.157130 B-G Test = 2.311912 ARCH LM Test = 1.895750

p-value = 0.100828 p-value = 0.169571

Contract 2-month ahead

$$\Delta\hat{S}_{t+n} = -0.063517\hat{e}_{t-1} + 0.156589\Delta S_{(t+n)-2} + 0.336620\Delta F_t$$

t-Stat (-2.785888)*** (2.683270)*** (3.629703)***

R^2 = 0.091859 B-G Test = 0.020615 ARCH LM Test = 1.578353

p-value = 0.979598 p-value = 0.209969

Contract 3-month ahead

$$\Delta\hat{S}_{t+n} = -0.042187\hat{e}_{t-1} + 0.143954\Delta S_{(t+n)-1} + 0.184680\Delta S_{(t+n)-2} + 0.208840\Delta F_t + 0.085392\Delta F_{t-4}$$

t-Stat (-2.198546)** (2.486341)*** (3.268302)*** (2.426747)*** (1.06991)

R^2 = 0.108767 B-G Test = 0.343307 ARCH LM Test = 0.204138

p-value = 0.709703 p-value = 0.651729

Contract 4-month ahead

$$\Delta\hat{S}_{t+n} = -0.030110 e_{t-1} + 0.177672 \Delta S_{(t+n)-1} + 0.219144 \Delta S_{(t+n)-2}$$

t-Stat (-1.639755)* (3.225566)*** (4.249410)***

R^2 = 0.083857 B-G Test = 0.327255 ARCH LM Test = 0.503085

p-value = 0.721158 p-value = 0.478699

Contract 5-month ahead

$$\Delta\hat{S}_{t+n} = -0.019909 \hat{e}_{t-1} + 0.161321 \Delta S_{(t+n)-1} + 0.223287 \Delta S_{(t+n)-2}$$

t-Stat (-1.140770) (2.751368)*** (3.975248)***

R^2 = 0.080171 B-G Test = 0.213135 ARCH LM Test = 0.354616

p-value = 0.808170 p-value = 0.551962

Contract 6-month ahead

$$\Delta\hat{S}_{t+n} = -0.021244 \hat{e}_{t-1} + 0.157942 \Delta S_{(t+n)-1} + 0.251635 \Delta S_{(t+n)-2}$$

t-Stat (-1.292974) (2.704711)*** (4.288275)***

R^2 = 0.087852 B-G Test = 0.981850 ARCH LM Test = 0.358628

p-value = 0.375834 p-value = 0.549724

Note: - *** significant at 0.01
- ** significant at 0.05
- * significant at 0.10

When we get ECM, we need to check the serial correlation problem by using Breusch-Godfrey Serial Correlation LM test (B-G Test). The results show that all contract-month cannot reject null hypothesis “no serial correlation”. After that continuing to test volatility on time by using ARCH LM Test in term of “Does the volatility on time depend on Heteroscedasticity?” The results imply that all contract-month cannot reject null hypothesis meaning that the volatility of future spot price on RSS3 has characteristic on “Homoscedasticity”. So, we do need not to work on GARCH Model.

The results from the models show that most of error correction models are significant for contract 1 to 3-month, but not for contract 4 to 6-month, the space of adjustment represented by error-correction term, also, have remarkable on the value. So, we can conclude that the contract 1-month ahead future spot price, will have the speed of adjustment to the equilibrium equal to 8.0458% per 1 period when there is the deviation from the equilibrium. On the others, the contract 2, 3, 4, 5 and 6-month future spot price have the speed on adjustment to the equilibrium equal to 6.3517%, 4.2187%, 3.0110%, 1.9909% and 2.1244% per 1 period, respectively. Considering at contract 1-month ahead finds that the future spot price has the speed of adjustment to the long rang equilibrium faster than the others. As mention in previous, the contract near-month future spot price will have less volatile comparing to contract far-month. The further contract far-month, the higher RSS3 volatile is. It is noticeable on contract 6-month, the speed of adjustment increases again after contract 5-month. It can explain that the contract 6-month has more liquidity than contract 5-month causing to reduce the short range volatility and can adjust so fast to be back at the long range relationship again. However, when we consider with the previous information on the long range relationship, we will see that the future price of futures contract 1 or 2-month can adjust be better than others. However, too far-month on contract will affect the market not efficient causing the price on futures price cannot predict the future spot price.

Moreover, we can test the leading indicators following as Table 4.10 to Table 4.13:

Table 4.10 OLS Results from Daily Leading Indicators

Leading Indicator	**Equation**	R^2
Exchange rate (Baht/$)	$\hat{F}_t = 9.161170 - 1.330318 FX1_{t,n}$	0.095723
Exchange rate (Yen/$)	$\hat{F}_t = -0.233263 + 1.033887 FX2_{t,n}$	0.196369
Crude Oil Price	$\hat{F}_t = 1.627421 + 0.618292 OIL_{t,n}$	0.787344
TOCOM	$\hat{F}_t = 0.206020 + 0.954212 TOCOM_{t,n}$	0.905142

Note: Estimated F_t and leading indicators are in log form. All equations are 1-month ahead.

From OLS results, if the residual is stationary, it will explain that futures price and leading indicator have cointegration. The Wald Test finds that most of the results reject the hypothesis at significant 0.01. Then, it cannot conclude that all leading indicators can be the representative for RSS3 futures price. Even though, the cointegration can explain that only both crude oil price and TOCOM with futures price have long range equilibrium relationship. From cointegration results, It shows that the capacity being the representative for predicting futures price will be drop on using both exchange rate (Baht/$) and (Yen/$). It can imply that for both exchange rate (Baht/$) and (Yen/$) being as leading indicators, the speculators cannot have much using as an effective response. For speculators, they should use crude oil price or/and TOCOM to be the leading indicators helping to make the decision for investment in futures market.

Table 4.11 Tests Stationary of Residual without Trend and Constant on Each Price from lnFutures and Leading Indicators, 1st August 2007 through 31st October 2008

Variable	**Augmented Dickey-Fuller Test Level**	
	Mackinnon t-Statistic	**p-value**
Residual FX1	-1.232946	0.85012
Residual FX2	-0.708478	0.94321
Residual Crude Oil Price	-4.319141	0.00280***
Residual TOCOM	-5.024858	0.00019***

Note: - *** significant at 0.01

According to Table 4.12 finds that we can reject null hypothesis (Mackinnon Test) at significant 0.01 only for crude oil price and TOCOM. It shows the residual value has no unit root being as stationary. We conclude that crude oil price, TOCOM and futures price have long range equilibrium relationship. When we know there is cointegration between futures price and both crude oil price and TOCOM.

In summary, the leading indicators are used in cointegration model are non-stationary from testing on Unit Root Test, The next step, we can do the First difference and Error Correction Model (ECM) along with an increasing the lag term into the equation for describing the relationship and the speed on adjustment of futures price.

The coming up process is on estimating daily error-correction model. When the equation $\ln Futures_t = \alpha + \beta_1 \ln(INDICATOR)_{t,\,n}$ has cointegration, the variable that has cointegrating relationship can adjust the short run to long run by calling as "Error-Correction Model: ECM" which model links between short and long run as following by first difference to solve the non-stationary problem:

$\Delta F_{t+n} = \alpha + \phi \hat{e}_{t-1} + \sum_{i=1}^{n} \delta \Delta F_{(t+n)-i} + \sum_{j=0}^{m} \gamma \Delta INDICATOR_{t-j} + \mu_t$ where

ΔF_{t+n}	= first difference at natural logarithm of futures price
$\Delta INDICATOR_{t,n}$	= first difference at natural logarithm of leading indicator price
ϕ	= speed of adjustment of spot future price
$\hat{e}_{t-1}$	= residual of cointegration coming from $F_{t+n} - \hat{F}_{t+n}$
μ_t	= residual of error correction model (ECM)

To find out the suitable daily ECM, we can consider from t-statistic of δ (coefficient on first difference at natural logarithm of futures price at time (t+n)-1) by putting many lag term of both variables and gradually cutting down lag term that has not significant until finding out the suitable daily ECM. We consider the case on n = 1 only following:

Exchange Rate (Baht/$)

$$\Delta\hat{F}_{t+n} = -0.006405\hat{e}_{t-1} + 0.389503\Delta F_{(t+n)-1} - 0.435817\Delta FX1_{t-4}$$

t-Stat (-1.133345) (7.322974)*** (-0.435817)

R^2 = 0.151354 B-G Test = 0.866995 ARCH LM Test = 44.59498

p-value = 0.421262 p-value = 0.000000

Exchange Rate (Yen/$)

$$\Delta\hat{F}_{t+n} = -0.006645\hat{e}_{t-1} + 0.389755\Delta F_{(t+n)-1} - 0.021290\Delta FX2_{t-1}$$

t-Stat (-1.117648) (7.347066)*** (-0.518007)

R^2 = 0.151024 B-G Test = 0.785088 ARCH LM Test = 43.95926

p-value = 0.457005 p-value = 0.000000

Crude Oil Price

$$\Delta\hat{F}_{t+n} = -0.033391\hat{e}_{t-1} + 0.382017\Delta F_{(t+n)-1} + 0.030947\Delta OIL_{t-1}$$

t-Stat (-2.920561)*** (7.320611)*** (2.130939)**

R^2 = 0.176547 B-G Test = 1.184774 ARCH LM Test = 39.05453

p-value = 0.307228 p-value = 0.000000

TOCOM

$$\Delta\hat{F}_{t+n} = 0.037172e_{t-1} + 0.248101\Delta F_{(t+n)-1} + 0.155631\Delta TOCOM_{t}$$

t-Stat (2.010409)** (4.594885)*** (5.689942)***

R^2 = 0.270201 B-G Test = 0.366790 ARCH LM Test = 11.92964

p-value = 0.693262 p-value = 0.000631

Note: *** significant at 0.01

** significant at 0.05

When we get daily ECM, we need to check the serial correlation problem by using Breusch-Godfrey Serial Correlation LM test (B-G Test). The results show that all leading indicators cannot reject the null hypothesis of “no serial correlation”. It means there is no autocorrelation problem. After that continuing to test ARCH effect or autoregressive conditional heteroskedasticity by using ARCH LM Test, all reject the null hypothesis autoregressive conditional heteroskedasticity. This provides evident of volatility clustering that forms in high frequently time-series, but the generalized autoregressive conditional heteroskedasticity or GARCH models are useful to obtain data with this. However, the GARCH is not target on this paper working. Note that the ECM coefficient is significantly for oil and TOCOM variables. That is consistent to result from cointegration that we found long run relationship in oil and TOCOM only.

Table 4.12 OLS Results from Monthly Leading Indicators

Leading Indicator	Equation	R^2
Exchange rate (Baht/$)	$\hat{F}_t = 10.34308 - 1.687659 FX1_{t,n}$	0.256868
Crude Oil Price	$\hat{F}_t = 1.010904 + 0.783652 OIL_{t,n}$	0.470146
Exchange rate (Yen/$)	$\hat{F}_t = 0.613013 + 0.772356 FX2_{t,n}$	0.057120
TOCOM	$\hat{F}_t = -0.099960 + 1.020107 TOCOM_{t,n}$	0.994257
Net Imports Natural Rubber Japan	$\hat{F}_t = 4.277361 - 0.008386 IMNJ_{t,n}$	0.000016
Net Imports Natural Rubber China	$\hat{F}_t = 2.313029 + 0.404208 IMNC_{t,n}$	0.113788
Net Imports Synthetic Rubber Japan	$\hat{F}_t = 3.921670 + 0.114024 IMSJ_{t,n}$	0.002505
Net Imports Synthetic Rubber China	$\hat{F}_t = 1.220249 + 0.647702 IMSC_{t,n}$	0.305775
World Consumption on Natural Rubber	$\hat{F}_t = -5.043746 + 1.399428 WNC_{t,n}$	0.208096
World Consumption on Synthetic Rubber	$\hat{F}_t = -9.969082 + 2.043489 WSC_{t,n}$	0.281331

From OLS results, we need to continue testing the cointegration by using Engle-Granger Two Step Procedure (Engle and Granger, 1987) on unit root test of residual. If the residual is stationary, it will explain that futures price and leading indicator have cointegration.

Table 4.13 Tests Stationary of Residual without Trend and Constant on Each Price from lnFutures and Leading Indicators, May 2004 through May 2009

Variable	**Augmented Dickey-Fuller Test Level**	
	Mackinnon t-Statistic	
Residual FX1	-2.099665	(0.48127)
Residual Crude Oil Price	-2.897416	(0.15173)
Residual FX2	-1.982837	(0.54090)
Residual TOCOM	-6.247495	(0.0001)***
Residual Net Imports Natural Rubber Japan	-1.880600	(0.59254)
Residual Net Imports Natural Rubber China	-2.517395	(0.28385)
Residual Net Imports Synthetic Rubber Japan	-1.863980	(0.60081)
Residual Net Imports Synthetic Rubber China	-3.125607	(0.09786)*
Residual World Natural Consumption	-2.832377	(0.17050)
Residual World Synthetic Consumption	-2.704672	(0.21201)

Note: -*** significant at 0.01
-* significant at 0.10
The number in the parenthesis is p-value.

According to Table 4.13 finds that we reject null hypothesis (Mackinnon Test) at significant 0.01 and 0.10 for only TOCOM and net imports synthetic rubber China; also, it shows the residual value has no unit root being as stationary. We conclude that TOCOM, net imports synthetic rubber China and futures price have long run equilibrium relationship. When we know there are cointegration between futures price and TOCOM, net imports synthetic rubber China. That can show the capacity being the representative for predicting futures price on TOCOM and net imports synthetic rubber China which it can imply that for other variables being as leading indicator on daily data, the speculators cannot have much using as an effective response. So, they should use either TOCOM or net imports synthetic rubber China to be the leading indicators helping to make the decision for investment in futures market.

The next step, we can do the First difference and Error Correction Model (ECM) along with an increasing the lag term into the equation for describing the relationship and the speed on adjustment of futures price.

The coming up process is on estimating monthly error-correction model. When the equation $\ln Futures_t = \alpha + \beta_1 \ln(INDICATOR)_{t-1}$ has cointegration, the variable that has cointegrating relationship can adjust the short run to long run by calling as "Error-Correction Model: ECM" which model links between short and long run as following by first difference to solve the non-stationary problem:

$$\Delta F_{t+n} = \alpha + \phi \hat{e}_{t-1} + \sum_{i=1}^{n} \delta \Delta F_{(t+n)-i} + \sum_{j=0}^{m} \gamma \Delta INDICATOR_{t-j} + \mu_t \text{ where}$$

ΔF_{t+n} = first difference at natural logarithm of futures price

$\Delta INDICATOR_{t,n}$ = first difference at natural logarithm of leading indicator price

ϕ = speed of adjustment of spot future price

$\hat{e}_{t-1}$ = residual of cointegration coming from $F_{t+n} - \hat{F}_{t+n}$

μ_t = residual of error correction model (ECM)

To find out the suitable ECM, we can consider from t-statistic of δ (coefficient on first difference at natural logarithm of futures price at time (t+n)-1) by putting many lag term of both variables and gradually cutting down lag term that has not significant until finding out the proper model. This process should consider to AIC statistic choosing the suitable model with the least AIC following:

Exchange Rate (Baht/$)

$$\Delta\hat{F}_{t+n} = -0.126762\hat{e}_{t-1} - 1.685863\Delta FX1_{t-2}$$

t-Stat (-1.890827)* (-1.943914)*

R^2 = 0.118331	B-G Test = 1.316820	ARCH LM Test = 0.077843
	p-value = 0.276453	p-value = 0.781289

Crude Oil Price

$$\Delta\hat{F}_{t+n} = -0.150014\hat{e}_{t-1} + 0.299670\Delta OIL_{t}$$

t-Stat (-1.882830)* (0.0038)***

R^2 = 0.149949	B-G Test = 0.738163	ARCH LM Test = 0.031471
	p-value = 0.482584	p-value = 0.859822

Exchange Rate (Yen/$)

$$\Delta\hat{F}_{t+n} = -0.127424\hat{e}_{t-1}$$

t-Stat (-2.180663)**

R^2 = 0.074418	B-G Test = 0.424835	ARCH LM Test = 0.020668
	p-value = 0.655931	p-value = 0.886195

TOCOM

$$\Delta\hat{F}_{t+n} = -0.845494e_{t-1} + 0.232528\Delta F_{t+n-1} + 1.018103\Delta TOCOM_{t} - 0.233229\Delta TOCOM_{t-1}$$

t-Stat (-5.991398)*** (1.993421) (54.62895)*** (-1.998972)

R^2 = 0.982086	B-G Test = 0.291958	ARCH LM Test = 0.654294
	p-value = 0.747993	p-value = 0.422005

Net Imports Natural Rubber Japan

$$\Delta\hat{F}_{t+n} = -0.102858\hat{e}_{t-1} - 0.155118\Delta IMNJ_{t}$$

t-Stat (-1.828165)* (-1.924534)*

R^2 = 0.112964 B-G Test = 0.330989 ARCH LM Test = 0.209549

p-value = 0.719609 p-value = 0.648862

Net Imports Natural Rubber China

$$\Delta\hat{F}_{t+n} = -0.127756\hat{e}_{t-1} + 0.170948\Delta F_{(t+n)-3} - 0.077020\Delta IMNC_{t-1}$$

t-Stat (-1.940931)** (1.253848) (-0.910356)

R^2 = 0.080953 B-G Test = 0.663417 ARCH LM Test = 0.005975

p-value = 0.519393 p-value = 0.938673

Net Imports Synthetic Rubber Japan

$$\Delta\hat{F}_{t+n} = -0.107998\hat{e}_{t-1}$$

t-Stat (-1.876867)*

R^2 = 0.056169 B-G Test = 0.427087 ARCH LM Test = 0.039064

p-value = 0.654477 p-value = 0.844025

Net Imports Synthetic Rubber China

$$\Delta\hat{F}_{t+n} = -0.124303\hat{e}_{t-1}$$

t-Stat (-1.778254)*

R^2 = 0.050697 B-G Test = 0.557499 ARCH LM Test = 0.029933

p-value = 0.575730 p-value = 0.863256

World Natural Consumption

$\Delta\hat{F}_{t+n} = -7.784285\hat{e}_{t-1}$

t-Stat (-1.630608)*

R^2 = 0.043017	B-G Test = 0.628457	ARCH LM Test = 0.003813
	p-value = 0.537069	p-value = 0.950980

World Synthetic Consumption

$\Delta\hat{F}_{t+n} = -0.119110\hat{e}_{t-1}$

t-Stat (-1.721924)*

R^2 = 0.047676	B-G Test = 0.400955	ARCH LM Test = 0.059922
	p-value = 0.671554	p-value = 0.807498

Note: *** significant at 0.01
** significant at 0.05
* significant at 0.10

When we get ECM, we need to check the serial correlation problem by using Breusch-Godfrey Serial Correlation LM test (B-G Test). The results show that all leading indicators do not reject hypothesis “no serial correlation”. It means there is no the autocorrelation problem.

ECM equations in monthly data, the variables do not significant in many equations excepting exchange rate (Baht/$), crude oil price, exchange rate (Yen/$), TOCOM, net imports natural rubber Japan, net imports synthetic rubber Japan and net imports synthetic rubber China.

4.2 Forecast Performance of RSS3 Futures Markets in Thailand

The concept describes how capacity the mathematic models predict future performance. To calculate future performance, nine mathematic models apply a transform to the data before performing a least-squares linear regression. With this transformed data, the each model computes a forecast line. The forecast duration is equal to the duration of the observed data. In this section we discuss the empirical result on the forecast performance of the RSS3 future. Firstly, Table 4.14 to 4.18 report the criteria values for univariate forecasts based model selection criteria in pure time series, leading indicators expressing by lag term and leading indicators expressing by ECM. Secondly, in particular Table 4.19 reports the pair wise model comparison statistics based on Diebold-Mariano predictive accuracy tests for RSS3. Finally, Table 4.20 report the relative ranking contains the Market-Timing criteria values. Only the results from one step-ahead forecast are reported here. Tables 4.14 through Table 4.18 showed the particular style on forecasting RSS3 futures price categorized as pure time series, daily period with leading indicators by lag term, monthly period with leading indicators by lag term, daily period with leading indicators by ECM and monthly period with leading indicators by ECM. The calculation results are shown as follows:

Table 4.14 Model Ranking by Univariate Criteria (1-Step-Ahead Forecasts) in Pure Time Series Models

Model	**RMSE (Ranking)**	**MAE (Ranking)**	**MAPE (Ranking)**	**THIL'S (Ranking)**
RW	1.495	0.981	0.011704	0.00774
	(7)	(4)	(5)	(7)
RWD	1.506	1.050	0.012393	0.00779
	(8)	(8)	(8)	(8)
VAR	1.259	0.929	0.010841	0.00652
	(1)	(2)	(2)	(1)
AR(1)	1.336	0.986	0.011599	0.00691
	(3)	(5)	(4)	(3)
MA(1)	1.370	1.004	0.011841	0.00709
	(5)	(6)	(6)	(5)
SES	1.359	0.974	0.011562	0.00704
	(4)	(3)	(3)	(4)
T	15.490	11.649	0.148322	0.07738
	(9)	(9)	(9)	(9)
RWDT	1.424	1.024	0.012150	0.00737
	(6)	(7)	(7)	(6)
ARIMA(1,1,1)	1.268	0.923	0.010759	0.00657
	(2)	(1)	(1)	(2)

Notes: Entries tabulate the ranking of the nine forecasting models considered. They are random walk without drift (RW), random walk with drift (RWD), vector autoregressive (VAR), autoregressive (AR1), moving average (MA1), simple exponential smoothing (SES), deterministic trend (T), random walk with drift and trend (RWDT) and autoregressive integrated moving average (ARIMA). An entry of 1 stands for the "best" performance according to the model selection criterion in the same row, while nine indicates the "worst" performance. The four criteria include root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Thil's U-statistic.

Table 4.14 reports the values of all univariate criteria in pure time series, for RSS3 commodities and forecast horizons.

The root mean square error (RMSE) or the root mean square deviation (RMSD) is a frequently-used measure of the differences between values predicted by a model or an estimator and the observed values. RMSE is a good measure of accuracy. In the field of statistics, accuracy is the degree of closeness of a measured or calculated quantity to its actual (true) value. Also, the RMSE serves to aggregate residuals into a single measure of predictive power. This means the RMSE is most useful when large errors are particularly undesirable. And the MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction. It measures accuracy for continuous variable which the variable here is RSS3 futures price. Expressed in words, the MAE is the average over the verification sample of the absolute values of the differences between forecast and the corresponding observation The MAE is a linear score which means that all the individual differences are weighted equally in the average. So, in this paper 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 the variance in the individual errors in the sample. If the RMSE = MAE, then all the errors are of the same magnitude. Both the MAE and RMSE can range from zero to infinity. They are negatively-oriented scores: Lower values are better. The MAE is very similar to the RMSE but is less sensitive to large forecast errors. For small or limited data sets the use of MAE is preferred. Then, if paper wants to measure the accuracy for the continuous RSS3 futures price, paper should check pass through RMSE and MAE. The results show that VAR is the most accurate model because it is in the first rank performance on the lowest values in RMSE and ARIMA(1,1,1) is the first rank performance on the lowest values in MAE which implies that the VAR and ARIMA(1,1,1) are the best accurate model by the univariate criteria in pure time series. Mean absolute percentage error or MAPE is measure of accuracy in a fitted time series value in statistics, specifically trending such as futures market price trends. It usually expresses accuracy as a percentage. Although the concept of MAPE sounds very simple and convincing it has two major drawbacks in the practical application: If there are zero values, there will be a division by zero;

when having a perfect fit, MAPE is zero. But in regard to its upper level the MAPE has no restriction. When calculating the average MAPE for a number of time series there might be a problem: a few numbers of series that have a very high MAPE might distort a comparison between the averages MAPE of time series fitted with one method compared to the average MAPE when using another method. In order to avoid this problem other measures have been defined, for example the sMAPE (symmetrical MAPE) or a relative measure of accuracy. So, if paper needs to measure the accuracy in a fitted RSS3 time series value in statistics, paper would examine through MAPE. The outcomes show that ARIMA(1,1,1) is also the fit model because it is in the first rank performance on the lowest values in MAPE which implies that the ARIMA(1,1,1) is the best fit model against others by the univariate criteria in pure time series. The other performance of models using in this chapter is measured by Theil's U-statistic (U). The Theil's U-statistic falls between zero and one. When U = 0, that means that the predictive performance of the model is excellent and when U = 1, then it means that the forecasting performance is not better than just using the last actual observation as a forecast. The difference between RMSE or MAPE and Theil's U is that the formers are measure of "fit"; measuring how well model fits to the historical data. The Theil's U on the other hand measures how well the model predicts against a 'naïve' model. A forecast in a naïve model is done by repeating the most recent value of the variable as the next forecast value. The forecasting model should be the one with lowest Theil's U. Notice that if the best Theil's U model is not the same as the best RMSE model then it needs to run Crystal Ball (CB) again by checking only the best Theil's U model to obtain forecasted value because the CB uses forecasting value of the lowest RMSE model (best model according CB).

Table 4.15 Daily Leading Indicators Express by Lag Term

Model Express by Lag Term		**Univariate**	**Criteria**	
Time-Series	**RMSE (Ranking)**	**MAE (Ranking)**	**MAPE (Ranking)**	**THIL'S (Ranking)**
RW	1.495	0.981	0.011704	0.00774
	(9)	(3)	(4)	(9)
RWD	1.506	1.050	0.012393	0.00779
	(10)	(10)	(10)	(10)
VAR	1.259	0.929	0.010841	0.00652
	(1)	(1)	(1)	(1)
AR(1)	1.336	0.986	0.011599	0.00691
	(2)	(4)	(3)	(2)
MA(1)	1.370	1.004	0.011841	0.00709
	(4)	(5)	(5)	(4)
SES	1.359	0.974	0.011562	0.00704
	(3)	(2)	(2)	(3)
T	15.490	11.649	0.148322	0.07738
	(12)	(12)	(12)	(12)
RWDT	1.424	1.024	0.012150	0.00737
	(5)	(6)	(6)	(5)
Leading Indicators				
Exchange Rate (Baht/$)	1.506	1.051	0.012408	0.00779
	(11)	(11)	(11)	(11)
Crude Oil Price	1.487	1.050	0.012392	0.00770
	(8)	(9)	(9)	(8)
Exchange Rate (Yen/$)	1.474	1.034	0.012192	0.00763
	(6)	(7)	(7)	(6)
TOCOM	1.476	1.043	0.012291	0.00764
	(7)	(8)	(8)	(7)

Note: Entries correspond to the values of univariate selection criteria. See notes to Table 4.14.

Next we consider the performance of forecasting model using the leading indicators to forecast the RSS3. The leading indicator models consist of variable in which data available are based on both daily and monthly basis. The Table 4.15 displays the results of forecasting of RSS3 based on daily basis with those of Table 4.16 are based on monthly basis.

Along with results' figures in Table 4.15, VAR is the best accurate, the perfect fit which the result is the same as in Table 4.14 in pure time series. Moreover, Theil's U-statistic determines the forecasting performance of the models and interpret in daily RSS3 futures price is as follows: The best model predicts against a naïve model is VAR with the lowest value 0.00652 which this number U is nearly to zero meaning that the predictive performance of the VAR model is excellent.

Table 4.16 Monthly Leading Indicators Express by Lag Term

Model Express by Lag Term		Univariate	Criteria	
Time-Series	**RMSE (Ranking)**	**MAE (Ranking)**	**MAPE (Ranking)**	**THIL'S (Ranking)**
RW	10.703	6.628	0.094058	0.06507
	(17)	(12)	(12)	(17)
RWD	10.563	6.558	0.092998	0.06386
	(15)	(11)	(8)	(15)
AR(1)	10.369	6.389	0.091418	0.06262
	(5)	(2)	(5)	(5)
MA(1)	10.441	6.376	0.091528	0.06309
	(8)	(1)	(6)	(9)
SES	10.574	6.539	0.093532	0.06415
	(16)	(8)	(11)	(16)
T	14.767	11.132	0.171854	0.08746
	(18)	(18)	(18)	(18)
RWDT	9.830	6.527	0.093244	0.05983
	(1)	(7)	(9)	(2)
ARIMA(1,1,1)	9.882	6.527	0.095577	0.05955
	(2)	(10)	(17)	(1)

Table 4.16 (Continued)

Model Express by Lag Term Time-Series	RMSE (Ranking)	Univariate MAE (Ranking)	Criteria MAPE (Ranking)	THIL'S (Ranking)
Leading Indicators				
Exchange Rate (Baht/$)	10.517	6.410	0.091237	0.06361
	(12)	(5)	(3)	(12)
Crude Oil Price	10.432	6.733	0.094809	0.06305
	(7)	(16)	(14)	(8)
Exchange Rate (Yen/$)	10.446	6.731	0.094653	0.06294
	(9)	(15)	(13)	(7)
TOCOM	10.318	6.397	0.091263	0.06230
	(4)	(3)	(4)	(4)
Net Imports Natural Rubber Japan	10.476 (11)	6.774 (17)	0.095546 (16)	0.06332 (11)
Net Imports Natural Rubber China	10.460 (10)	6.639 (13)	0.094849 (15)	0.06323 (10)
Net Imports Synthetic Rubber Japan	10.117 (3)	6.399 (4)	0.090862 (1)	0.06118 (3)
Net Imports Synthetic Rubber China	10.543 (13)	6.645 (14)	0.093411 (10)	0.06373 (13)

Note: Entries correspond to the values of univariate selection criteria. See notes to Table 4.14.

Table 4.16, RWDT and MA(1) are the best accurate following by the lowest number of RMSE and MAE. But on the best predictive performance model in term of MAPE is for Net Imports Synthetic Rubber Japan. According to Thiel's U-statistic, ARIMA(1,1,1) is the best predictive performance.

Next we consider the performance of forecasting model using the error-correction (ECM) model of the leading indicators as follows:

Table 4.17 Daily Leading Indicators Express by ECM

Model Express by Lag Term		**Univariate**	**Criteria**	
Time-Series	**RMSE**	**MAE**	**MAPE**	**THIL'S**
	(Ranking)	**(Ranking)**	**(Ranking)**	**(Ranking)**
RW	1.495	0.981	0.011704	0.00774
	(10)	(7)	(8)	(10)
RWD	1.506	1.050	0.012393	0.00779
	(11)	(11)	(11)	(11)
VAR	1.259	0.929	0.010841	0.00652
	(3)	(2)	(2)	(2)
AR(1)	1.336	0.986	0.011599	0.00691
	(6)	(8)	(7)	(6)
MA(1)	1.370	1.004	0.011841	0.00709
	(8)	(9)	(9)	(8)
SES	1.359	0.974	0.011562	0.00704
	(7)	(5)	(6)	(7)
T	15.490	11.649	0.148322	0.07738
	(12)	(12)	(12)	(12)
RWDT	1.424	1.024	0.012150	0.00737
	(9)	(10)	(10)	(9)
Leading Indicators by ECM				
Exchange Rate (Baht/$)	1.309	0.979	0.011501	0.00678
	(5)	(6)	(5)	(5)
Crude Oil Price	1.257	0.931	0.010949	0.00652
	(2)	(3)	(3)	(3)
Exchange Rate (Yen/$)	1.299	0.973	0.011468	0.00674
	(4)	(4)	(4)	(4)
TOCOM	1.250	0.928	0.010779	0.00648
	(1)	(1)	(1)	(1)

Note: Entries correspond to the values of univariate selection criteria. See notes to Table 4.14.

For expressing by ECM in Table 4.17 and 4.18, the results were different from Table 4.14 to Table 4.16 in term of showing the results by the leading indicators are the outstanding for both best accurate and best predictive performance models. The four leading indicators are ranked within top five and provide better forecasting performance than the univariate model based on daily data model.

The accurate model and forecasting model are valuable for the making decision process of private and public entities regarding investment and planning in the futures market. Reliable forecasts also constitute a solid basis for the implementation of policies and futures market strategies in this area. Since forecast accuracy comparisons of alternative models allow for deciding which are best to supply that crucial information, assessing models' forecasting performance is an important prior task in advising course of action to futures agents.

Thus, the results in this chapter indicated that the forecast performance of reduced form VAR models is good for both short and long-run horizons. Moreover, adding the leading indicators expressing as lag term in daily does not affect the forecast performance of VAR model being as the best accurate and best perfect fit. Excepting a small change in monthly is MA(1) instead.

This implies that when the data changed to monthly that due to the data-frequency problem reduce the VARs from daily to monthly model and was with lag term making the forecasts significantly worse than those by the pure time series and with lag term. The results also supported by Diebold and Rudebusch (1999) on the structural econometric forecasting that is based on explicit theory and therefore "it rises and falls with new theories, typically with a lag". TOCOM is the best accurate, best perfect fit and best predictive performance according to RMSE and MAE, MAPE and Thil's, respective.

Table 4.18 Monthly Leading Indicators Express by ECM

Model Express by Lag Term Time-Series	RMSE (Ranking)	Univariate MAE (Ranking)	Criteria MAPE (Ranking)	THIL'S (Ranking)
RW	10.703	6.628	0.094058	0.06507
	(17)	(12)	(11)	(17)
RWD	10.563	6.558	0.092998	0.06386
	(15)	(9)	(6)	(15)
AR(1)	10.369	6.389	0.091418	0.06262
	(12)	(2)	(1)	(11)
MA(1)	10.441	6.376	0.091528	0.06309
	(13)	(1)	(2)	(13)
SES	10.574	6.539	0.093532	0.06415
	(16)	(6)	(8)	(16)
T	14.767	11.132	0.171854	0.08746
	(18)	(18)	(18)	(18)
RWDT	9.830	6.527	0.093244	0.05983
	(3)	(5)	(7)	(4)
ARIMA(1,1,1,)	9.882	6.543	0.095577	0.05955
	(5)	(7)	(15)	(3)
Leading Indicators by ECM				
Exchange Rate (Baht/$)	9.991	6.584	0.093771	0.06086
	(7)	(11)	(9)	(6)
Crude Oil Price	10.203	6.733	0.094809	0.06305
	(11)	(15)	(13)	(12)
Exchange Rate (Yen/$)	10.480	6.831	0.095807	0.06386
	(14)	(17)	(16)	(14)

Table 4.18 (Continued)

Model Express by Lag Term Time-Series	**RMSE (Ranking)**	**Univariate MAE (Ranking)**	**Criteria MAPE (Ranking)**	**THIL'S (Ranking)**
TOCOM	10.178	6.440	0.091604	0.06172
	(10)	(3)	(3)	(9)
Net Imports Natural Rubber	10.104	6.696	0.095049	0.06181
Japan	(9)	(14)	(14)	(10)
Net Imports Natural Rubber	9.677	6.543	0.092599	0.05920
China	(2)	(8)	(5)	(2)
Net Imports Synthetic	9.663	6.786	0.096651	0.05917
Rubber Japan	(1)	(16)	(17)	(1)
Net Imports Synthetic	10.046	6.681	0.094768	0.06136
Rubber China	(8)	(13)	(12)	(8)
World Natural Rubber	9.853	6.493	0.091921	0.06009
Consumption	(4)	(4)	(4)	(5)
World Synthetic Rubber	9.985	6.581	0.093816	0.06091
Consumption	(6)	(10)	(10)	(7)

Note: Entries correspond to the values of univariate selection criteria. See notes to Table 4.14.

This scenario was carried out only for the leading indicators, especially in TOCOM and net imports synthetic rubber Japan. Comparison of the results (see Table 4.17 and 4.18) revealed, especially in the case of TOCOM where both daily and monthly for the leading indicator expressing on ECM and the VAR lag number were smaller as comparing. This scenario suggested that it was desirable to augment the leading indicator set by the ECM terms embodying the relevant long-run theories when the set was chosen under a priori theoretical guidance and this was shown to produce relatively good forecasts.

In the next step, we further investigate the forecasting performance in term of the statistic test that provide the benefit in term of the more accurate result compared with the naïve random walk model. The DM Statistics are used for this purpose.

Diebold-Mariano test takes the loss function to determine whether one model predicts better than another. With the null hypothesis of the two models having the same loss function, the Diebold-Mariano test statistics (Zivot, 2004:6-7) is

$S = \frac{\bar{d}}{\left(LRV_{\bar{d}/T}\right)^{1/2}}$ where $\bar{d} = \frac{1}{T_0}\sum_{t=t_0}^{T}(d_t)$; $d_t = e^{i\,2}_{t+h|t} - e^{i\,2}_{t+h|t}$ i=1,2; $LRV_{\bar{d}} = \mathrm{cov}(d_t, d_{t-j})$. Diebold and Mariano show that under the null hypothesis of equal accuracy, $S^A \sim N(0,1)$ where we reject the null hypothesis at 5% level if $|S| > 1.96$. Specifically for the 104 sample tests that we done for this paper, $\bar{d} = 1/104\sum_{t=1}^{104}\left\{e^2_{\mathrm{mod}elbase,t} - e^2_{\mathrm{mod}elcompare,t}\right\}$; $e^2 = (\mathrm{Actual} - \mathrm{Forecast})^2$; $LRV = \frac{SE_d}{\sqrt{104}}$. The results of the Diebold-Mariano test are in Table 4.19:

Table 4.19 Diebold-Mariano Statistics of Predictive Accuracy

UNIVARIATE	**RMSE**	**MAE**	**MAPE**	**5% level** $\lvert S \rvert > 1.96$	**Reject or Unable to reject Null hypothesis**
RW – RWD	0.195	0.190	0.001793	-0.1675	Unable to reject null hypothesis
RW – VAR	0.169	0.131	0.001222	3.1532	Reject null hypothesis
RW – AR(1)	0.179	0.155	0.001448	2.1902	Reject null hypothesis
RW – MA(1)	0.180	0.157	0.001471	1.7352	Unable to reject null hypothesis
RW – SES	0.099	0.064	0.000617	1.8874	Unable to reject null hypothesis
RW – T	6.029	5.209	0.050018	-2,714.61	Reject null hypothesis
RW – RWDT	0.210	0.180	0.001680	0.9952	Unable to reject null hypothesis
RW – ARIMA (1,1,1)	0.196	0.170	0.001613	3.0268	Reject null hypothesis

Table 4.19 showed the results that RW - SES; RW - MA(1); RW - RWD and RW - RWDT are unable to reject the null hypothesis of equal predictive accuracy according with RMSE, MAE and MAPE. Moreover, statistically, the Diebold-Mariano test also shows that the pairs of model that do not able to reject the null hypothesis mean that those pairs do not differ in terms of their squared forecast errors.

However, for the VAR, AR(1), RWDT and ARIMA(1,1,1) we can find better forecast performance as we can reject the null hypothesis at 5% level.

The last criterion is attempting to predict future market directions, usually by examining recent price and volume data or economic data, and investing based on those predictions; also, called timing the market showing in Table 4.20:

Table 4.20 Model Ranking by Market Timing Criterion

Market Timing	Confusion Matrix	Confusion Rate	Ranking	Chi-Square
RW	-597	0.596154	4	2.918402
RWD	-510	0.567308	1	0.838801
VAR	-834	0.644231	5	0.723896
AR(1)	-1,096	0.692308	7	0.621158
MA(1)	-1,192	0.711538	9	0.733287
SES	-1,103	0.692308	8	0.680194
T	-393	0.586538	2	0.135285
RWDT	-569	0.586538	3	0.865951
ARIMA(1,1,1)	-979	0.673077	6	0.556971

Notes: An entry of 1 stands for the "best" performance according to the model selection criterion in the same row, while 9 indicates the "worst" performance.

Table 4.20 reports the values of market timing criterion, for RSS3 commodity and forecast horizons. Judging by the confusion rate values, it is interesting to note that most of the models are quite accurate and correctly predict the direction of price changes in time. All of the chi-square values suggest rejecting the null hypothesis of statistical independence. In other words, most of models are useful for predicting the direction of futures price changes.

4.3 The Determinants of RSS3 Price

As compared to other commodities in AFET, RSS3 accounted for the largest share of trade in terms of value, followed by rice and others (Agricultural Futures Exchange of Thailand, 2009). A well-developed and effective commodity futures market, unlike physical market, facilitates offsetting the transactions without impacting on physical goods until the expiry of a contract. Futures market attracts hedgers who minimize their risks, and encourages competition from other traders who possess market information and price judgment. While hedgers have long-term perspective of the market, the traders, or arbitragers as they are often called, hold an immediate view of the market. A large number of different market players participate in buying and selling activities in the market based on diverse domestic and global information, such as price, demand and supply, climatic conditions and other market related information. All these factors put together result in efficient price discovery as a result of large number of buyers and sellers transacting in the futures market.

Futures market, as observed from the cross-country experience of active commodity futures markets, helps in efficient price discovery of the respective commodities and does not impair the long-run equilibrium price of commodities. At times, however, price behavior of a commodity in the futures market might show some aberrations reaching to the element of speculation and “Bandwagon effect” inherent in any market, but it quickly reverts to long-run equilibrium price, as information flows in, reflecting fundamentals of the respective commodity. In futures market, speculators play a role in providing liquidity to the markets and may sometimes benefits from price movements, but do not have a systematic causal influence on prices.

An effective architecture for regulation of trading and for ensuring transparency as well as timely flow of information to the market participants would enhance the utility of commodity exchanges in efficient price discovery and minimize price shocks triggered by unanticipated supply demand mismatches (Ghosh, Gilbert and Hallett: 1987). Are you tired to losing money in the AFET? Are you searching for the breakthrough formula of RSS3 futures market? Would you like to have the same competitive edge as some of the most successful traders and investors on AFET? You would never guess how simple but powerful the answer is. The only intelligent way to approach the market is simply to know what the so called “Leading Indicators” is doing and you can eliminate much of the stress by calmly following what the pros do. Almost everyone has heard of “Leading Indicators” and the so called “Determinants of Factors”, and that is exactly what the indicators of this part are all about. The key is known “what does economic indicator mean?” A piece of economic data, usually of macroeconomic scale, that is used by investors to interpret current or future investment possibilities and judge the overall health of an economy. Economic indicators can potentially be anything the investor chooses, but specific pieces of data released by government and non-profit organizations have become widely followed – these include: world natural rubber consumption, world synthetic rubber consumption, net imports natural rubber of Japan, net imports synthetic rubber of Japan, net imports natural rubber of China, net imports synthetic rubber of China, crude oil price, and exchange rate (Baht/Dollar) pros until now (Somprattana Panpim, 2009).

Before heading toward to the determinants affect on RSS3 futures price, we should use the knowledge earning from previous parts to support the coming up results as refer to Table 4.15.

Regarding on comparison between time-series and leading indicators models for daily period found that the top five rank of univariate selection criteria for checking on the most accurate model according to the lowest values in both RMSE and MAE for time-series models were VAR, AR(1), SES, MA(1) and RWDT. Also, for leading indicators the outstanding rank around them was exchange rate (Yen/$), but when we compare with the others on the decimal point not quite much different. It is noticeable seeing that even though exchange rate (Yen/$) is in the outstanding rank for both RMSE and MAE in these leading indicators; however, the others are not different which this reason can be supported the continuing idea on finding the determinants for RSS3 futures price movement in daily by multiple regression because when the model was added by these variables, it would make an optional idea looking on the model for forecasting.

Now, for the last part of chapter 4, is finding the factors affects on the daily rubber futures price movement by multiple regression collecting all data from all variables within 1st August 2007 through 31st October 2008 totally 310 days. The descriptive statistics, comparative analyses and an advanced technologies model were established to determine positive and negative factors affecting RSS3 futures price of RSS3 futures market (AFET). Defining the variables is as following:

Dependent Variable:

Futures	=	monthly RSS3 futures price AFET at time t

Independent Variables:

oil	=	crude oil price
fx1	=	exchange rate (Baht per Dollar US.)
fx2	=	exchange rate (Yen per Dollar US.)
TOC	=	monthly RSS3 futures price TOCOM at time t

From bringing all four independent variables analyzes as following:

$$\widehat{DLOG(FUTURES)} = -0.003157 - \underset{(-0.629306)}{0.303780DLOG(FX1)} - \underset{(-0.315250)}{0.018149DLOG(FX2)} + \underset{(1.153457)^{*}}{0.021432DLOG(OIL)} + \underset{(6.467578)^{****}}{0.231522DLOG(TOC)}$$

R^2	=	0.310906	R^2 Adjust	=	0.282780
Durbin Watson	=	1.107085	F statistic	=	11.05394

Note: the number in parenthesis is t-Statistic.

**** is significant at level 0.01.

* is significant at level 0.25.

Table 4.21 Positive and Negative Factors Affecting RSS3 Futures Market in Daily Period

Factors	**Affect**	**Significant**
Crude Oil Price	+	Not significant
Futures Price TOCOM	+	Significant
Exchange rate (Baht per Dollar US.)	-	Not significant
exchange rate (Yen per Dollar US.)	-	Not significant

Note: + is Positive affect.
- is Negative affect.

According to Table 4.21, DLOG model, descriptive statistics and comparative analyses are used to identify the positive and negative factors affecting RSS3 futures price at AFET. The results are:

Crude oil price positively affect to RSS3 futures price because the price of crude oil causes higher the cost of natural rubber produces, so the higher production process dominated less supply of natural rubber from Thailand.

TOCOM price positively affect to RSS3 futures price as the change in demand-supply of the agents in the market.

Exchange rate (Baht per Dollar US.) negatively affect to RSS3 futures price because when Baht is depreciated, there is much attractive to the investors doing more investments on natural rubber market causing the futures price will be high as the relationship between spot and futures.

Exchange rate (Yen per Dollar US.) negatively affect to RSS3 futures price because when Yen is appreciated, no attractive to the investors doing investment on the TOCOM price affecting the price be cheap. It will cause the RSS3 futures price going the same direction with TOCOM.

In addition, the chapter brings some variables that expect to be the leading indicator of daily rubber futures price constructing the line chart to compare the relationship of monthly rubber futures price movement. Before constructing the line chart paper has to adjust the variables' data to be the same unit measuring by using Microsoft Excel. The data uses 103 months from 4th June 2008 through 31st October 2008 and variables are crude oil price, and monthly RSS3 futures price TOCOM at time t; also, the reference variable is RSS3 futures price AFET (one month ahead) showing the relationship on the graph as:

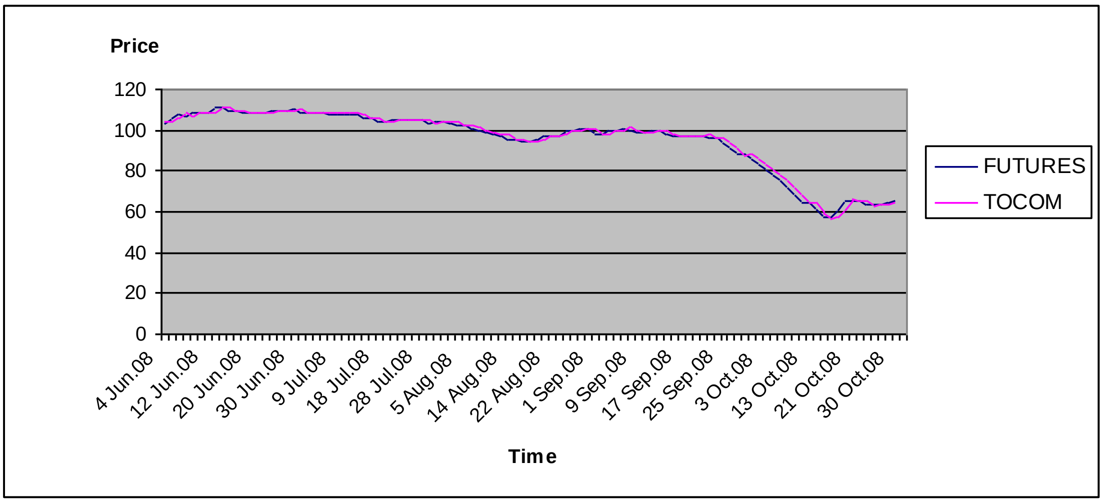

Figure 4.8 Line Graph between Rubber Futures and Futures Price TOCOM

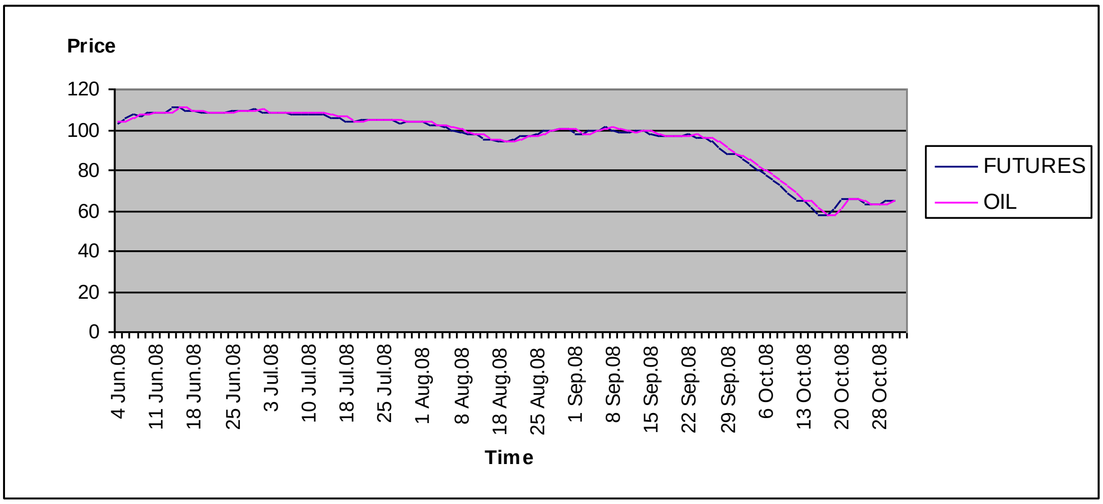

Figure 4.9 Line Graph between Rubber Futures and Crude Oil Price

From all significant leading indicators' graphs, we cut only last seven days from 22nd October 2008 through 31st October 2008 to analyze future trend considering as

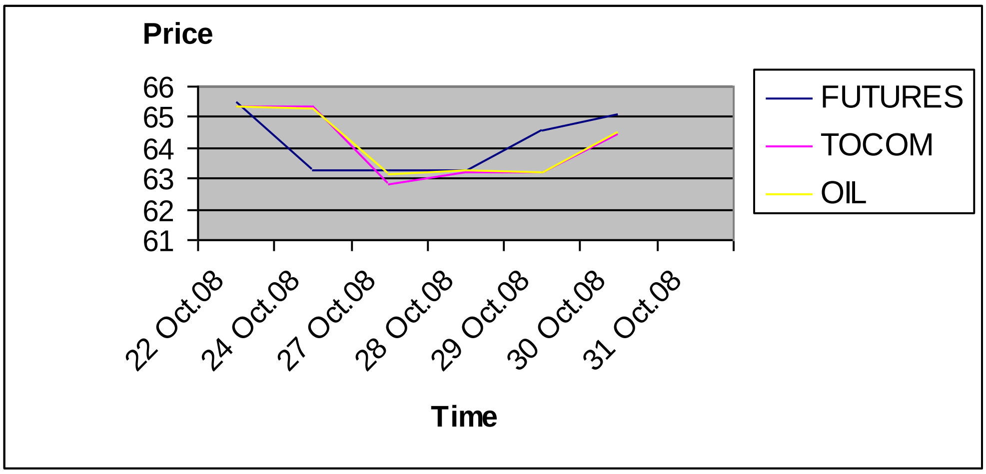

Figure 4.10 Seven Days Movements on Graph of Rubber Futures Price and Leading Indicators

From Figure 4.10, we select the line graph again by visual comparing with the reference graph, FUTURES regarding on these characteristics. One is that particular line graph should be the leading character for reference graph. Two is that the convert of point for both leading and reference graph should not be much different from each other. So, according to previous information we found that the crude oil price can be the proper leading indicator for futures price in the future.

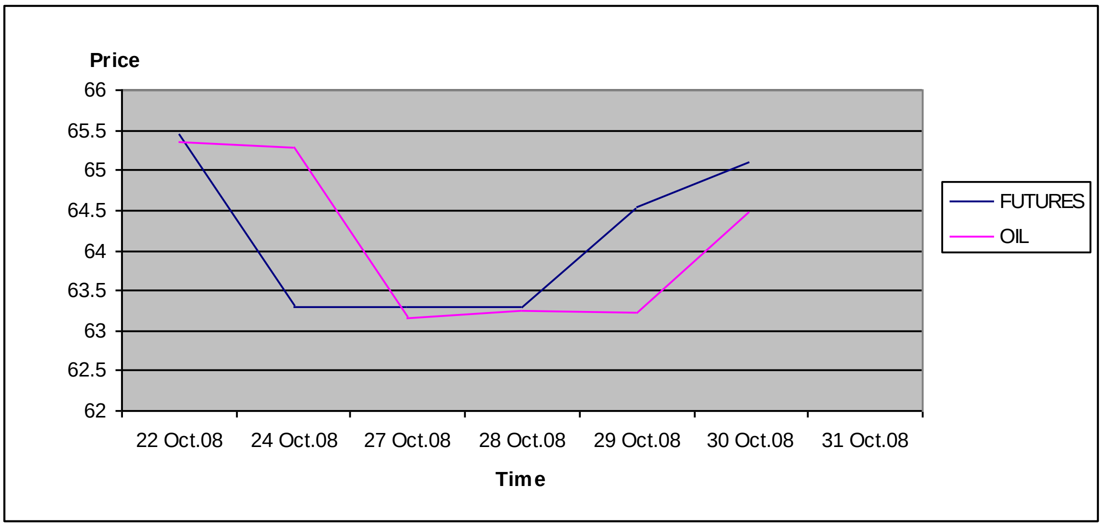

Figure 4.11 Seven Days Movements on Graph of Rubber Futures Price and Crude Oil Price Leading Indicator

Refer to Table 4.16, regarding on comparison between time-series and leading indicators models found that the top five rank of univariate selection criteria for checking on the most accurate model according to the lowest values in both RMSE and MAE for time-series models were RWDT, ARIMA, MA(1), and AR(1). Also, for leading indicators were TOCOM, net imports synthetic rubber Japan, and exchange rate (Baht/$). It is noticeable seeing that TOCOM and net imports synthetic rubber Japan are in the top rank for both RMSE and MAE which this reason can be supported the continuing idea on finding the determinants for RSS3 futures price movement by multiple regression because when the model was added by these variables, it would make the model much accurate than before.

Now, for the last part of chapter 4, is finding the factors affects on the monthly rubber futures price movement by multiple regression collecting all data from all variables within May 2004 through December 2009 totally 61 months. The descriptive statistics, comparative analyses and an advanced technologies model were established to determine positive and negative factors affecting RSS3 futures price of RSS3 futures market (AFET). Defining the variables is as following:

Dependent Variable:

Futures	=	monthly RSS3 futures price AFET at time t

Independent Variables:

oil	=	crude oil price
fx1	=	exchange rate (Baht per Dollar US.)
fx2	=	exchange rate (Yen per Dollar US.)
wnc	=	quantity of consuming natural rubber in the world
wsc	=	quantity of consuming synthetic rubber in the world
imnj	=	quantity of imports natural rubber (Japan)
imsj	=	quantity of imports synthetic rubber (Japan)
imnc	=	quantity of imports natural rubber (China)
imsc	=	quantity of imports synthetic rubber (China)
TOC	=	monthly RSS3 futures price TOCOM at time t

From bringing all ten independent variables analyzes as following:

^

DLOG(FUTURES) = -0.000334 + 0.332232DLOG(FX1) – 0.019043DLOG(FX2) –
(1.547714) (-0.244799)

0.058152DLOG(IMNC) + 0.043065(IMNJ) –
(-2.765738)**** (2.0866898)***

0.039270DLOG(IMSC) – 0.019384DLOG(IMSJ) –
(-1.467763) (-0.478745)

0.018523DLOG(WNC) + 0.353234DLOG(WSC) +
(-0.239469) (3.081708)****

0.048834DLOG(OIL) + 0.999364DLOG(TOC)
(2.292687)*** (40.48587)****

R^2	=	0.995702	R^2 Adjust	=	0.992633
Durbin Watson	=	1.530013	F statistic	=	324.3701

Note: the number in parenthesis is t-Statistic.
**** is significant at level 0.01.
*** is significant at level 0.05.

To classify as the significant result that exchange rate (Baht/$), monthly RSS3 futures price TOCOM at time t, quantity of imports natural rubber (China), quantity of imports natural rubber (Japan), quantity of consuming synthetic rubber in the world, quantity of imports rubber (China) and crude oil price affect on the monthly rubber futures price which this model can show the relationship as following:

$$\widehat{DLOG(FUTURES)} = -0.000305 - \underset{(-4.481363)^{****}}{0.072949DLOG(IMNC)} + \underset{(3.507576)^{****}}{0.232344DLOG(WSC)} + \underset{(2.225023)^{***}}{0.031489DLOG(OIL)} + \underset{(48.43469)^{****}}{0.992509DLOG(TOC)}$$

R^2	=	0.993141	R^2 Adjust	=	0.991769
Durbin Watson	=	1.841389	F statistic	=	723.9529

Note: the number in parenthesis is t-Statistic.
**** is significant at level 0.10.
*** is significant at level 0.05.

Table 4.22 Positive and Negative Factors Affecting RSS3 Futures Market in Monthly

Factors	**Affect**	**Significant**
Net Imports Natural Rubber China	-	4.481363
World Synthetic Rubber Consumption	+	3.507576
Crude Oil Price	+	2.225023
Futures Price TOCOM	+	48.43469

Note: + is Positive affect.
- is Negative affect.

According to Table 4.22, DLOG model, descriptive statistics and comparative analyses are used to identify the positive and negative factors affecting RSS3 futures price at AFET. The results are:

Net imports natural rubber China negatively affect RSS3 futures price because the number of imports causes higher the number of stocks, so the stocks dominated less order of natural rubber from Thailand.

World synthetic rubber consumption, futures price TOCOM and crude oil price positively affect the RSS3 futures price as the change in demand-supply of the market.

Furthermore, the chapter brings some variables that expect to be the leading indicator of monthly rubber futures price constructing the line chart to compare the relationship of monthly rubber futures price movement. Before constructing the bar chart paper has to adjust the variables' data to be the same unit measuring by using Microsoft Excel. The data uses 61 months from May 2004 through May 2009 and variables are quantity of imports natural rubber (China), quantity of consuming synthetic rubber in the world, crude oil price, and monthly RSS3 futures price TOCOM at time t; also, the reference variable is RSS3 futures price AFET (one month ahead) showing the relationship on the graph as:

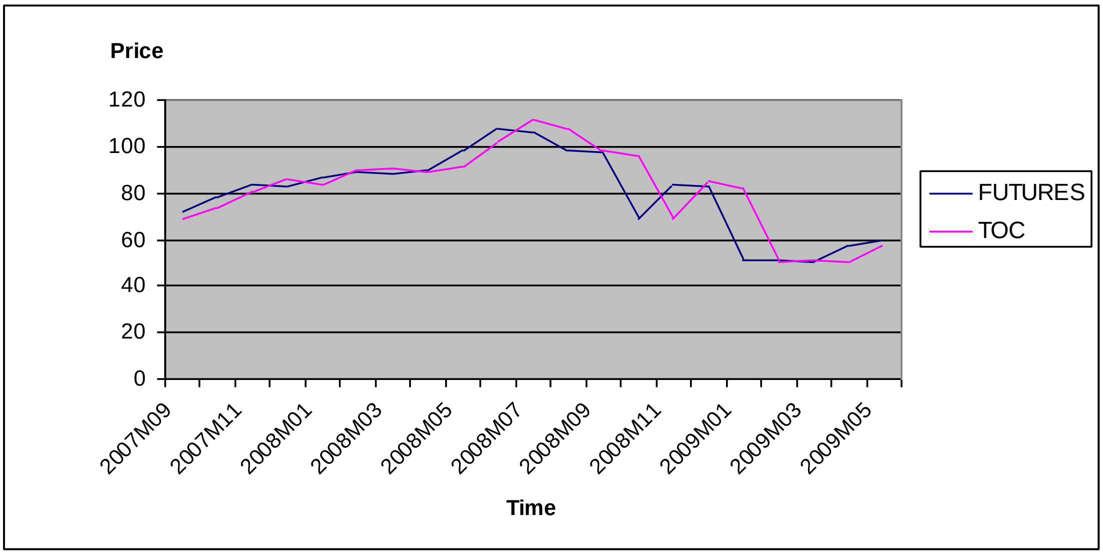

Figure 4.12 Line Graph between Rubber Futures and Futures Price TOCOM

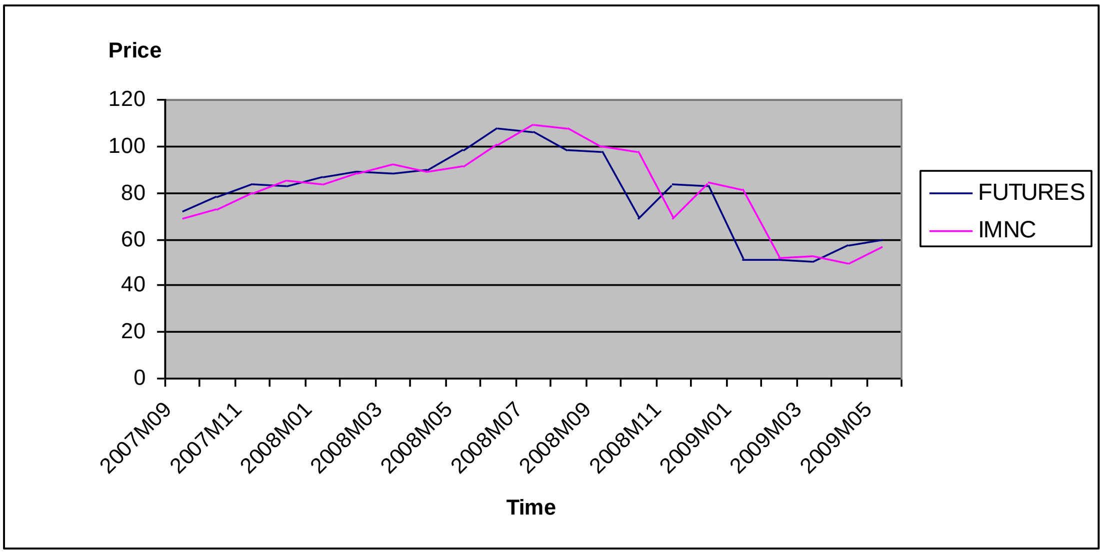

Figure 4.13 Line Graph between Rubber Futures and Net Imports Natural Rubber China

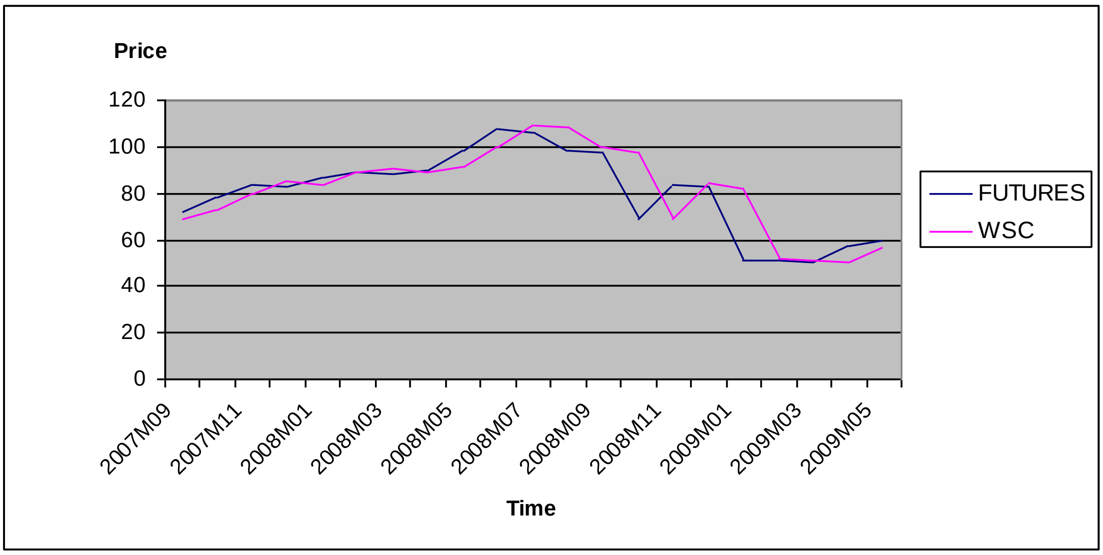

Figure 4.14 Line Graph between Rubber Futures and World Synthetic Rubber Consumption

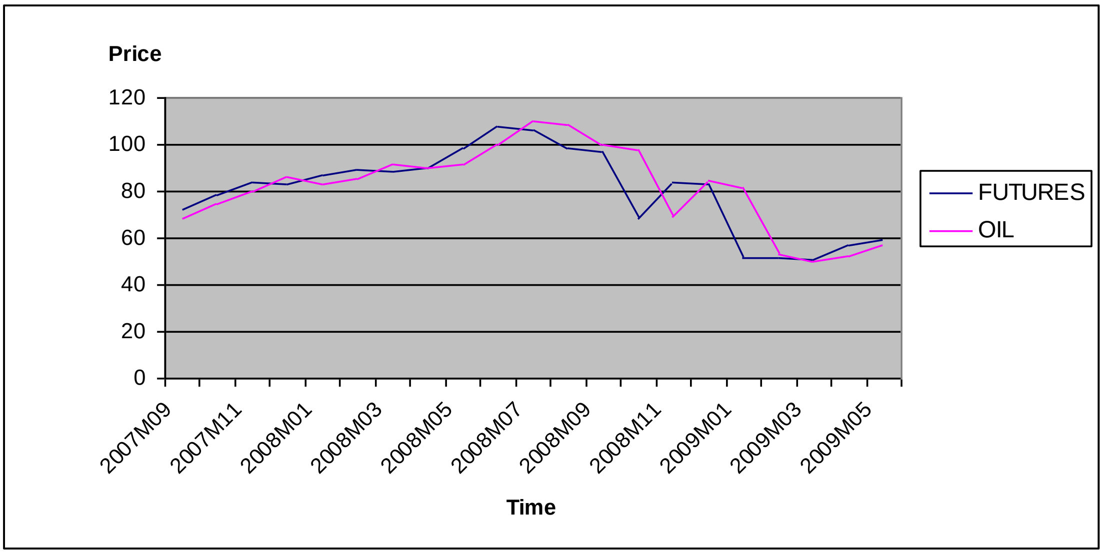

Figure 4.15 Line Graph between Rubber Futures and Crude Oil Price

From all significant leading indicators' graphs, we cut only last six months from December 2008 through May 2009 to analyze future trend considering as

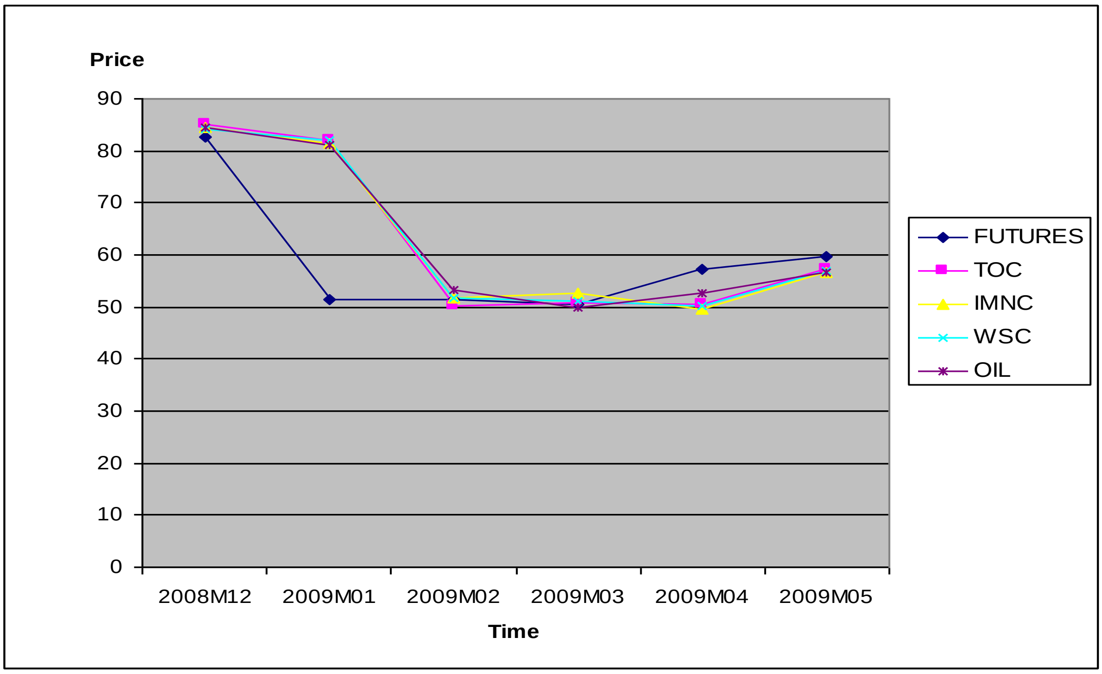

Figure 4.16 Six Months Graph Rubber Futures Price and Leading Indicators

From Figure 4.16, we select the line graph again by visual comparing with the reference graph, FUTURES regarding on these characteristics. One is that particular line graph should be the leading character for reference graph. Two is that the convert of point for both leading and reference graph should not be much different from each other. So, according to previous information we found that the crude oil price can be the proper leading indicator for futures price in the future.

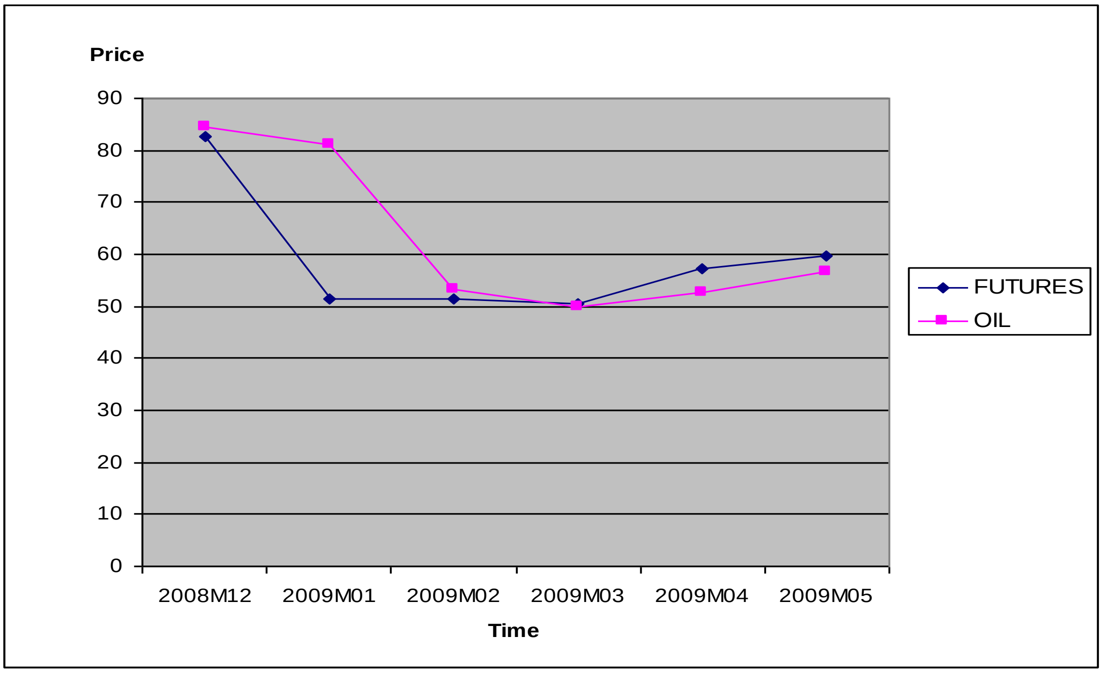

Figure 4.17 Six Months Graph of Rubber Futures Price and Crude Oil Price Leading Indicator

From Figure 4.17, considering rubber futures price trend that is going to be happened in January 2009, the crude oil price is an outstanding continuously decreasing to the mid of March 2009. Hence, the higher period on supply of crude oil estimating around two and a half months which it can expect that the rubber futures price also will drop for two and a half months period. Again from March 2009 expect to be lowest in this period and after that the price continues to increase again. So, the rubber futures price also has an increasing trend in the same period.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

The objective of this study was to provide better insight into the forecasting models for RSS3 futures market. The concept of price discovery and determinants of RSS3 price affecting to RSS3 futures price has been extensively studied for decades. Many researches have been done in the area of forecasting by examining how to test unit root, what to use for testing long term relationship or short term relationship, how to test the volatility by using ARCH model and how to test univariate criteria. Moreover, most of these studies futures markets in developed countries were based on non-agricultural futures markets such as metal futures, financial futures, energy futures contexts. In order to expand on previous research especially for Thailand's culture futures market's style, this study focused on RSS3 agricultural commodity futures market and adds more criterions testing such as market timing and Deibold-Mariano.

Unlike other studies, efficiency and determinants on RSS3 futures price as well as the forecasting models were examined by using two analyses: fundamental and technical. The analyses were conducted by using periods' data set: 1st August 2007 to 31st October 2008 based on sample of 310 daily data along with in-sample 207 data and out-of-sample 104 data including by using periods' data set: May 2004 to May 2009 based on sample of 61 monthly data along with in-sample 41 data and out-of-sample.

5.1 Efficiency in Price

The purpose of the study was to examine the efficiency of futures pricing for RSS3 products during the period 1st August 2007 to 31st October 2008 and May 2004 to May 2009. The results indicated that

1) The results from each method concluded as:

Autocorrelation Function (ACF): At 5 % significant level, the null hypothesis was rejected, so the return on RSS3 futures was independence. It meant that it did not follow the random walk theory and the market was not weak form.

Unit Root Tests: By ADF-test, when we considered p-value, the results shown that the null hypothesis could not be rejected at this level. It implied that spot and futures were non-stationary and followed by random walk.

Unit Root Tests: By KPSS-test, when we considered from LM-Stat. of KPSS statistic, the value was greater than LM-Statistic. of Asymptotic critical value at all significant level (0.01 and 0.05). So, it rejected the null hypothesis “no unit root” meaning that the time series of future spot price and futures price was non-stationary in the period studied and it followed the random walk theory. Then, the market was weak form efficient.

Run Test: the results shown that the total actual number of runs on all contracts-month ahead was in the acceptance on null hypothesis “the different return was independent”. So, it concluded that RSS3 futures market on only contract 1-month ahead was weak form efficient market.

First-Order Autoregressive Scheme or AR(1): when we considered on p-value found that p-values from all contract-month were less than significant level 0.01. It concluded that we rejected the null hypothesis “$\rho = 0$” meaning that RSS3 futures price at time t had the relationship with RSS3 futures price at time t-1. So, RSS3 futures market was not weak form efficient market at significant 0.01.

Variance Ratio Tests: the results found that Z computed was less than Z critical (1.96). So, it accepted the null hypothesis “VRT(d) =1” meaning that the order changing in price of RSS3 futures followed random walk theory. It concluded that the market was weak form efficient.

Table 5.1 Results Expressed Tools Analyzing Efficiency in Price

Tools for analyzing	Results
Autocorrelation Function (ACF)	Not Weak Form Efficient
Unit Root Tests:	
-Augmented Dickey-Fuller (ADF) Test	Weak Form Efficient
-The KPSS Test	Weak Form Efficient
Run Test	Weak Form Efficient*
First-Order Autoregressive Scheme or AR(1)	Not Weak Form Efficient
Variance Ratio Tests	Weak Form Efficient

Note: * is referred to contract 2, 5 and 6 month ahead.

The results from above table concluded that there were two methods that concluded "RSS3 futures market was not weak form efficient". Those were Autocorrelation Function (ACF) and First-Order Autoregressive Scheme or AR (1), but the other three methods summarized that "RSS3 futures market was weak form efficient". Those were Unit Root Tests, Run Test, and Variance Ratio Tests. The two methods that shown "not weak form efficient market" were parametric test which this test needs to use with only the normal distribution data, but is less favor used when compares with non parametric test in Unit Root Tests, Run Test, and Variance Ratio Tests. Also, now a day, the non parametric test such as Run Test and Variance Ratio Tests is acceptable used in research both Thailand and Foreign countries such as Islam and Watanapalachaikul (2005), Verma (2006), and Simons and Laryea (2006). Therefore, Run Test and Variance Ratio Tests will be reliable more than Autocorrelation Function (ACF) and First-Order Autoregressive Scheme or AR(1) which those two tests concluded in the study that the RSS3 futures market was weak form efficient. Furthermore, the Unit Root Tests by Augmented Dickey-Fuller (ADF) test and The KPSS test of stationary showing on "non-stationary" following by random walk theory also supported the weak form efficient market of RSS3 futures.

2) The study tested the relationship between future spot price and

RSS3 futures price in AFET which RSS3 futures was the product that has the most volume on buying and selling more than four years. The study started from analyzes on efficient market by testing on short range relationship and continued to test on long range relationship. The results, from logarithm term from cointegration, could explain that the futures price and future spot price had cointegration for contract 1 to 6 month ahead. Also, it can imply that after contract 2-month the speculators cannot have much effective response to the information in AFET causing the market is not efficient in form of unbiasness of the future price. Because it might have less liquidity on buying and selling RSS3 or none of volume occurs on that particular further contract 2-month or the investors and agents have problem on predicting the future spot price or the investors might not have enough understanding on products in AFET. Furthermore, investors might not have enough understanding about AFET finally affecting on the market not efficient in semi strong form. For contract far-month such as contract 6-month even though it has liquidity more than contract near-month, but it cannot be the representing for RSS3 in AFET. This reason can mention that the contract far-month cannot be the represent of RSS3 futures price because of high volatile even though there is high liquidity.

Risk Premium analytical part found that all contracts-month of RSS3 are not risk neutral affecting to the investors bearing on risk premium. Therefore, the conclusion is that Thailand’s RSS3 futures market is not efficient, and that it does not aid the processes of price discovery in term of being the representative for future spot price when future contract is more than 2 month ahead. However, the RSS3 contract near-month especially 1-month is a good representing more than contract far-month. Therefore, the hedgers can use this aspect idea on suitable buying-selling at AFET by “Long assets and short futures” to protect the lower price in the future. For speculators, they should buy and sell in contract near-month because to earn an extra profit, they can use the contract near-month to predict the future spot price be easier than the contract far-month.

The results of the test are summarized followed as: Table 5.2 tests on ADF for a unit root in a time series. Table 5.3 tests on Wald Test for the null hypothesis: $\beta_0 =$

0, $\beta_1 = 1$. Table 5.4 tests on speed of adjustment for autocorrelation in the residuals from a regression analysis.

Table 5.2 Numbers Expressed Tests Stationary of Residual

Variable	**ADF Test**	**P-Value**	**Result**
Daily Time-Series			**Reject Null Hypothesis means no unit root being as stationary.**
1-month	-3.615106	0.02532	Reject at 0.05
2-month	-3.794369	0.01516	Reject at 0.01
3-month	-3.638018	0.02376	Reject at 0.05
4-month	-3.473208	0.03707	Reject at 0.05
5-month	-3.577940	0.02803	Reject at 0.05
6-month	-4.213114	0.00403	Reject at 0.01
Daily Leading Indicator			
Exchange Rate (Baht/$ U.S.)	-1.232946	0.85012	Cannot Reject
Exchange Rate (Yen/$ U.S.)	-0.708478	0.94321	Cannot Reject
Crude Oil Price	-4.319141	0.00280	Reject at 0.01
TOCOM	-5.024858	0.00019	Reject at 0.01
Monthly Leading Indicator			
Exchange Rate (Baht/$ U.S.)	-2.099665	0.48127	Cannot Reject
Crude Oil Price	-2.897416	0.15173	Cannot Reject
Exchange Rate (Yen/$ U.S.)	-1.982837	0.54090	Cannot Reject
TOCOM	-6.247495	0.0001	Reject at 0.01
Net Imports Natural Rubber Japan	-1.880600	0.59254	Cannot Reject
Net Imports Natural Rubber China	-2.517395	0.28385	Cannot Reject
Net Imports Synthetic Rubber Japan	-1.863980	0.60081	Cannot Reject
Net Imports Synthetic Rubber China	-3.125607	0.09786	Reject at 0.10
World Consumption Natural Rubber	-2.832377	0.17050	Cannot Reject
World Consumption Synthetic Rubber	-2.704672	0.21201	Cannot Reject

Note: ADF is a test for a unit root in a time series. ADF is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there is a unit roots at same level of confidence.

P-value is from Mackinnon t-statistic.

Table 5.3 Numbers Expressed Wald Test

Variable **Daily Time-Series**	**F-Test**	**P-Value**	**Result** **Reject Null Hypothesis means** $\beta_0 \neq 0, \beta_1 \neq 1$
1-month	0.373517	0.69	Cannot Reject
2-month	1.585307	0.21	Cannot Reject
3-month	3.169698	0.04	Reject at 0.05
4-month	2.985500	0.05	Reject at 0.05
5-month	4.128831	0.02	Reject at 0.05
6-month	2.291173	0.10	Reject at 0.10

Note: Wald Test is on null hypothesis: $\beta_0 = 0, \beta_1 = 1$

Table 5.4 Numbers Expressed Relationship and Speed on Adjustment

Dependent Variable Spot Future Price Daily Time-Series	**Speed of Adjustment**	**B-G Test Reject Null Hypothesis means there is autocorrelation problem**	**ARCH LM Test Reject Null Hypothesis means there is Hetoroscedasticity**
1-month	-0.080458	Cannot Reject	Cannot Reject
2-month	-0.063517	Cannot Reject	Cannot Reject
3-month	-0.042187	Cannot Reject	Cannot Reject
4-month	-0.030110	Cannot Reject	Cannot Reject
5-month	-0.019909	Cannot Reject	Cannot Reject
6-month	-0.021244	Cannot Reject	Cannot Reject
Daily Leading Indicator			
Exchange Rate (Baht/$ U.S.)	-0.006405	Cannot Reject	Reject at 0.01
Exchange Rate (Yen/$ U.S.)	-0.006645	Cannot Reject	Reject at 0.01
Crude Oil Price	-0.033391	Cannot Reject	Reject at 0.01
TOCOM	0.037172	Cannot Reject	Reject at 0.01
Monthly Leading Indicator			
Exchange Rate (Baht/$ U.S.)	-0.126762	Cannot Reject	Cannot Reject
Crude Oil Price	-0.150014	Cannot Reject	Cannot Reject
Exchange Rate (Yen/$ U.S.)	-0.127424	Cannot Reject	Cannot Reject
TOCOM	-0.845494	Cannot Reject	Cannot Reject
Net Imports Natural Rubber Japan	-0.102858	Cannot Reject	Cannot Reject
Net Imports Natural Rubber China	-0.127756	Cannot Reject	Cannot Reject
Net Imports Synthetic Rubber Japan	-0.107998	Cannot Reject	Cannot Reject
Net Imports Synthetic Rubber China	-0.124303	Cannot Reject	Cannot Reject
World Consumption Natural Rubber	-7.784285	Cannot Reject	Cannot Reject
World Consumption Synthetic Rubber	-0.119110	Cannot Reject	Cannot Reject

Note: 1) BG-LM Test is a robust test for autocorrelation in the residuals from a regresstion analysis. It is considered more general than the standard Durbin-Watson statistic. The null hypothesis is “there is no serial correlation of any order up top”.

2) ARCH (Autoregressive Conditional Heteroscedasticity) considers the variance of the current error term to be a function of the variances of the previous time periods’ error terms. It relates the error variance to the square of a previous period’s error. It is employed commonly in modeling financial time series that exhibit-varying volatility clustering.

Table 5.5 Results Expressed on Stationary, Cointegration and Volatility of Efficiency in Price

Tests	Results
Without Leading Indicators:	
Stationary of residual without trend and constant (Mackinnon t-statistic)	Reject null hypothesis: futures price and future spot price have long range equilibrium relationship.
Wald Test	Cannot Reject the null hypothesis for both contracts 1 and 2-month: futures price can be the representative for future spot price.
ECM:	
Breusch-Godfrey Serial Correlation LM	Reject null hypothesis on no serial correlation: there is the autocorrelation problem excepting contract 1-month.
ARCH LM	Cannot reject null hypothesis: the models are following the theory; also, the volatility of future spot price has the stationary of characteristic on “Homoscedasticity”.
With Leading Indicators:	
Stationary of residual without trend and constant (Mackinnon t-statistic)	Reject null hypothesis: leading indicators and futures price have long range equilibrium relationship only crude oil price, TOCOM for daily and only TOCOM and net imports synthetic rubber China for monthly.
ECM: with leading indicators:	
Breusch-Godfrey Serial Correlation LM	Cannot reject hypothesis on no serial correlation: there is autocorrelation problem.
ARCH LM	Cannot Reject hypothesis for monthly: the model was following the theory; also, the volatility of leading indicators has stationary of characteristic on “Homoscedasticity”. Then, we continue to the main part which the part was on “forecasting model”.

In summary, the results in this part attribute the empirical results to the regulatory made in vision and mission of AFET and the increased financial skills and acumen of the participants in the market. The traders in commodity futures are companies, state owned enterprises, and individual investors. They have learnt about futures trading by experience and have done so at a rapid pace. The relatively small lot size of contracts encourages smaller investors to participate and this increases liquidity. Thailand’s RSS3 futures market has prospered even though the physical spot market has developed somewhat slowly and with numerous commercial disputes. The relative success of futures, vis-à-vis the spot market, is testament to the entrepreneurial spirit of the futures exchanges. The exchanges are rubber tires and they have borrowed and best features of exchanges in other countries.

5.2 Evaluation of Econometric Forecasting Model

The predictive evaluation of econometric forecasting models in RSS3 commodity futures market, paper investigates the predictive accuracy of nine econometric models including random walk without drift (RW), random walk with drift (RWD), vector autoregressive model with time trend (VAR), autoregressive (AR), moving average (MA), simple exponential smoothing (SES), deterministic trend (T), random walk with drift and trend (RWDT), and autoregressive integrated moving average (ARIMA).

All models are estimated and evaluated by both in-sample and out-of-sample performance measures. The criteria considered include univariate forecast accuracy criteria, market timing forecast the direction of assert price movements and Diebold-Mariano test model selection criteria test equal accurate based on predictive ability. The four univariate criteria are root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Thiel's U-statistic. The two market timing criterion is confusion matrix (CM) and confusion rate (CR). Also, one of Diebold-Mariano is DM Test.

By Adopting a Model Selection Approach to RSS3 Price in a Real Time Forecasting Scenario, the results suggest that

5.2.1 Univariate Criteria in Pure Time Series

1) VAR and ARIMA (1,1,1) is the best accurate model regarding to RMSE and MAE.

2) ARIMA (1,1,1) is the best perfect fit model relying on MAPE.

3) VAR is the best predictive performance model according to Thiel's U-statistic.

5.2.2 Univariate Criteria in Daily Leading Indicators Expressing by Lag Term

1) VAR is the best accurate model regarding to both RMSE and MAE.

2) VAR is the best perfect fit model relying on MAPE.

3) VAR is the best predictive performance model according to Thiel's U-statistic.

5.2.3 Univariate Criteria in Monthly Leading Indicators Expressing by Lag Term

1) RWDT and MA(1) is the best accurate model regarding to RMSE and MAE.

2) MA(1) is the best perfect fit model relying on MAPE.

3) ARIMA(1,1,1) is the best predictive performance model according to Thiel's U-statistic.

5.2.4 Univariate Criteria in Daily Leading Indicators Expressing by ECM

1) TOCOM is the best accurate model regarding to RMSE and MAE.

2) TOCOM is the best perfect fit model relying on MAPE.

3) TOCOM is the best predictive performance model according to Thiel's U-statistic.

5.2.5 Univariate Criteria in Monthly Leading Indicators Expressing by ECM

1) Net imports synthetic rubber Japan and MA(1) is the best accurate model regarding to RMSE and MAE.

2) AR(1) is the best perfect fit model relying on MAPE.

3) Net imports synthetic rubber Japa is the best predictive performance model according to Thiel's U-statistic.

5.2.6 The Diebold-Mariano (DM)

DM statistics suggest that each pair of models is equally accurate in terms of prediction where RW-RWD; RW-MA(1); RW-SES; RW-RWDT. This result supports the idea on using market timing criteria that almost the models are useful for predicting the direction of RSS3 price changes.

5.2.7 Market Timing Criteria

Judging by the CR values, the models consist of RWD, T, RWDT and VAR are useful for predicting the direction of RSS3 price changes.

5.3 Determinants of RSS3 Price

The cause of moving on daily and monthly RSS3 futures price besides the decision of investors might come from other factors else. So, the paper studied the fundament factors that affect on the change in daily and monthly RSS3 futures price particular in this paper on demand-supply factor which it mirrors to market mechanism and rubber futures price.

5.3.1 Analyses on Time Series Multiple Regression with 310 Days

used that daily exchange rate (Baht per Dollar US.), exchange rate (Yen per Dollar US.), crude oil price and TOCOM affect on monthly RSS3 futures price. Regarding on comparison between time-series and leading indicators models found that the first rank of univariate selection criteria for checking on the most accurate model according to the lowest values in both RMSE and MAE for time-series model was VAR. Furthermore, the outstanding rank in both RMSE and MAE for leading indicator was exchange rate (Yen per Dollar US.). However, it is noticeable that there are not different much along with the decimal number between the others. Therefore, for multiple regression, the model can add by all those variables to be an optional idea looking on the model for forecasting with leading indicators.

5.3.1.1 Multiple regression can create forecasting model as following:

$$\widehat{\text{dlog(futures)}} = -0.003366 + \underset{(1.237687)^{*}}{0.022657\,\text{dlog(oil)}} + \underset{(6.504277)^{****}}{0.230491\,\text{dlog(TOCOM)}}$$

Regarding on the model means that RSS3 futures price in AFET at time t has the directly relationship with both crude oil price and TOCOM at a time when others are “ceteris paribus”.

5.3.1.2 The study on the variable that can be the leading indicator for analyzing the trend of future RSS3 futures price by using the graph found that the crude oil price can be the proper leading indicator for futures price in the future.

5.3.2 Analyses on Time Series Multiple Regression with 61 Months

used that monthly exchange rate (Baht per Dollar US.), crude oil price, exchange rate (Yen per Dollar US.), TOCOM, net imports natural rubber Japan, net imports natural rubber China, net imports synthetic rubber Japan, net imports synthetic rubber China, world natural rubber consumption and world synthetic rubber consumption affect on monthly RSS3 futures price. Regarding on comparison between time-series and leading indicators models found that the first top two rank of univariate selection criteria for checking on the most accurate model according to the lowest values in RMSE for time-series model was RWDT and ARIMA (1,1,1). In MAE for time-series model was MA (1) and AR (1). Furthermore, the outstanding rank in RMSE and MAE for leading indicator was net imports synthetic rubber Japan and TOCOM, respectively. However, it is noticeable that there are not different much along with the decimal number between the others. Therefore, for multiple regression, the model can add by all those variables to be an optional idea looking on the model for forecasting with leading indicators.

5.3.2.1 Multiple regression can create forecasting model as following:

$$\widehat{\text{dlog(futures)}} = -0.000305 - 0.072949\,\text{dlog(IMNC)} + 0.232344\,\text{dlog(WSC)}$$

$$(-4.481363)^{****} \qquad (3.507576)^{****}$$

$$+\ 0.031489\,\text{dlog(oil)} + 0.992509\,\text{dlog(TOC)}$$

$$(2.225023)^{***} \qquad (48.43469)^{****}$$

Regarding on the model means that RSS3 futures price in AFET at time t has the positively relationship with world synthetic rubber consumption, crude oil price and TOCOM, but has the negatively relationship with net imports natural rubber China at a time when others are “ceteris paribus”.

5.3.2.2 The study on the variable that can be the leading indicator for analyzing the trend of future RSS3 futures price by using the graph found that one month decreases and two months increase affect on crude oil price, the RSS3 futures price will affect in the same direction.

5.4 Policy Implication and Further Study

The rapid growth of Thailand's agriculture output has been driven by large increases in the export of basic commodities such as natural rubber and rice. The demand for these commodities had resulted in a dramatic increase in spot prices as well as price volatility in recent years. Thus the development of futures market was seen as a vital step in reducing uncertainty on price. The result indicated that daily and monthly futures prices served as unbiased estimators of future spot prices. Therefore, Thailand's RSS3 futures market was weak form efficient market. Moreover, RSS3 futures price can be predicted by net imports natural rubber China, world synthetic rubber consumption, crude oil price and futures price TOCOM; investors can use this information with futures price prediction. Because futures price lead spot price and both futures and spot price will converse lastly.

In this regard, the people who involve with the market are speculators, so the government should motivate and inform the hedgers who the direct agricultural group is using the futures market as the optional choice on reducing or protecting the risk in the future when the RSS3 price drops. When the volume of RSS3 futures contract is widely accepted, it should reconsider on the other commodities to be the instruments on reducing the fluctuation of agricultural prices. Furthermore, if the futures market has the professional investors using the sophisticated trade to set up the funds for trading, this might be the case that futures price can be the representative of future spot price followed by the theory on the ratio of expected representative equal to one. This will make more knowledgeable in futures market expansion. Therefore, the government should support on setting up the funds to make the futures market efficiency and to develop the potential of agents in the futures market.

And finally, it is interesting to academic researchers and explorers for future research. In future period, the data should collect in addition when the time goes by to make the suitable equation. The study does not include other commodities such as rice (BHMR and BWR5) and potato (TC); if there is available data and more volumes, it interest to test on. In addition, the test of GARCH may be a suggesting for future research on price volatile.

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APPENDICES

APPENDIX

UNDERSTANDING ON AGRICULTURAL FUTURES MARKET

Futures market is the market that evolution from the normal market or cash market or spot market which the movement is for increasing the efficiency of cash market especially price in efficient. It states that the major problem of spot market for agriculture is the problem in price; for example, farmers have less negotiate in price and do not know how change in the future price. So, they can not plan for producing or when they should sell because they only realize that on harvest time is the period that price absolutely dropped regarding to the reason they can do nothing. It might mention that farmers take the risk on price. The way of solving problem no matter Government sector or exporters in agriculture goods will use the term of making the advance contract which advance contract characterizes the delivery date of future goods relying on type, price, and place that commitment in contract. This type of contract is called forward contract. However, this contract is the deal only between buyer and seller that there is no authorize by the institution. So, the chance is the most probability cheating when each side is in the lose position from volatile of market. One of the objectives creating the futures market for agriculture product is to maintain the trust on contract fulfilling in the process and to make the standard on characteristic of goods. Therefore, if the contract holder wants to sell the contract to the next person before due date, he can manage it or it he wants to give up the contract, he still makes it without harm to the contract partner.

Fundamental Knowledge on Agricultural Futures Market

There are two main groups who are getting in Agricultural Futures Exchange following as:

First is the hedger who wants to use futures market for hedging such as transformational agricultural goods producers and agricultural exporters.

Second is the trader who searches for the profits.

Buying – Selling agricultural futures market must pass through brokerage house which it must be the member of futures market; also, the reality in buying – selling agricultural futures market is used along with the contract that represents the goods buying – selling in this market.

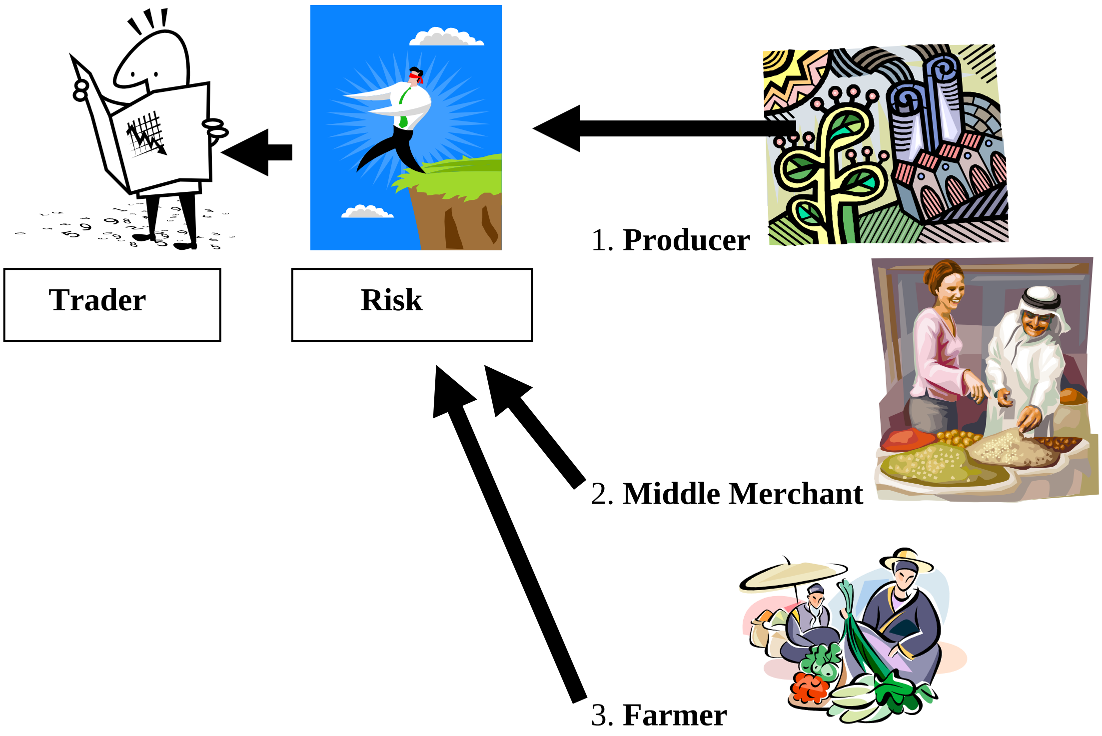

Figure A.1 Transforming the Risk from Volatile on Price

The Goods are Buying – Selling in Futures Market.

Seller is not necessary showing goods or own goods in his hand because this activity does for delivering in future via by contract. So, to understand between seller and buyer, futures market must set the standard of goods by type, grade, and quality besides each contract will be designed equal to how much volume of goods does.

Trading guide

Entering into AFET market for the first time is a relatively simple process. Whether you are seeking to minimize risk through hedging or looking for opportunities to invest in challenging environment, the procedures in getting started are the same. The following are the steps or general rules which you should be aware of before you begin.

1) Know the rules in futures trading
2) Choosing a broker in futures trading
3) Opening an account with a broker
4) Initial margin is only 3 – 5 percents of the commodity contract value
5) Executing trade orders
6) Check your status or position at the end of each trading day (mark to market)
7) Taking physical delivery of the commodity

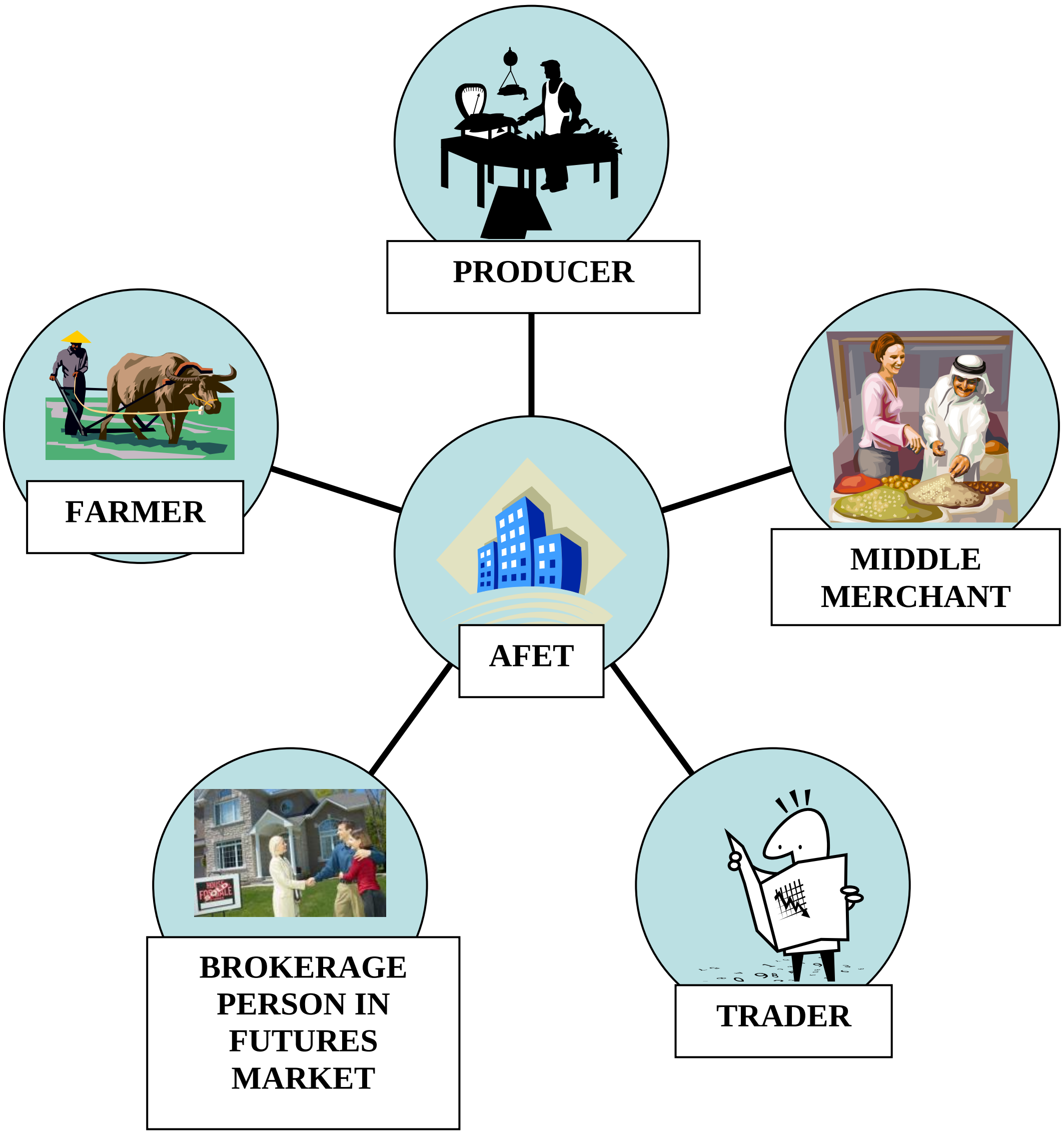

Figure A.2 Beneficial Persons from AFET

The Benefits are from Futures Market.

They can be provided in 3 characteristics following as

Hedging: there are two types which are risk on selling and risk on buying. The outcomes from insurance risk on buying are cash market or spot market looses because the cash market is higher than price on selling contract; futures market earns profit because price in the selling contract is higher than price in the buying contract; and the profit from futures market can be compensated to cash market which can summarize that the insurance risk is perfect. Moreover, the outcomes from insurance risk on selling are cash market or spot market looses because the cash market is lower than price at break-even capital; exchange market earns profit because price in selling contract is higher than price in buying contract; profit from exchange market can be compensated with lost in spot market which can conclude that insurance risk is perfect. Rubber price may not lower than the expected price.

Trader and others: using information in futures market: price information in the future will be distributed via many channels in every day and it is delivering due date which can be implied that how to change on agricultural future price. Farmers can use these data making the decisions that should stock goods for selling in which month and when. In the same way, owner of market can apply data and volume buying – selling as references.

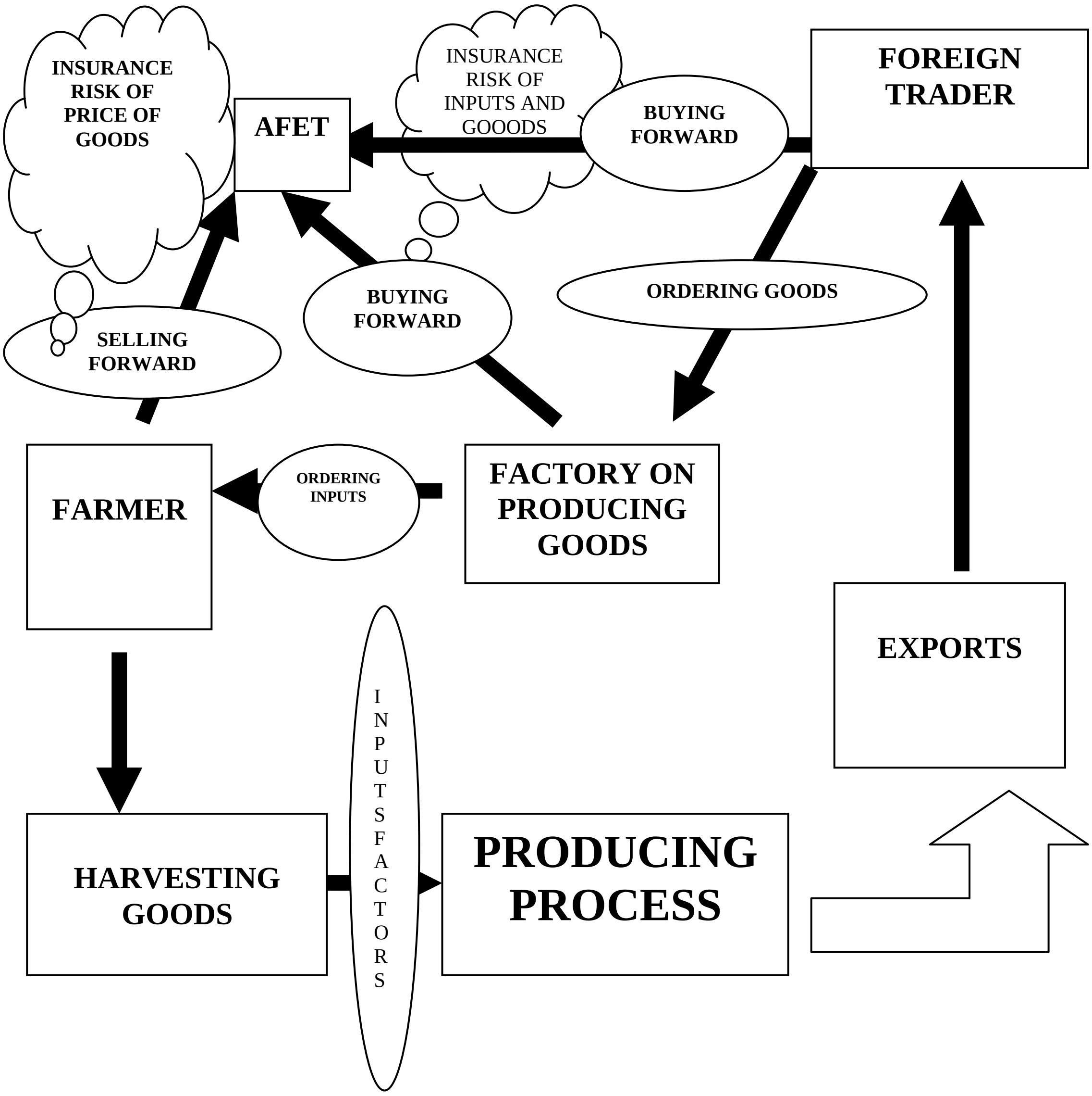

Figure A.3 Using Futures Market for Protecting the Risk

BIOGRAPHY

NAME	Mrs. Suppanunta Romprasert
ACADEMIC BACKGROUND	Bachelor Degree (Hons.) in Major: Psychology and in Minor: Political Science at Srinakarinwirot University, Thailand, May 1995.
	Master Degree in Human Resource Development at National Institute of Development Administration (NIDA), Thailand, November 1997. Thesis: The Impacts of Role Conflict and Ambiguity on Job Satisfaction: A Case Study of The Foreign Exchange Services Department of The Bangkok Bank (Public Co., LTD.), Head Office.
	Post Degree Specialization Certificate (PDSC) in Economics at Saskatchewan University, Canada, October 2002.
	Master Degree in Economics at Saskatchewan University, Canada in Economic, May 2003. Project: Older Workers in the Canadian Labor Market.
PRESENT POSITION	Coordinator Macroeconomics, Lecturer Department of Business Economics, School of Management, Assumption University

EXPERIENCES

June 2004 – Present

Full-Time Lecturer, Assumption University, Thailand

May 2003 – May 2004

Secretary, The Regent's School (Pattaya), Thailand

June 1999 – April 2004

Studying abroad, University of Saskatchewan, Canada in Post Degree Specialization Certificate and Master Degree in Economics.

August 1998 – May 1999

Administration Officer, Unity Engineering Construction Company Ltd., Thailand