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Full Length Research Paper

Market efficiency and forecasting of rubber futures

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This study, addresses the question "Is price process in rubber futures market efficient?" Time series data from rubber futures was used as leading indicator for the spot price of Thailand. The results indicate that, the daily futures prices served as unbiased estimators of future spot prices and there was independence on daily price changes. The tests, consistently supported the unbiased hypothesis which implies that, Thailand's rubber futures market is efficient and aids the process of price. This study, would fill the information gap in the prediction of future spot prices with a guide to understanding how the futures market behaves. Part of forecasting, the study employs univariate, market timing and Diebold-Mariano as the criterions for the selection of the best prediction model. It includes an analysis of factors affecting the rubber futures prices in Thailand's futures market. The results, show that, TOCOM, world synthetic rubber consumption, net imports natural rubber (China) and crude oil price significantly affect futures prices in the same direction. Particularly, crude oil price is the leading indicator for the trend in rubber futures prices in Thailand. The analytical model is shown to be applicable and would facilitate related studies in forecasting the futures prices of other commodities.

Keywords: Efficiency, forecasting, futures, commodities.

INTRODUCTION

Thailand had bought and sold rubber in future contracts with traders from China, Japan and the United States of America, but had to do so through brokers in these countries. Thailand, had been less competitive than these other countries but the establishment of the futures market in Thailand provided an opportunity for Thai traders to reduce brokers' fees, plan their buying and selling and plan on stocking rubber in the country. The development of futures market in Thailand and the unique institutional characteristics, prompted researchers to study the basic properties of how price behaves, at the moment, there are few published literatures on futures market in Thailand and fewer yet that are based on statistical characteristics of prices. The study would provide better information and fill some gap in the literature by making a detailed examination of futures price especially rubber product in Thailand. So, the paper seeks to answer the questions on efficiency and forecasting in price of RSS3 in Thailand.

The comprehensive test on efficiency of rubber futures was conducted by examining a period of time over which rubber futures had existed. It examined the random walk and unbiased hypotheses for RSS3. Based on the empirical evidence, the paper argues that Thailand's RSS3 futures market is efficient and aids the process of price because futures price could be unbiased predictor of future spot price.

The forecasting logic of rubber prices in futures market is to a certain extent similar to the price movement in stock market. It can also provide an estimate, taking into consideration the effects of external factors. This is because adjustment of rubber price in the long term may be affected by the law of supply and demand. However, the purpose of the futures market is to serve as an instrument for agricultural rubber groups, producers, agricultural suppliers, and investors to manage risks associated with fluctuations in commodity prices. This involves the 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 in which it focuses only on the duration of rubber prices without considering exogenous variables. The second, the fundamental analysis, accounts for the effects of exogenous variables.

Each analysis has its strong and weak points. The paper integrates the technical and fundamental analyses in investigating the probability of the fundamental analysis results to see the extent to which the fundamental analysis can be trusted. The fundamental analysis in the 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). In addition, the study highlights proper method in determining the movement of rubber price data in futures market and finds proper period of time and appropriate number of data used in forecasting. The line graph is used in considering trend of rubber prices that occurs in subsequent periods. Generally, the fundamental analysis is used to examine the factors that influence rubber prices and determine the rubber price when the factors that influence rubber price are dynamic. However, the paper focuses on the market price mechanism.

The paper's objectives include the following: 1) to answer the question on efficiency price; 2) to discover the proper forecasting model and 3) to identify the appropriate fundamental factors affecting the change in daily and monthly time period applicable 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. The reason is because it makes up a major share of exports, taking into account the observation on the level of exports FOB that is applied as the selling price in the futures market. Third, the forecasting model used in the study. They are classified into two cases: (a) short time prediction, targeted at finding a forecasting model which is most suitable for daily rubber prices, and (b) long time prediction through the use of monthly forecasting. Before making the final decision, the paper considers and examines external factors that may affect the rubber futures prices. The graph-leading indicators are built to determine the period that rubber prices move up or down. Fourth, the time period used in short time prediction. The 310-day period of gathering data starts from 1st August 2007 to 31st October 2008. Fifth, the monthly time period, comprises of 61 months during May 2004 to May 2009. Both daily and monthly periods use 2/3 of the period as the estimator and 1/3 as the forecasting.

Sixth, for both short and long time prediction, the paper observes the variables that affect rubber prices by using multiple regressions. The daily data used are taken during 1st August 2007 to 31st October 2008 while the monthly data is taken during May 2004 through May 2009. The variables used include the exchange rates between the Thai baht and U.S. dollar, the exchange rate between the Japanese yen and U.S. dollar, the price of crude oil, TOCOM, net imports of natural and synthetic rubber in Japan, net imports of natural and synthetic rubber in China, and the world consumption of natural and synthetic rubber. Lastly, periods when rubber prices expand or shrink via indicated factors are examined by graphical analysis between monthly rubber prices. The construction of the monthly rubber price model is derived from indicated variables, with the monthly natural rubber ribbed smoked sheets no. 3 price as the reference line.

Literature Review

Given the importance and the interest in the pricing efficiency of the futures markets, numerous studies have examined the efficiency of the agricultural futures markets. Nearly every agricultural futures contract listed by an exchange today has been examined in some context Garcia et al., (1988). In examining the necessary conditions for futures market efficiency, three sets of forecasts are used 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 the 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 et. al., (1997) is used. The more stringent test of pricing efficiency, the forecast encompassing, is then tested in a multiple encompassing framework using the MS test statistic put forth by Hervey and Newbold, in which they suggest as a test statistic MS based on Hotelling's generalized T2-statistic. Intuitively, the futures market efficiency should be intimately linked to the ability of the market to be forecasted. Nevertheless, working (1985) was reluctant to call futures prices forecasts.

Tomek and Gray (1970) suggested that cash prices of non-storable commodities may be able to forecast deferred prices better than futures prices. 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. Fama (1970) suggested that a futures market is efficient if the prices contain all relevant information. He also describes 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 added 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. Besides these, Makridakis, Wheelwright and McGee (1983) studied the accuracy of the combination method by emphasizing on the method of averaging from 14 forecasting methods such as naïve, simple moving average, exponential, ratio, Brown, Holt's, regression, Holt's and Winter, Automaic AEP, Lewandowski's FORSYS, Parzen'ARIMA' methodology, Bayesian forecasting, and BOX by MAPE. They found that accuracy depends on the number of methods that are used to combine because the more we join each method; the higher is the accuracy of forecasting. It is found that the prediction is stable if more than four methods are combined.

There are three forecast selection/combination techniques used to enhance the plausibility of dynamic forecast selection over a long period. When evaluating the ex-post effectiveness of forecasts, standard statistical measures are commonly used. The 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 et al., (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 (Leuthod, 1974:271-279) while more recent studies have examined the statistical difference in forecast error (Irwin et al., 1994:861-875). As previously stated, the necessary standard condition for the futures market efficiency is that no competing forecast such as a time series, econometric, or expert opinion forecast can provide 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 et al., 1998:281-291), stating the necessary condition for the futures market inefficiency strictly in a comparative MSE framework is potentially misleading. The Root Mean Square Error (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) including 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.

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. This alternative model selection criterion is 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 2*2 contingency table, called Confusion Matrix (CM). The best model according to Confusing Rate (CR) is the least confusing one (the one 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.

The Diebold-Mariano Predictive Accuracy Test (DM Test): Harvey et al., (1998:281-291) originally proposed a modification of the Diebold-Mariano test for the 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 the rectangular lag window defined by $L(\tau / S(T) = 1$ for $\left|\tau / S(T)\right| < 1,$ = 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 estimation of f(0), so that S(T)=h-1.

METHODOLOGY

The methods can be classified into Quantitative forecasting and Qualitative forecasting. The quantitative forecasting is divided into two main groups: 1) Time Series Model, which views that the past behavior of an object that we want to predict should be enough to forecast behavior in the future, and includes the naïve method, RWD method, VAR method, AR method, moving average method, simple exponential smoothing method, trend method, RW with drift and trend method and ARIMA; 2) the Casual Model, which views that the behavior of an object can be predicted from others that have suitable aspects to relate to each other, such as the regression method and econometrics method. The forecasting methods have different characteristics, strong points and weak points. None can provide a perfect forecast, therefore the most proper and reliable forecasting method should be selected. Selection criteria include the factors used in the method; for example, time period, data, number, validity, reliability and cost of applying the method (Makridakis et al., 1998).

There are 10 statistical methods used in this paper: 1) the regression analysis was used to examine the relationship of a dependent variable or response variable to specified independent variables or explanatory variables. It can be used as a descriptive method of data analysis, such as curve fitting, without relying on any assumptions about the underlying processes in generating the data (Richard 2004:2) Random walk method, to model the diffusion of vorticity was first proposed by Chorin (1973). To simulate the diffusion of vorticity in vortex methods, the positions of the vortices are given random displacements (a random walk) (Chorin and Marsden, 1990). The basic idea of the random walk method is that the random displacements spread out the vortices like the diffusion process spreads out the vorticity; 3) Random walk with drift method, the best forecast of tomorrow's price is today's price plus a drift term. One could think of the drift as measuring a trend in the price (perhaps reflecting long-term inflation). Given the drift is usually assumed to be constant. Related: Mean reversion; 4) Vector auto regression; an econometric model used to capture the evolution and the interdependencies between multiple time series, generalizing the univariate AR models. All the variables in a VAR are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all the other variables in the model. Based on this feature, Christopher Sims advocates the use of VAR models as a theory-free method to estimate economic relationships, thus being an alternative to the "incredible identification restrictions" in structural models (Sim, 1980) Auto regression; a type of random process which is often used to model and predict various types of natural and social phenomena; 6) Moving average, commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. Mathematically, a moving average is a type of convolution and so it is also similar to the low-pass filter used in signal processing. When used with non-time series data, a moving average simply acts as a generic smoothing operation without any specific connection to time, although typically some kind of ordering is implied; 7) Exponential smoothing method, in statistics, exponential smoothing refers to a particular type of moving average technique applied to the time series data, either to produce smoothed data for presentation or to make forecasts. Exponential smoothing is commonly applied to financial markets and economic data, but it can be used with any discrete set of repeated measurements. One disadvantage of this technique is that it cannot be used on the first k-1 term of the time series. A slightly more intricate method for smoothing a raw time series X_t is to calculate a weighted moving average by first choosing a set of weighting factors and then using these weights to calculate the smoothed statistics; 8) Trend, the relatively constant movement of a variable throughout a period of time. The period may be short-term or long-term, depending on the trend itself; 9) Random walk with drift, and 10) Box-Jenkins approach to modeling ARIMA processes was described in a highly influential book by statisticians George Box and Gwilym Jenkins in 1970. The original Box-Jenkins modeling procedure involves an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process (Makridakis et al., 1998) often add a preliminary stage of data preparation and a final stage of model application or forecasting. One of the attractive features of the Box-Jenkins approach to forecast is that ARIMA processes are a very rich class of possible models and it is usually possible to find a process that provides an adequate description to the data. The original Box-Jenkins modeling procedure involved an iterative three-stage process of model selection, parameter estimation and model checking. This is a complicated method and needs specialized expertise in data analysis. However it gives a higher accuracy than others in short-term prediction (Newbold and Granger, 1974).

All time series data of RSS3 in the futures market, particularly the daily and monthly data, were collected. The reason for considering both daily and monthly prices is the benefit from studying the change in rubber price for both short and long periods. The rubber prices in time series were used for plotting graph checks for moving characteristic.

The equation of each method for daily and monthly rubber price are constructed from the methods previously mentioned. The value of regression on the prediction method is compared to the true monthly value. The model of rubber price for the monthly time series is constructed by studying the variables that affect the rubber price through the regression from May 2004 through May 2009. The paper also constructs the model and looks for the variables affecting rubber prices. It considers the period when the trend in rubber price is influenced by expansion or recession, as well as the business cycle index. This is done by graph analysis showing the relations between monthly rubber price and quantity of variables.

RESULTS

The discussion focuses on analyzing efficiency in price and on determining, the suitable forecasting model on the movement of rubber prices in the futures market. The variables are examined with the view of determining the rubber futures price that can help guide, plan, and control rubber price thereby making it less volatile. The last part analyzes the trends of rubber prices using the relationship between rubber prices and the leading indicator variables. The results are classified into four parts, as follows:

Studying 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 by using tools, that is, autocorrelation function test, and 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 as in Table 1 and the second part; we test the independent between futures and spot as in Table 2.

The results from Table 1 concluded that there were two methods that showed the RSS3 futures market was not weak form efficient, namely the Autocorrelation Function (ACF) and the First-Order Autoregressive Scheme or AR (1). The other three methods, namely the Unit Root Tests, Run Test, and Variance Ratio Tests, summarized that the RSS3 futures market was weak form efficient. The two methods that showed "not weak form efficient market" were parametric tests, which use only the normal distribution data. The parametric tests are less favorable when compared to the non parametric tests. The non parametric tests are now more accepted for research in Thailand and foreign countries. Moreover, the Run Test and Variance Ratio tests are considered more reliable than the Autocorrelation Function (ACF) and First-Order Autoregressive Scheme or AR(1), in which the two latter tests concluded 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 showed "non-stationary", following the random walk theory, also supported the weak form efficient market of the RSS3 futures.

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 showing in Table 2.

By adopting the model selection approach to RSS3 price in a real time forecasting scenario, the paper attempts to shed light on the usefulness of econometric forecasting, and the empirical relevance of modeling theoretical relationships between the futures and spot prices when constructing forecasting models providing. The univariate criteria in pure time series, VAR and ARIMA (1,1,1) is the best accurate model regarding to RMSE and MAE; ARIMA (1,1,1) is the best perfect fit model relying on MAPE; VAR is the best predictive performance model according to Thiele's U-statistic. Also, the univariate criteria in daily leading indicators expressed by lag term, VAR is still the best accurate

Table 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

Table 2. 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 the leading indicators has stationary of characteristic on “Homoscedasticity”.

model regarding to both RMSE and MAE including is the best perfect fit model relying on MAPE and the best predictive performance model according to Thiel’s U-statistic. For monthly, The univariate criteria in monthly leading indicators expressed by lag term, RWDT and MA(1) is the best accurate model regarding to RMSE and MAE; MA(1) is the best perfect fit model relying on MAPE; ARIMA(1,1,1) is the best predictive performance model according to Thiele’s U-statistic.

The univariate criteria in daily leading indicators expressed by ECM, TOCOM is the best accurate model regarding to RMSE and MAE including the best perfect fit model relying on MAPE and the best predictive performance model according to Thiele’s U-statistic. Univariate criteria in monthly leading indicators expressing by ECM is a quite different because the net imports synthetic rubber Japan and MA(1) is the best accurate model regarding to RMSE and MAE; AR(1) is the best perfect fit model relying on MAPE. When we concern on Thiele’s U-statistic, Net imports synthetic rubber Japan is the best predictive performance model.

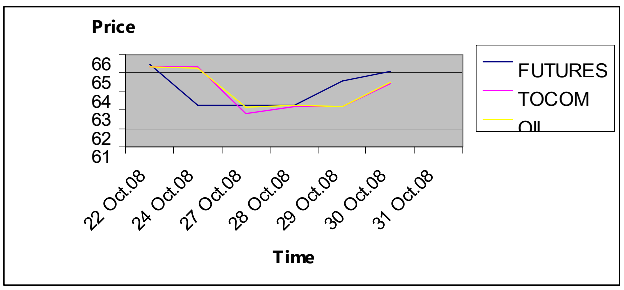
Table 3 showed the results that RW - SES; RW – MA (1); RW - RWD and RW - RWDT are unable to reject the null hypothesis of equal predictive accuracy according with RMSE, MAE and MAPE. Moreover, statistically, the Diebold-Mariano test also shows that the pairs of model that do not able to reject the null 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

Table 3. 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

Figure 1. Seven Days Movement on Graph of Rubber Futures Price and Leading Indicators



directions, usually by examining recent price and volume data or economic data, and investing based on those predictions; also, called timing the market reports that 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.

Analyses on the 310-day time-series multiple regression used the daily exchange rates between the Thai baht and U.S. dollar, the exchange rate between the Japanese yen and the U.S. dollar, the crude oil price and TOCOM that affect the monthly RSS3 futures price. The 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 the exchange rate between the yen and the U.S. dollar. It is noticeable that there is not much difference between the numbers. Therefore, the multiple regression model enables for all the variables to be used as an option for forecasting with leading indicators. Multiple regression can create forecasting model as follows:

dlog(futures) = -0.003366 + 0.022657 dlog(oil) +0.230491 dlog(TOCOM)

(1.237687)* (6.504277)****

The model shows that RSS3 futures price in AFET at time t has positively relationship with both crude oil price and TOCOM at the time when others are "ceteris paribus". If the crude oil price increases by 1 percent, it will affect the RSS3 futures price in AFET at time t which will increase by 0.022657 percent. If the TOCOM price increases by 1 percent, it will affect the RSS3 futures price in AFET at time t and will increase by 0.230491 percent.

In Figure 1, we select the line graph by visually comparing with "FUTURES" as the reference line. One of the reasons is because the particular line graph should be the leading character for reference graph. Another reason is that change for both leading and reference graph should not be much different from each other.

The study on selecting variables appropriate to be leading indicators for analyzing the RSS3 futures prices trend by using the graph found that the crude oil price can be the proper leading indicator for the futures price.

Analyses on the time-series multiple regression of 61 months used the effect of monthly exchange rate

Figure 2. Six Months Movements on Graph of Rubber Futures Price and Leading Indicators

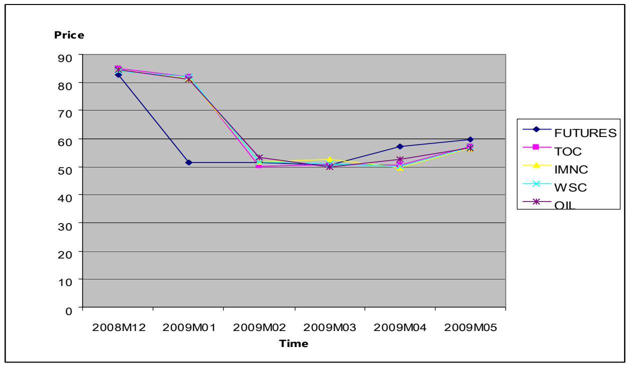
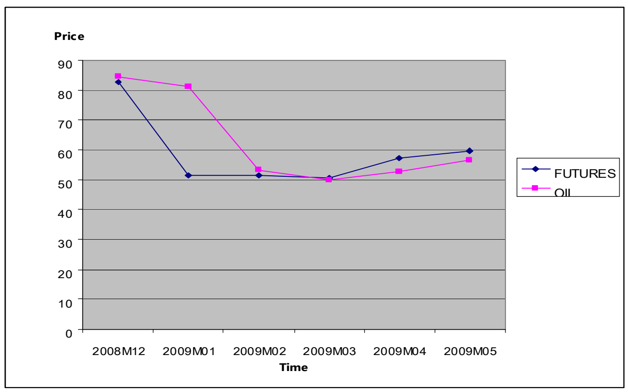


Figure 3. Six Months Movements on Graph of Rubber Futures Price and Crude Oil Price Leading Indicator



between Thai baht and U.S. dollar, crude oil price, exchange rate between yen and U.S. dollar, TOCOM, net imports of natural and synthetic rubber in Japan, net imports of natural and synthetic rubber in China, and the world natural and synthetic rubber consumption on the monthly RSS3 futures price. According to a comparison made between the time-series and leading indicators models, it was found that the top two ranks of univariate selection criteria for the most accurate model according to the lowest values in RMSE for time-series model was the 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. The forecasting model can be created as follows:

dlog(futures) = -0.000305 - 0.072949dlog(IMNC) + 0.232344dlog(WSC) + 0.031489dlog(oil) + -0.992509dlog(TOC)
(-4.481363)**** (3.507576)**** (2.225023)*** (48.43469)****

The model shows 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”. If the world synthetic rubber consumption increases by 1 percent, it will affect on RSS3 futures price in AFET at time t increased by 0.232344 percent. If the crude oil price increases by 1 percent, it will affect the RSS3 futures price in AFET at time t a by 0.031489 percent increase. If the TOCOM price increases by 1 percent, it will affect the RSS3 futures price in AFET at time t by a 0.992509 percent increase. However, if the net imports of natural rubber in China increase by 1 percent, it will decrease the RSS3 futures price in AFET at time t by 0.0575 percent.

In Figure 2, we select the line graph again by visual comparing with the reference graph, FUTURES regarding on these characteristics. The graph shows that the trend of one-month decrease then two- month increase affects crude oil price, and will also affect the RSS3 futures price in the same direction.

In Figure 3, considering the rubber futures price trend that is going to be happen in January 2009, the crude oil price is continuously decreasing to the mid of March 2009. The period with high supply of crude oil is estimated to be around two and a half months which it can expect that the rubber futures price will also drop for two and a half months period. It is expected that in March 2009 the price will be the lowest and then will increase again afterwards. So, the rubber futures price also has an increasing trend in the same period following: Compare True Value with Expected Trend March 2009 is 50.65; April 2009 is 57.20; May 2009 is 59.56; June 2009 is 57.75; July 2009 is 59.11 and August 2009 is 68.68.

The results shown in the graph and the true value are corresponding to each other which it depicts that the there will be one month decrease and two months increase. The price dropped in March 2009 and after that during April and May 2009 increased to 59.56. In June 2009, the price decreased to 57.75 and increased back for two months until August 2009. However, if this pattern is correct, we expect to see a dropping price trend again in September 2009 and an increasing price trend in October and November 2009, respectively.

CONCLUSION

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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