APPENDICES

Appendix A

Predicting Malaysian palm oil price using Extreme Value Theory

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Predicting Malaysian palm oil price using Extreme Value Theory[1]

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Predicting Malaysian palm oil price using Extreme Value Theory

Abstract

This paper uses the extreme value theory (EVT) to predict extreme price events of Malaysian palm oil in the future, based on monthly futures price data for a 25 year period (mid-1986 to mid-2011). Model diagnostic has confirmed non-normal distribution of palm oil price data, thereby justifying the use of EVT. Two principal approaches to model extreme values – the Block Maxima (BM) and Peak-Over-Threshold (POT) models – were used. Both models revealed that the palm oil price will peak at an incremental rate in the next 5, 10, 25, 50 and 100 year periods. The price growth level in Year-5 is estimated at 17.6% and 44.6% in Year-100 using BM approach. Use of the POT approach indicated a growth rate of 37.6% in Year-5 and 50.8% in Year 100, respectively. The key conclusion is that although the POT model outperformed the BM model, both approaches are effective in providing predictions of growth in prices caused by extreme events. The results could serve as a useful guide to farmers, exporters, governments, and other stakeholders of the palm oil industry informing strategic planning for the future.

Keyword: Price forecasting, Extreme Value Theory, Block Maxima model, Peak-Over-Threshold model, Malaysian palm oil.

1. Introduction

The past few years have seen an increase in the production of renewable fuels because of rising crude oil prices, limited supply of fossil fuels and increased concerns about global warming. The increase in oil price has caused many countries to consider using alternative renewable energy from the agricultural sector, particularly vegetable oils such as soybean, rapeseed, sugarcane, corn and palm oil. This increase in production reflects rising global demand for vegetable oils dominated by palm oil production (Carter, 2007). However, there are regional differences in the choice of vegetable oils used for conversion to biodiesel. For example, in Europe, the primary production of biodiesel is based on the use of rapeseed oil, in Brazil and the USA, the base is soybean oil, and in Malaysia, palm oil is the main source (Yu et al., 2006).

In the international market, expanding trade, continuous rises in demand, irregular supply, and other related factors (e.g., weather variations) have caused the price of palm oil to fluctuate. Apart from the unpredictable fluctuations in the natural production environment, the other main source of palm oil price movement is driven by its demand. The world demand for palm oil depends on demand for food, as well as demand for biofuels in the industrial sector. These two types of demand are currently fluctuating due to small share of palm oil in food as well as a decline in usage for biofuels. Therefore, the price of palm oil remains uncertain in the future. Figure 1 illustrates the fluctuation in monthly Malaysian palm oil futures price over a 25 year period (1986–2011). The price was only $182.00 per metric ton in July 1986, rising to a high of $1,033.57 per metric ton in July 2011, an increase of 468%. Instability in palm oil prices can create significant risks to producers, suppliers, consumers, and other stakeholders. With production risk and instability in prices, forecasting is very important to make informed decisions. Forecasting price changes is however, quite challenging, as its behaviour is very unpredictable in nature (MPOB, 2010).

[Figure 1 about here]

The forecasting of agricultural prices has traditionally been carried out by applying econometric models such as Autoregressive Integrated Moving Average (ARIMA), Autoregressive Conditional Heteroscedastic (ARCH) and Generalized Autoregressive Conditional Heteroscedastic models (GARCH) (Assis et al., 2010). These models assume that the data are normally distributed. Therefore, predicting future prices using such approaches ignores the possibility of extreme events. We believe, however, that palm oil price predictions involve determining the probability of extreme events. To this end, the application of Extreme Value Theory (EVT) enables the analysis of the behaviour of random variables both at extremely high or low levels (e.g., caused by financial shocks, weather variations, etc.).

Given this backdrop, the main objectives of this paper are: (a) to predict future prices of Malaysian palm oil, by applying EVT which takes into account the possibilities of extreme events; and (b) to compare two principal approaches to the modelling of extreme values – the Block Maxima (BM) and the Peak-Over-Threshold (POT) models – to predict the rates of growth of palm oil prices in the next 5, 10, 25, 50 and 100 year periods. The importance arises because forecasting future prices of palm oil using the most accurate method can help the government, buyers (e.g. exporters), sellers (e.g. farmers), as well as other key stakeholders of the palm oil industry, to plan strategically for the future.

The structure of the paper is as follows. Section 2 presents a brief overview of the major palm oil producers and production trends, a review of selected literature on forecasting palm oil prices and the application of EVT in forecasting future events. Section 3 presents the analytical framework and methods employed in this study. Section 4 presents the results leading to conclusions in Section 5.

2. Literature Review

2.1 Major palm oil producers and production trends

Palm oil is a type of fatty vegetable oil derived from the fruit of the palm tree. It is used in both food and non-food products. Palm oil is a highly efficient and high yielding source of food and fuel. Approximately 80% of the palm oil is used for food such as cooking oils, margarines, noodles, baked goods, etc. (World Growth, 2011). In addition, palm oil is used as an ingredient in non-edible products such as biofuels, soaps, detergents and pharmaceuticals. With such a wide range of versatile use, the global demand for palm oil is expected to grow further in the future (USDA, 2011).

Many countries plant oil palm trees to produce oil to fulfil their local consumption. World trade in palm oil has increased significantly due to an increase in global demand and the world production of palm oil has increased rapidly during the last 30 years, caused through the fast expansion of oil palm plantation in the south-east Asian countries. The world production of palm oil was 13.01 million tons in 1992, increasing to 50.26 million tons in 2011, a 286% increase in 19 years (USDA, 2011).

The major world producers and exporters of palm oil are Malaysia and Indonesia. For these countries, palm oil production for export purposes is found to be highly viable, and oil palm has become a favourite cash crop to replace other traditional crops such as rubber. Even here, the maintenance of high yields of the palm throughout the year is essential to achieve viability for the export market (MPOB, 2010). Indonesia is the largest exporter of palm oil in the world, exporting around 19.55 million tons a year during 2008-2011 (USDA, 2011). Malaysia is the second largest exporter nowadays and was the largest exporter of palm oil in the world until 2007, producing about 15 million tons of palm oil a year. Malaysia, has therefore, played an important role supporting consumption and remaining competitive in the world's oils and fats market (World Growth, 2011).

The main consumer and business market for palm oil is the food industry and, for this, the major importers are India, China and the European Union. India is the largest and leading consumer of palm oil worldwide, importing about 7.8 million tons in 2011. China is the second largest importer of palm oil importing about 6.65 million tons in 2011 (USDA, 2011). Current production of the world palm oil suggests an increase by 32% to almost 60 million tons by 2020 (FAPRI, 2010).

2.2 Forecasting palm oil prices

Previous works on forecasting palm oil prices and other agricultural prices were conducted by Arshad and Ghaffar (1986), Nochai (2006), Liew et al., (2007) and Karia and Bujang (2011) employing a range of forecasting techniques to predict palm oil prices. For example, Arshad and Ghaffar (1986) used a univariate ARIMA model developed by Box-Jenkins to forecast the short-run monthly price of crude palm oil. They found that the Box-Jenkins model is limited to short-term predictions. Nochai (2006) identified an appropriate set of ARIMA models for forecasting Thailand palm oil price, based on minimum Mean Absolute Percentage Error (MAPE) at three levels. For farm level price, ARIMA (2,1,0) was seen to most suitable, ARIMA (1,0,1) or ARMA(1,1) is suitable for wholesale price and ARIMA (3,0,0) or AR(3) is suitable for pure oil price. A further study on forecasting other agricultural prices using methods from the ARMA family was reported by Liew et al., (2007) which used the ARMA model to forecast Sarawak black pepper prices. This found that the ARMA model 'fits' the price and correctly predicts the future trend of the price series within the sample period of study. Assis et al., (2010) compared four methods – exponential smoothing, ARIMA, GARCH and mixed ARIMA/GARCH models – to forecast cocoa bean prices. They concluded that the mixed ARIMA/GARCH model outperformed the other three models within the sample period of study.

All of the above studies have used approaches from the ARMA family, which is widely known as the Box-Jenkins time series model. Karia and Bujang (2011) have attempted to forecast crude palm oil price using ARIMA and Artificial Neural Network (ANN). They concluded that the ARMA family works better with the linear time series data, whereas ANN performs better with the nonlinear time series data.

It should be noted that both the ARMA family and ANN approaches assume that the data is normally distributed. Therefore, all of the aforementioned studies suffer from this weakness of normality assumption. The next section briefly reviews the literature that has used EVT to analyse extreme events in largely used in the finance and disaster studies.

2.3 Use of EVT in forecasting extreme events in finance and natural disasters

Extreme value methods have been used widely in environmental science, hydrology, insurance and finance. More often these have been used to forecast extreme events in finance. For example, Silva and Mendes (2003), as well as Bekiros and Georgoutsos (2004), used EVT to forecast Value at Risk (VaR) of stock and found that EVT provided accurate forecasts to be made of extreme losses with very high confidence levels. Moreover, Peng et al., (2006) have compared EVT and GARCH models to predict VaR concluding that EVT method is superior to GARCH models in estimating and predicting VaR.

In disaster studies, Lai and Wu (2007), Lei and Qiao (2010) and Lei et al., (2011) have used EVT to evaluate and analyse the distribution of agricultural output loss and VaR is used to assess agricultural catastrophic risk. Lai and Wu (2007) have found that the distribution of loss data is heavy-tailed implying that it is also non-normal. Extreme value theory (EVT) describes the behaviour of random variables at extremely high and low levels of risk and provides the procedures to find distributions and quantiles for Maxima and to check models. Lei and Qiao (2010) used the extreme value methods, namely, Block Maxima (BM) and Peak-Over-Threshold (POT) models, to predict risk values and found that both of these models are significantly below the corresponding predictions. In addition, Lei et al., (2011) applied the POT approach to model distribution and assess VaR of agricultural catastrophic risk. They found that catastrophic risk negatively affects agricultural production and is severe within a 100-year scenario and thus expected to recur.

3. Analytical framework

As mentioned earlier, the main objective of this study is to forecast Malaysian palm oil prices accounting for extreme events. This is because palm oil price is characterized by a high degree of volatility and is subject to the occurrence of extreme events (see Figure 1). The extreme value method provides a strong theoretical basis with which one can construct statistical models that are capable of describing extreme events (Manfred and Evis, 2003). The use of EVT provides statistical tools to estimate the tails of probability distributions (Diebold et al., 1998) with evidence of substantial use in the financial sector. The closest application of EVT in agriculture has been for the forecasting of losses in the agricultural output due to natural disasters (Lei and Qiao, 2010; Lei et al., 2011). Thus far, EVT has not been applied to predict agricultural product prices, particularly, palm oil prices, although it is characterized with extreme events.

The next section explains the theory and presents the two principal approaches to modelling extreme values: the BM and POT models.

3.1 The Extreme Value Theory

The main idea of EVT is the concept of modelling and measuring extreme events which occur with very small probability (Brodin and Kluppelberg, 2008). It provides a method to statistically quantify such events and their consequences. Embrechts et al. (1997), note that the main objective of the EVT is to make inferences about sample extrema (maxima or minima). Generally, there are two principal approaches to identifying extremes in real data. The BM and the POT are central to the statistical analysis of maxima or minima and of exceedance over higher or lower thresholds (Lai and Wu, 2007).

3.1.1 Block Maxima model

The BM model studies the statistical behaviour of the largest or the smallest value in a sequence of independent random variables (Lei and Qiao, 2010; Lei et al., 2011). One approach to working with extreme value data is to group the data into blocks of equal length and to fit the data to the maximums of each block whilst assuming that n (number of blocks) is correctly identified.

Let Z_i (i=1,…,n) denote the maximum observations in each block (Coles, 2001). Z_n is normalized to obtain a non-degenerated limiting distribution. The BM approach is closely associated with the use of Generalized Extreme Value (GEV) distribution with cumulative density function (c.d.f) (Lei and Qiao, 2010):

$$G(z) = \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}$$

Where μ, σ > 0 and ξ are location, scale and shape parameter, respectively. The GEV includes three extreme value distributions as special cases: the Frechet distribution is ξ > 0, the Fisher-Tippet or Weibull distribution is ξ < 0, and the Gumbel or double-exponential distribution is ξ = 0. Depending on the parameter ξ, a distribution function is classified as fat tailed (ξ > 0), thin tailed (ξ = 0) and short tailed (ξ < 0) (Odening and Hinrichs, 2003). Under the assumption that Z_1, …, Z_n are independent variables having the GEV distribution, the log-likelihood for the GEV parameters when ξ ≠ 0 is given by (Coles, 2001):

$$\ell(\xi, \mu, \sigma) = -n\log\sigma - (1+1/\xi)\sum_{i=1}^{n}\log\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right] - \sum_{i=1}^{n}\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right]^{-1/\xi}$$

provided that $1+\xi\left(\frac{Z_i-\mu}{\sigma}\right) > 0$, for i=1,….,n

The case ξ = 0 requires separate treatment using the Gumbel limit of the GEV distribution (Coles, 2001). The log-likelihood in that case is:

$$\ell(\mu, \sigma) = -n\log\sigma - \sum_{i=1}^{n}\left(\frac{Z_i-\mu}{\sigma}\right) - \sum_{i=1}^{n}\exp\left\{-\left(\frac{Z_i-\mu}{\sigma}\right)\right\}$$

The maximization of this equation with respect to the parameter vector (μ, σ, ξ) leads to the maximum likelihood estimate with respect to the entire GEV family (Coles 2001; Castillo 1988)

3.1.2 Peak-Over-Threshold model

The POT approach is based on the Generalized Pareto Distribution (GPD) introduced by Pickands (1975) (cited in Lei and Qiao, 2010). The GPD estimation involves two steps, the choice of threshold u and the parameter estimations for ξ and σ which can be done using Maximum Likelihood Estimation (Bensalah, 2000). These are models for all large observations that exceed a high threshold. The POT approach deals with the distribution of excess over a given threshold wherein the modelling is to understand the behaviour of the excess loss once a high threshold (loss) is reached (McNeil, 1999). Previous studies have shown that if the block maxima have an approximate distribution of GEV, then the excesses from the threshold have a corresponding Generalized Pareto Distribution (GPD) with c.d.f. (Lai and Wu, 2007, Lei and Qiao, 2010):

$$H(y) = 1 - \left(1+\frac{\xi y}{\sigma}\right)^{-1/\xi}$$

defined on {y: y > 0 and $\left(1+\frac{\xi y}{\sigma}\right)$ > 0}, where y (growth rate price exceeds) is random variable, σ (σ > 0) and ξ (-∞ < ξ < +∞) are scale and shape parameters, respectively. The family of distributions defined by this equation is called the GPD family. Having determined a threshold, the parameters of GPD can be estimated by log-likelihood.

Suppose that the values $Y_1, \ldots, Y_n$ are the n excesses of a threshold u. For ξ ≠ 0, the log-likelihood is (Coles 2001)

$$\ell(\sigma, \xi) = -n\log\sigma - (1+1/\xi)\sum_{i=1}^{n}\log\left(1+\xi y_i/\sigma\right)$$

provided that $(1+\xi y_i/\sigma) > 0$ for i=1,…,n

The maximum likelihood procedures can also be utilized to estimate the GPD parameters, given the threshold (Lei and Qiao, 2010).

4. Empirical results

In this paper, the monthly palm oil price data from July 1986 to June 2011 from the indexmundi website was utilized. Monthly prices are computed as growth rate of price relatives: $Gr = (p_t - p_{t-1})/p_{t-1} * 100$, where p_t is the monthly Malaysian palm oil futures at time t. A test was conducted to check whether the palm oil price growth rate (PPGR) has a non-normal distribution. The Jarque-Bera test, which summarizes deviations from the normal distribution with respect to skewness and kurtosis, provides further evidence about the non-normality of the distribution (Odening and Hinrichs, 2003). The Jarque-Bera test rejects normality, at the 5% level for the PPGR distribution (see Table 1). Thus the test results provide evidence that the PPGR distribution is non-normal and, therefore, justifying the use of EVT and the estimation of an extreme value distribution.

[TABLE 1 about here]

4.1 Results from the BM model

The data in this study are 300 observations of monthly Malaysia Palm Oil Futures price, covering a 25 year period (Jul, 1986 to Jul, 2011). In the case of the BM model, we focus on the statistical behaviour of block maximum data. Therefore, the source data is a set of 26 records of maximum annual palm oil price growth rates (PPGR). Figure 2 shows the scatter plot of annual maximum PPGR. These data are modelled as independent observations from the GEV distribution.

Maximization of the GEV log-likelihood for these data provides the following estimates of the necessary parameters: $\hat{\xi} = 0.2106$, $\hat{\sigma} = 4.5000$, $\hat{\mu} = 9.6435$. Figure 3 shows various diagnostic plots for assessing accuracy of the GEV model fit the PPGR data. The plotted points of the probability plot and the quantile plot are nearly-linear. The return level curve converges asymptotically to a finite level as a consequence of the positive estimate, although the estimate is close to zero and the respective estimated curve is close to a straight line. The density plot estimate seems consistent with the histogram of the data. Therefore, all four diagnostic plots give support to the fit of GEV model.

[Figures 2 and 3 about here]

Table 2 presents the T-year return/growth levels based on the GEV model for the 25 year period, to forecast the extreme values in the PPGR for the next 5, 10, 25, 50 and 100 year in the future. The probability of 95% confidence interval (CI) for future 5-, 10-, 25-, 50-, 100-years growth levels, based on the profile likelihood method, is also provided. Empirical results show that the extreme values of the PPGR will increase in the future. Under the assumption of the model, the extreme value of

PPGR will be 17.58% overall, with 95% CI (14.05–24.43%) in year-5. In year-10 the extreme value of PPGR will be 22.59%, with 95% CI (17.51–37.59%). Finally, in year-100, the extreme value figures for PPGR are 44.57%, with 95% CI (27.86–165.68%). These figures reveal that the PPGR values are going to be incrementally higher further in the future. For instance, the value of PPGR increases from 17.58% in year-5 to 44.57% in year-100.

[Table 2 about here]

4.2 Results from the POT model

In this section, although the same data is used, the model focuses on the statistical behaviour of exceedances over a higher threshold. The data is analysed by modelling exceedances of individual observations over a threshold according to the following method. The scatter plot of PPGR data is presented in Figure 4 and the mean residual life plot is presented in Figure 5. In the POT model, the selection of a threshold is a critical problem. If the threshold is too low, the asymptotic basis of the model will be violated and the result will be biased. If the threshold is too high, it will generate few observations to estimate the parameters of the tail distribution function, leading to high variance (Gilleland and Katz, 2005). The assumption, therefore, is that GPD is the asymptotically correct model for all exceedances. The mean residual life plot for these data suggested a threshold of u=6. The vertical lines in Figure 6 show the 95% confidence intervals for the correct choice of the threshold value u=6. This gives 61 records of PPGR. The parameters of GPD using the MLE approach, with the threshold value of u=6 was then estimated. The parameters of GPD are estimated at σ =6.0619 and ξ = -0.0435. Figure 7 shows the diagnostic plots for GPD fit to the PPGR data. Neither the probability plot nor the quantile plot presents any doubt on the validity of the model fit.

[Figures 4, 5, 6 and 7 about here]

In Table 3, the probability of 95% confidence intervals, based on the profile likelihood method to forecast the extreme value of growth rate of palm oil price for the next 5, 10, 25, 50 and 100 years into the future, is provided. Table 3 exhibits T-year return level based on the GPD model. In year-5, the extreme value of

PPGR will be 37.62%, with 95% CI (29.19–76.97%). In year-10 the extreme value figures are 40.82%, with 95% CI (30.76–94.33%). Finally, in year-100 the extreme value of PPGR are 50.78% with 95% CI (34.48–180.54%). Again the value of PPGR increases at an incremental rate further into the future. For example, the value of PPGR increases from 37.6% in year-5 to 50.78% in year-100.

[Table 3 about here]

4.3 Discussion

The previous sections have explained that the Malaysian PPGR has a non-normal distribution, shown in Table 1. Past studies (e.g., Arshad and Ghaffar, 1986; Nochai, 2006; Karia and Bujang, 2011) that predicted palm oil price using ARMA family methods, assuming normal distribution of the data, and, therefore failed to recognize that actual palm oil prices tend to exhibit extreme values.

The quality of the EVT enhances the data movements toward the tail of a distribution (Odening and Hinrichs, 2003). Using the BM and the POT approaches of extreme value modelling, both GEV and GPD models were applied to PPGR covering a 25 year period to predict growth rate of palm oil prices in the next 5, 10, 25, 50 and 100 year periods (Tables 2 and 3). The results presented in Tables 2 and 3 show that the BM method provides lower estimates than the POT method. The discrepancy in forecasts, however, narrows as the forecasting horizon expands. For example, the difference in PPGR for Year-5 is 20% whereas it is 14.7% for Year-25 and only 6% for Year-100 between the two methods of forecasting. Overall, the POT approach ‘outperformed’ the BM approach. This is because BM only considers the largest events. The most common implementation of this approach is to take a block of data from the PPGR and treat the maximum from that block as single observations for one year. The approach becomes ‘incapable’ if other data on the tail of the distribution are available. On the other hand, the POT approach can compensate for such weaknesses and can be used to model all large observations that exceed a high/given threshold. Similar conclusions on the superiority of the POT approach over the BM have been observed by previous researchers (e.g., Lai and Wu, 2007; Lei and Qiao, 2010).

5. Conclusion

This paper applies extreme value methods to the prediction of Malaysian palm oil prices in the future, using monthly futures price data for the 25 year period (July 1986 – June 2011) which is characterized by non-normal distribution caused by extreme events. The diagnostic test confirmed that the Malaysian palm oil price is characterised by non-normal distribution, thereby justifying the use of EVT. This is a major improvement on the forecasts of palm oil prices based on the assumption of normal distribution, as seen in the literature. Both the BM and the POT approaches were used which revealed that the Malaysian palm oil price will have higher extremes in the next 5, 10, 25, 50 and 100 year periods, with acceleration in growth further into the future. The discrepancy in forecasting between the two methods decreases as the forecasting horizon expands. Although the POT approach outperformed the BM approach, both of them are effective in predicting prices caused by extreme events. The results could be useful for the farmers, exporters, governments, and other key stakeholders involved in the palm oil industry as it will enable them to undertake better strategic planning and mitigate against risk and instability.

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Table 1: Descriptive statistics of the Malaysian palm oil price growth rate (July 1986 – June 2011)

	PPGR
Mean	0.88208
Median	0.800682
Maximum	33.68552
Minimum	-27.08083
Std. Dev.	7.842985
Skewness	0.324795
Kurtosis	4.915701
Jarque-Bera	51.14846
Probability	0
Observations	264.624

Table 2: T-year return/growth level based on GEV model (BM approach)

Item	GEV fit	95% CI
ξ	0.2106	
σ	4.5000	
μ	9.6435	
Year-5	17.5810	(14.0515,24.4286)
Year-10	22.5982	(17.5190,37.5984)
Year-25	30.1837	(21.8648,67.3767)
Year-50	36.8748	(24.9560,105.3495)
Year-100	44.5726	(27.8615,165.6797)

Table 3: T-year return/growth level based on GPD model (POT approach)

Item	GPD fit	95% CI
ξ	-0.0435	
σ	6.0619	
Year-5	37.6226	(29.1853,76.9672)
Year-10	40.8219	(30.7610,94.3344)
Year-25	44.9058	(32.4901,122.6481)
Year-50	47.8887	(33.5656,149.0050)
Year-100	50.7830	(34.4789,180.5439)

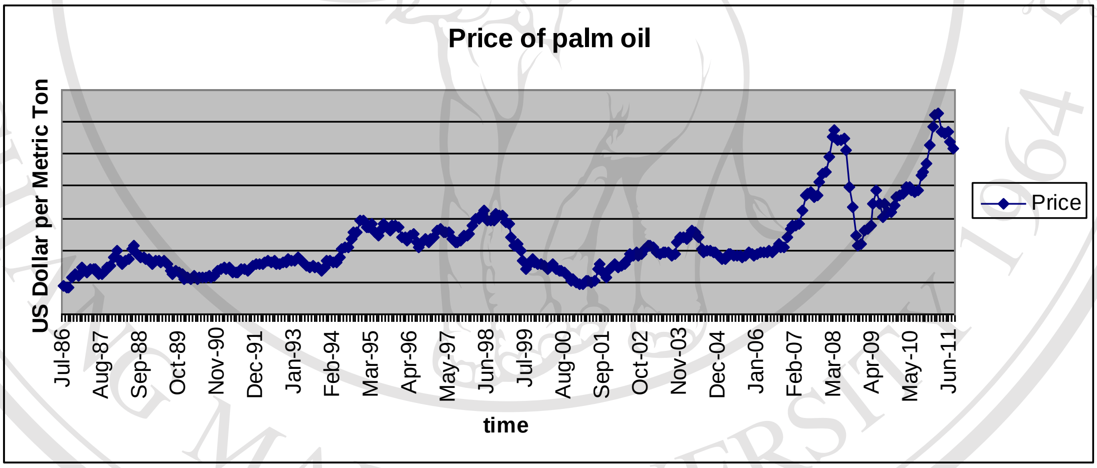

Figure 1: Palm oil monthly price, Jul 1986 - Jul 2011

Source: www.indexmundi.com

Note: The Palm oil price of this paper is Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA, US Dollars per Metric Ton.

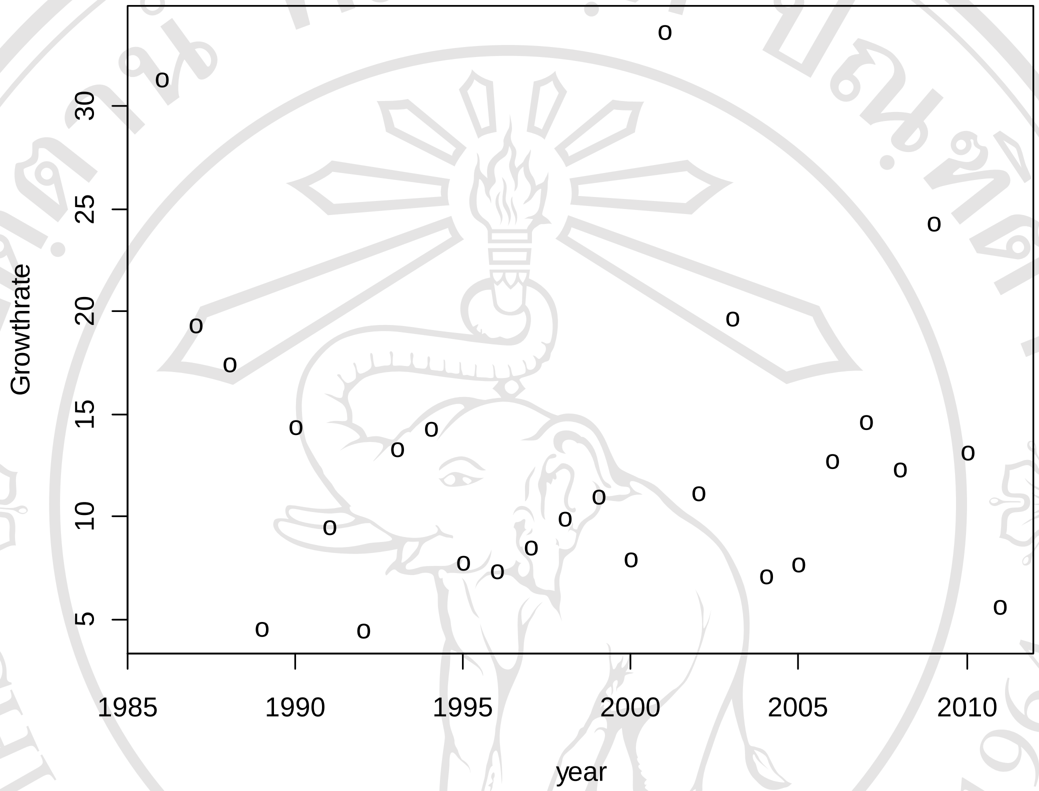

Figure 2: The scatter plot of annual maximum palm oil price growth rate (PPGR)

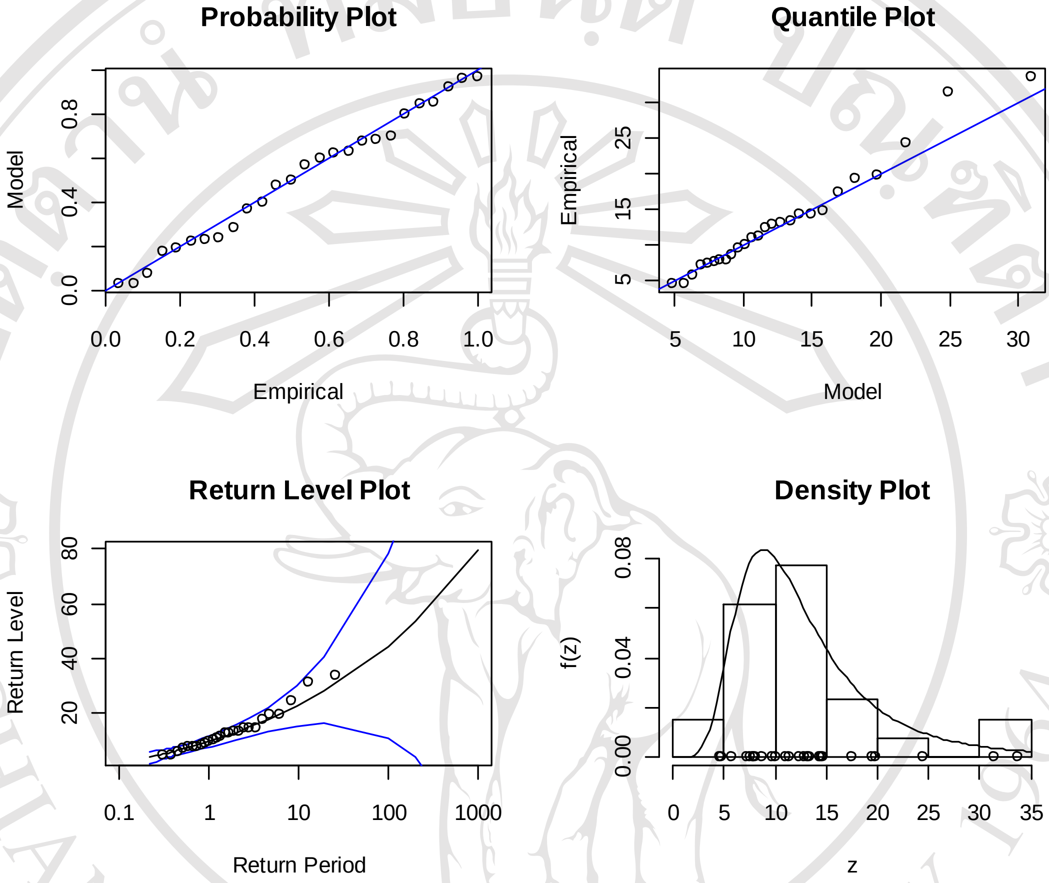

Figure 3: Diagnostic plots for GEV fit to the annual maximum PPGR

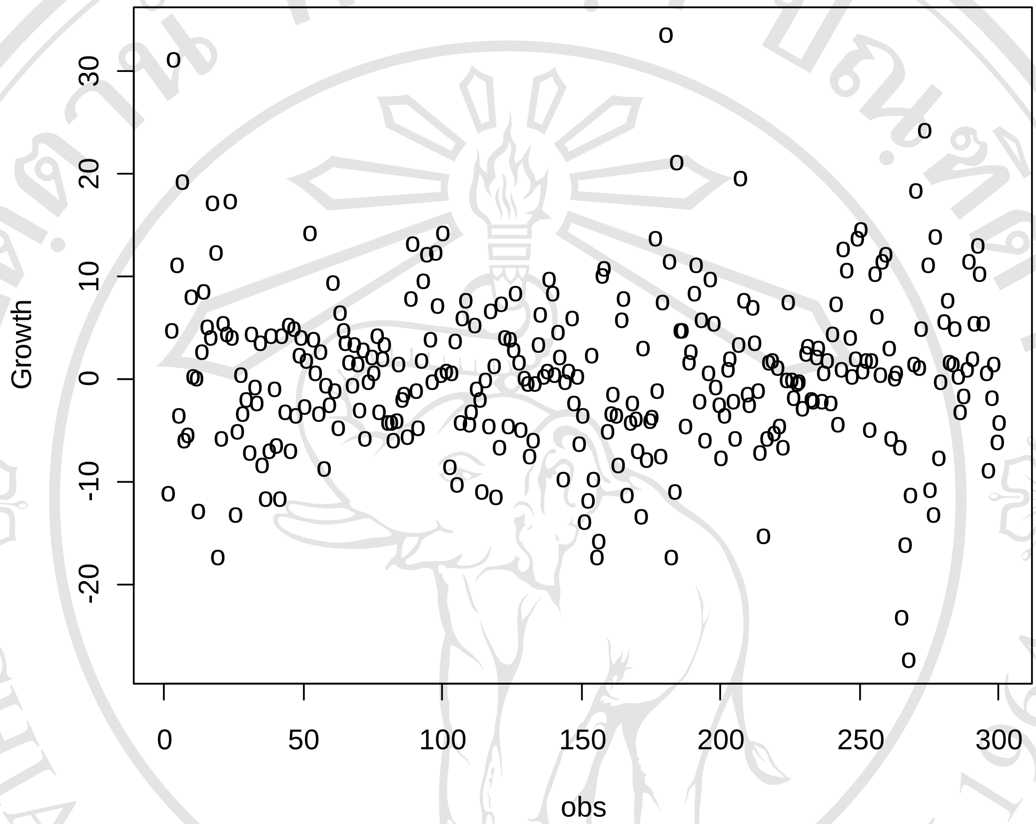

Figure 4: The scatter plot of monthly PPGR

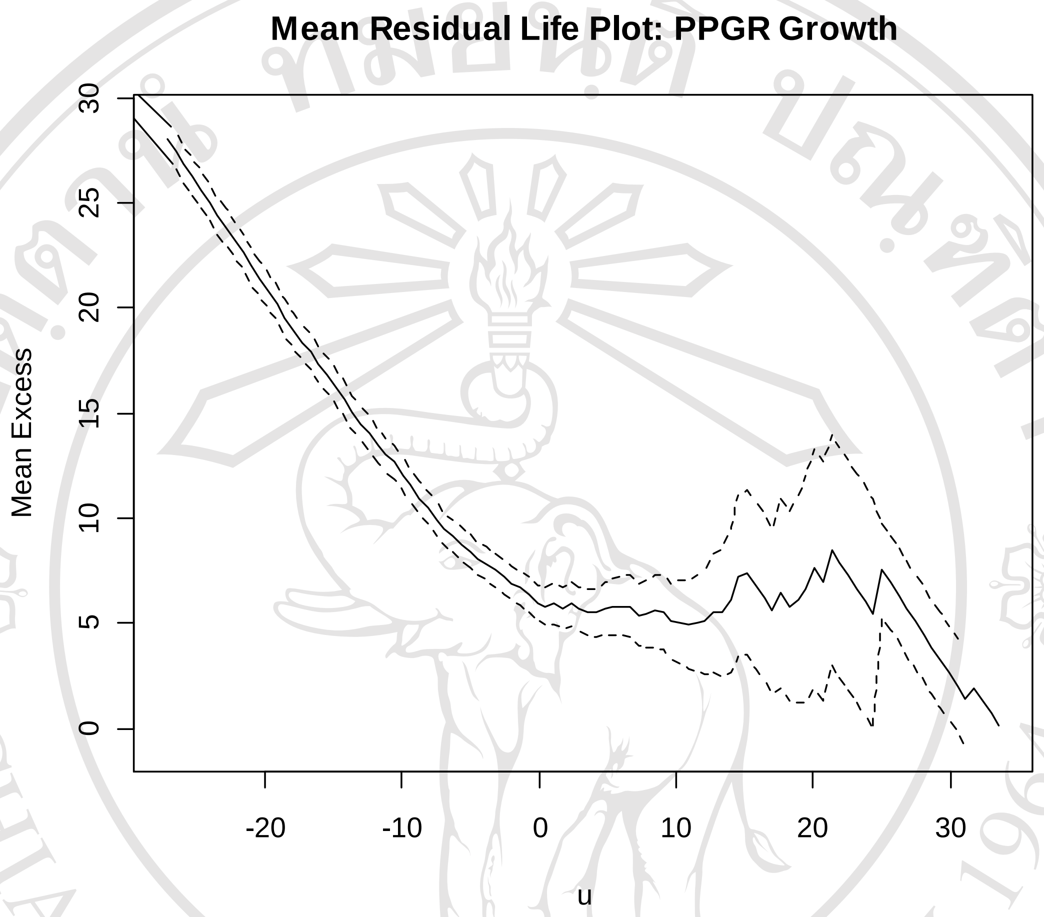

Figure 5: Mean Residual Life Plot of PPGR

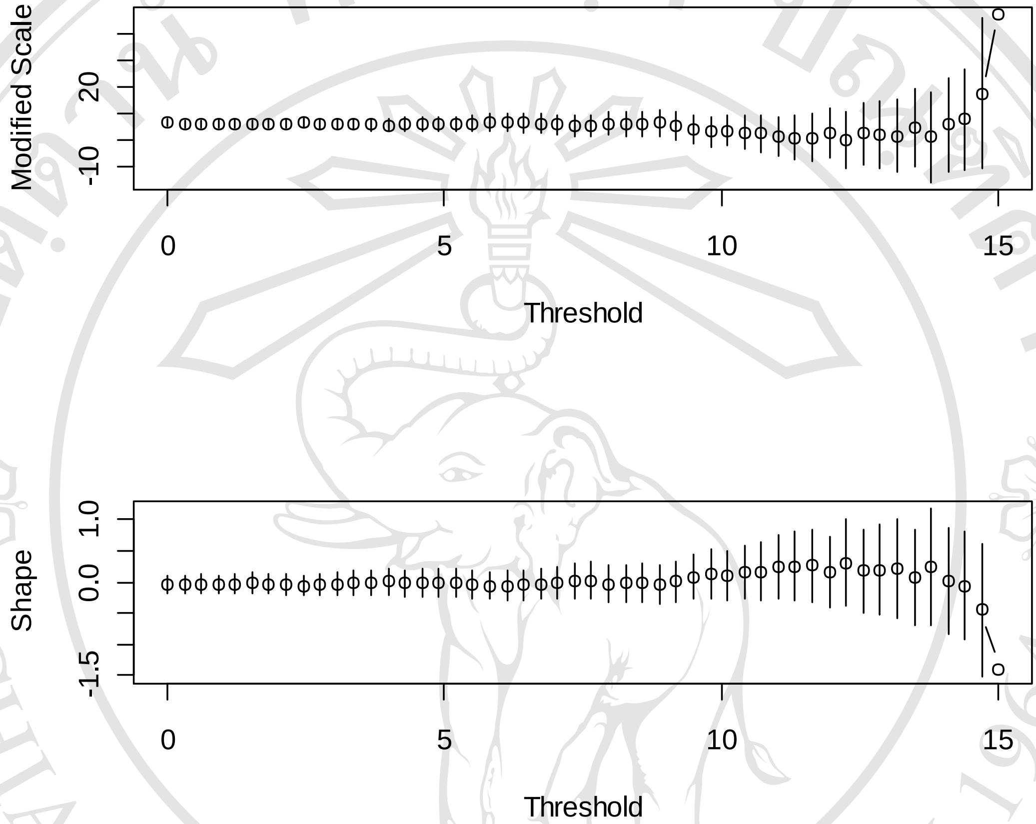

Figure 6: Parameter stability plots for PPGR

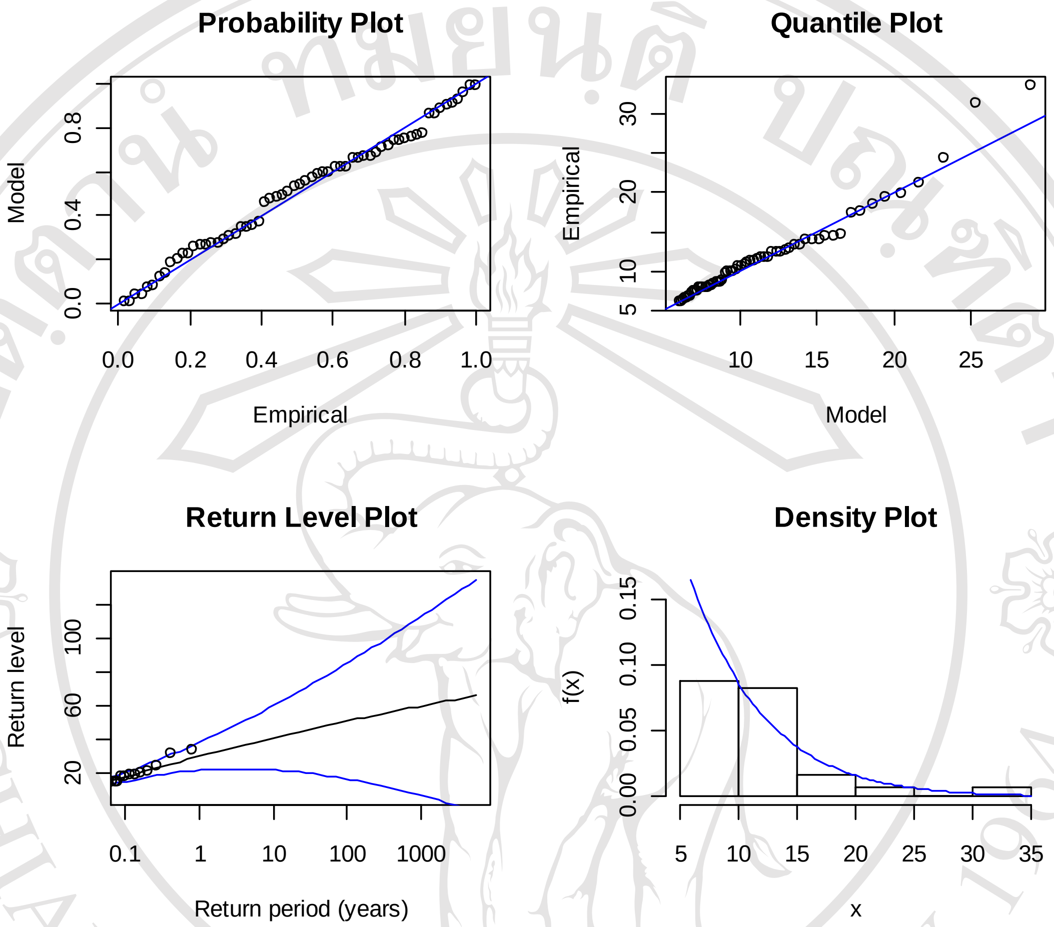

Figure 7: Diagnostic plots for GPD fit to PPGR.

Appendix B

Factors affecting palm oil price based on Extremes Value Approach

Kantaporn Chuangchid, Aree Wiboonpongse, Songsak Sriboonchitta & Chukiat Chaiboonsri

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Factors affecting palm oil price based on Extremes Value Approach

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Abstract

This study examines the dependence structure of extreme realization of growth rate between palm oil prices and factors affecting, which are soybean oil and crude oil prices. We employ the Bivariate Extreme Value methods for daily palm oil, soybean oil and crude oil prices ranging from July 1988 to January 2012. The results provide that the growth rate of palm oil and soybean oil prices have some dependence in extremes, but growth rate of palm oil and crude oil prices have fairly weak dependence or even independence in extremes. Therefore, the authors of this study hoped that these findings not only have made a contribution to our understanding of what drives palm oil price movement of soybean oil and change in crude oil prices, but also for the practitioner who want to devise an updated model to enhance a further comprehension of the prices that drive these article of trade.

Keywords: Dependence structure, Bivariate Extreme Value, Palm oil prices, Soybean oil prices, Crude oil prices

1. Introduction

In the consumption sector of oil and fats, palm oil is by far one of the highly well-known energy crop leaders in terms of production. The growth of palm oil production can be attributed to the demand of the local consumers as well as a price that is affordable to buy. The process of producing this natural wonder is made from a combination of other energy crops, such as soybean, sunflower, rapeseed and coconut oils (USDA, 2011). The factors that are involved in establishing the prices for palm oil are quite unique. With the rise in an increasing population, rapid economic growth and an elevated production of biodiesel, the worldwide demand for palm oil has brought about a changing shift towards the prices marked in palm oil. Such a rise in the factors will always lead to uncertainty or angst that makes decision making to sway by the extreme side such as hoarding the goods on part of the consumers while leaving scarce items for others (Khaneman, 2011). Nevertheless, it is a compelling fact that when there is an increase in crude oil and soybean oil prices, a recession in the world economy, and variations in the weather, the prices of palm oil tends to fluctuate. Figure 1 demonstrates the prices of palm oil fluctuating on a day to day basis that is based on these factors mentioned. Although uncertainty may be deemed as undesirable for nations that are trying to maintain the stability of palm oil prices, the advantages that it provides for other nations to reap some benefits in the international market are worth the venture. Therefore, for countries like Malaysia who involved in the palm oil plantation, they stand to gain the following: selling a product that is considered as one of the most competitively priced vegetable oil in the global market for the past 20 years and continues to be so today, being assured that the product is in the highest market penetration level of all vegetable oils (Dekeloil, 2012).

With the high price of palm oil, it influences more capital for investment and recruitment of labor to increase the production of palm oil. Since the price of palm oil is determined by many factors, the factor that influences palm oil prices is the availability of substitutes such as the prices of soybean oil. As an oil commodity, it has become an important influence on palm oil prices because of its similar application in the food industry (Rahman, Shariff, Abdullah, & Sharif, 2007). Figure 2 shows the palm oil and soybean oil daily prices series. Moreover, the price of crude oil is also an important factor that influences palm oil prices. Because of the recent price increase in crude oil and growing environmental concerns, biodiesel has become an important alternative fuel that acts as the lifeblood of the retailing industries that are highly depended on the logistics and transportations to deliver their goods on time. Figure 3 demonstrates the daily price series of palm oil and crude oil. This information is of particular importance as it shows the movement of palm oil prices that is affected by the prices of soybean oil and crude oil.

In this study, we attempt to investigate the relationship between palm oil prices and the two factors (soybean oil and crude oil prices) with a daily data. Since the data demonstrates an apparent tendency for non-normal distribution (see in table 1), the way to proceed this is to use the extreme value theory and to model it as the tail of an extreme value distribution. The aim of this paper is to employ the Bivariate extreme value to determine the dependence between the prices of palm oil and soybean oil, as well as the prices between palm oil and crude oil. The rest of the paper is structured as followed: Section 2 gives a literature review, Section 3 presents the data and methodologies, Section 4 discusses the empirical results, and finally Section 5 offers the conclusion.

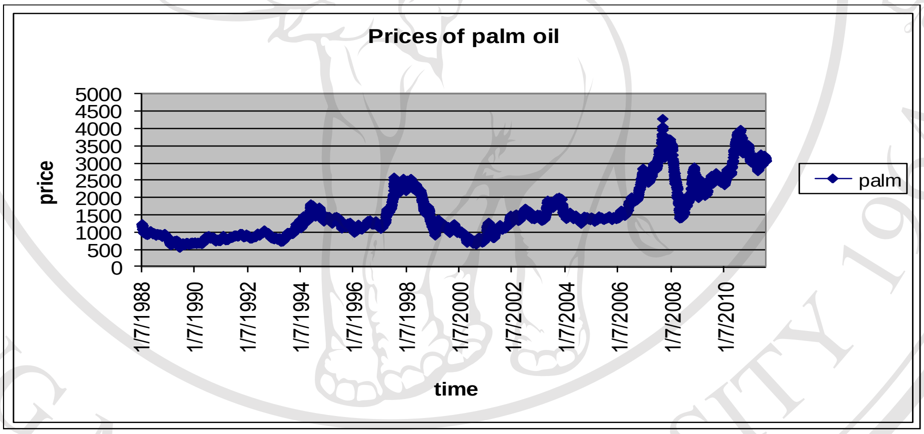

Figure 1. Palm oil daily price, Jul 1988 - Jan 2012

Source: Ecowin

Note: The Palm oil price of this paper is Palm Oil Futures 1-Pos, MYR

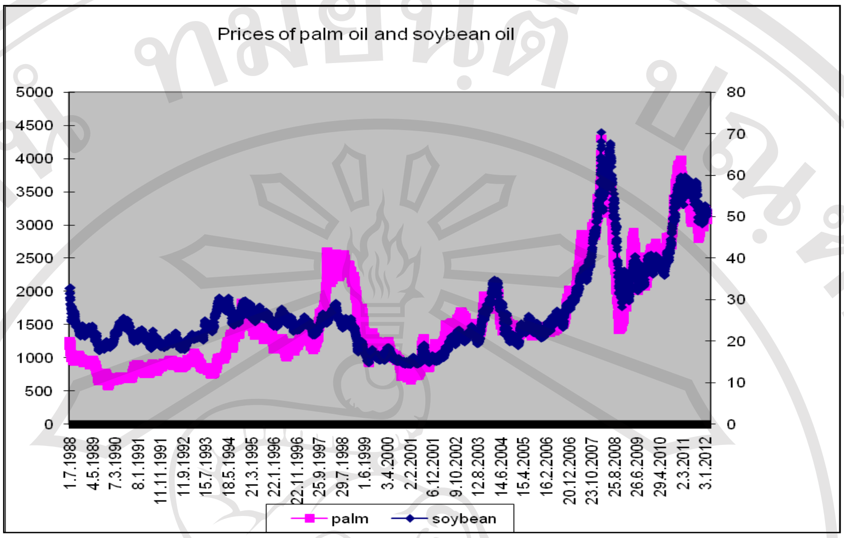

Figure 2. Palm oil and Soybean oil daily prices, Jul 1988 - Jan 2012

Source: Ecowin

Note: The Palm oil price of this paper is Palm Oil Futures 1-Pos, MYR, The Soybean oil price of this paper is Soybean Oil Futures 1-Pos, USD.

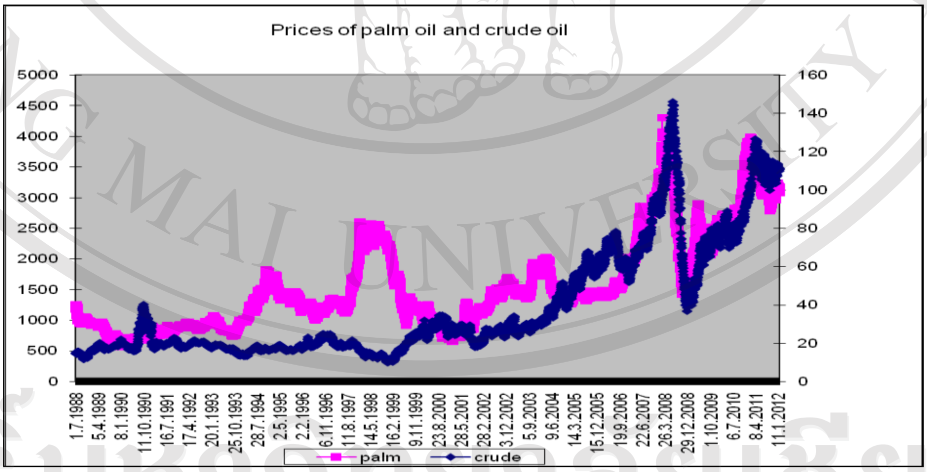

Figure 3. Palm oil and Crude oil daily price, Jul 1988 - Jan 2012

Source: Ecowin

Note: The Palm oil price of this paper is Palm Oil Futures 1-Pos, MYR, The Crude oil price of this paper is Brent Crude Futures 1-Pos, USD.

2. Literature Review

The authors of the study draw upon the fact that many palm oil producing countries have confirmed involvement with organizations and research institutes. When these two form into a working partnership, they become a unit that generate data and information that adds to the knowledge on oil palm cultivation, palm oil processing, and related applications. We see that Talib & Darawi (2002) have studied upon a structural model for the purpose of describing the Malaysian palm oil industry from 1997 to 1999 by taking into account the total palm oil area, oil palm yield, domestic consumption, exports and imports. In their study, it was proclaimed that the importance of Malaysian economy and its affecting factors were palm oil stock level, price of palm oil, the exchange rate, world population, and the price of soybean oil. According to Wahid, Simeh, & Nordin (2007) who have investigated the development in the world prices for palm oil, their findings considered that the impact of the trends on world palm oil price was derived from consumption, trade, price competitiveness, investment in oil palm/palm oil, and the use of palm oil producing biodiesel. In relevance to this work, the high rise in the trend of the oil palm price had a great implication for the agricultural and industrial sector in producing countries (Pleanjai, Gheewala, & Garivait, 2007). However, it's important to be aware on the fact that the price of oil palm surges over time due to the uncertain price of oil palm. Therefore, the work reminds us that there are risks and unreliability for tree-crop farmers, shareholder, traders, and producers. In order to configure the trends as a way for decreasing risk and uncertainties, there should be some effective risk management strategies implemented to ensure a sound policy to take for action (Karia & Bujang, 2011).

Our review of the work comes across upon other scholars who have studied factors that affect prices of palm oil. There are some studies that indicate an existing relationship between soybean oil and palm oil prices. We refer to Arshad, Shamsudin, & Hameed (2011) who described the soybean oil as a competitor to palm oil. Arhsad and his colleagues used the 'two stage least squares method' to estimate soybean and palm oil prices. With regards to the application employed, their work found that soybean prices would have a positive relationship with world palm oil price. Based on the analysis of relationship with Abdullah, Abas, & Ayatollah

(2007), his group reveals that soybean oil and palm oils are two good examples of agricultural commodities that have similar characteristics. They are also substitutable in many applications, and have prices of soybean and palm oil that are highly correlated.

In terms of the relationship between crude oil and palm oil prices, Hameed & Arshad (2009) studied the relationship between the prices of crude oil and selected vegetable oils using the Granger causality test. According to this study, the results show that in the long-run there was a one direction relationship between crude oil price and the prices of each of four vegetable oils, i.e., palm, rapeseed, soybean, and sunflower oils, but the reverse was not true. Moreover, our work points to Hadi, Yahya, Shaari, & Huridi (2011) studying the effect of changes in crude palm oil prices on the price of crude oil. Upon applying the Engle-Granger Cointegration test and Error Correction Model to find a significant long-term result, their work found that the prices of crude palm oil and crude oil are also positively correlated. However, we wish to mention that previous works assume that the data is normally distributed. Therefore, all of the aforementioned studies have suffered from this weakness of normality assumption since the prices of palm oil, soybean oil, and crude oil are assumed to have a non-normal distribution. In this paper we find that the extreme information flows from soybean oil and crude oil prices to palm oil prices.

We assert that the Extreme Value Theory (EVT) provides a strong theoretical basis where we can construct statistical models that are capable of describing extreme events (Gilli & Kellezi, 2006). Extreme value methods have been used in environmental science, hydrology, insurance, and finance. Furthermore, EVT can describe the behavior of random variables both at extremely high or low levels. The theory enables us to describe the performance of the heavy-tail properties of a high frequency time series data, such as financial returns (Onay & Unal, 2012). Univariate extreme value theory was used to analyze and evaluate extreme risks in finance and disaster sector. In addition, the bivariate EVT was used in studied on financial and disaster, such as Brodin & Rootzen (2009) who have used univariate and bivariate extreme value methods for predicting extreme wind storm losses. Based on their study, they believed that the bivariate model provided the most realistic picture of the real uncertainties. To substantiate this idea, Escalante-Sandoval (2007) used bivariate extreme value distribution to analyze the flood frequency. According to his results, it showed that estimating the parameters of marginal distribution with bivariate reduced the standard error of fit than pair of univariate distribution.

3. Data and Methodology

The research instruments used in this study involve bivariate extreme value. Time series data of this paper was obtained from Ecowin. In this paper, the palm oil price is Palm Oil Futures 1-Pos, MYR, the soybean oil price is Soybean Oil Futures 1-Pos, USD and the crude oil price is Brent Crude Futures 1-Pos, USD. We took daily prices in palm oil, soybean oil and crude oil in local currencies and converted to growth rate of prices. Daily prices are computed as growth rate of prices relatives: $Gr = (p_t - p_{t-1}) / p_{t-1} * 100$, where p_t is the daily futures 1-Pos price at time t. The study period was from July 1988 till January 2012.

3.1 Bivariate Extreme Value

The Extreme Value Theory (EVT) is a concept of modeling and measuring extreme events which occur with a very small probability (Brodin & Kluppelberg, 2008). There are two principal approaches to identify extremes in real data, Block Maxima (BM) and Peaks-Over Threshold (POT). BM and POT are central for the statistical analysis of maxima or minima and exceedances over a higher or lower threshold (Lai & Wu, 2007). In this research, we use both bivariate BM and POT models to analyze the relationship between the prices of soybean oil and palm oil, as well as on the prices of crude oil and palm oil.

3.2 Bivariate Block Maxima

This method is concerned with parametric and non-parametric cases. In this study, we choose the parametric models. A brief summary of bivariate BM is given below:

Let (X, Y) denote a bivariate random vector representing the component-wise maxima of an i.i.d. sequence over a given period of time. Under the appropriate conditions the distribution of (X, Y) can be approximated by a bivariate extreme value distribution (BEVD) with c.d.f. G. The BEVD is determined by its two univariate margins G_1 and G_2 respectively, which are necessarily EVD, and by its Pickands dependence function A (Rakonczai & Tajvidi, 2010).

$$G(x,y)=\exp\left\{\log(G_1(x)G_2(y))\times A\left(\frac{\log(G_2(y))}{\log(G_1(x)G_2(y))}\right)\right\} \quad (1)$$

A(W) is responsible for capturing the dependence structure between the margins and determines only up to the condition that it is convex, passes through the points (0,1), (1,1) and (1/2,1/2) binds the upper left and right corners. The properties of function A are (1) A(w) is convex, (2) max{(1 − w), w} ≤ A(w) ≤ 1 and (3) A(0) = A(1) = 1. Rakonczai and Tajvidi, (2010**)** explained in their paper that the lower bounds in the second item of the properties of A corresponds to the complete dependence G(x,y) = min{G1(x),G2(y)}, while the upper bound corresponds to (complete) independence G(x,y) = G1(x)G2(y).

In this BM case, we chose one parametric models form nine models ,which minimizes AIC (Akaike Information Criterion), to use for A(w) is logistic distribution function. Details about these and other models can be found in Stephenson (2011).

The logistic distribution function with parameter dep = r is

$$G(x,y)=\exp[-(x^{\frac{1}{r}}+y^{\frac{1}{r}})^{r}] \quad (2)$$

where $0<r\le 1$. The independence case corresponds to $r=1$. For $r\to 0$, we get complete dependence.

3.3 Bivariate Threshold Exceedances

There are at least two ways of defining exceedances in higher dimensions. In the first definition, a distribution is fitted to the observations $\{(x,y)|(x,y)>(u_x,u_y)\}$ where u_x and u_y are suitable thresholds for each margin. Second definition aims to fit a distribution to $\{(x,y)|(x,y)\nless(u_x,u_y)\}$ where (u_x,u_y) is defined as before. These distributions will be called Type I and Type II bivariate generalized Pareto distributions (BGPD), respectively (Coles & Tawn, 1991), (Coles, 2001).

In this study, the strength of the dependence between extreme prices of palm oil and soybean oil, palm oil and crude oil is estimated by fitting joint exceedances to bivariate extreme value distribution using MGPD type I. From univariate GPD, the details for approximating the tail of X by

$$G(x) = 1 - \eta_u \left(1 + \xi \frac{x-u}{\sigma}\right)^{-\frac{1}{\xi}}, x \geq u \tag{3}$$

$\eta_u = P(X > u)$

Suppose $(x_1, y_1), \ldots, (x_n, y_n)$ are independent realizations of a random variable (X, Y) with joint distribution function $F(x, y)$ on regions of the from $x > u_x, y > u_y$, for large enough u_x and u_y. The marginal distributions of F each have an approximation of equation (3), with respective parameter sets $(\eta_x, \sigma_x, \xi_x)$ and $(\eta_y, \sigma_y, \xi_y)$ (Coles, 2001). We can approximate the tail of X and Y for $x > u_x, y > u_y$ with $G(x : \eta_x, \sigma_x, \xi_x)$ and $G(y : \eta_y, \sigma_y, \xi_y)$, respectively. The Bivariate Generalized Pareto Distributions (BGPD) type I is

$$\mathrm{G(x, y) = exp\{-V(x, y)\}, x > 0, y > 0} \tag{4}$$

The dependence functions of this case use The Husler-Reiss models (palm oil and soybean oil prices) and asymmetric negative logistic models (palm oil and crude oil prices). A brief summary of these models are given below:

The Husler-Reiss (HR) distribution function with parameter dep = r is

$$G(x, y) = \exp(-x\Phi\{r^{-1} + \tfrac{1}{2} r[\log(x/y)]\} - y\Phi\{r^{-1} + \tfrac{1}{2} r[\log(y/x)]\}) \tag{5}$$

where $\Phi(.)$ is the standard normal distribution function and $r > 0$. Independence is obtained in the limit as $r \to 0$. Complete dependence is obtained as r tends to ∞.

The asymmetric negative logistic distribution function with parameters dep = r and asy = (t_1, t_2) is

$$G(x, y) = \exp\{-x - y + [(t_1 x)^{-r} + (t_2 y)^{-r}]^{-1/r}\} \tag{6}$$

where $r > 0$ and $0 < t_1, t_2 \leq 1$. When $t_1 = t_2 = 1$, the model reduces to the negative logistic model. Independence is obtained in the limit as either r, t_1 or t_2 approaches zero. Complete dependence is obtained in the limit when $t_1 = t_2 = 1$ and r tends to infinity (Stephenson, 2011).

4. Empirical Results

Table 1 presents the descriptive statistics of the growth rate of palm oil, soybean oil and crude oil prices. An examination of the descriptive table reveals that most of the growth rates of 3 oil prices have excess kurtosis, which indicates the influence of extremes on all growth rates of prices distributions. The Jarque-Bera test rejects normality at 5% level for all distributions.

Table 1. The descriptive statistics of Growth rates of Palm oil, Soybean oil and Crude oil prices

	PALM	SOYBEAN	CRUDE
Mean	0.0277	0.0179	0.0581
Median	0	0	0.0425
Maximum	10.4275	8.3707	14.0545
Minimum	-10.8527	-7.4739	-34.7682
Std. Dev.	1.6032	1.4669	2.2289
Skewness	0.0952	0.1306	-0.5933
Kurtosis	8.2815	5.5438	16.5524
Jarque-Bera	7159.42	1676.162	47440.95
Probability	0	0	0
Observations	6152	6152	6152

4.1 Bivariate Block Maxima

We use the growth rate of prices daily data into blocks of equal length and fit it to the maximums of monthly. In case of BM, we chose the logistic parametric model which minimizes AIC from nine models, to find the dependence functions between growth rate of palm oil and soybean oil prices and between growth rate of palm oil and crude oil prices.

The test results from using bivariate BM are shown in table 2. This table reveals distribution function parameter (r) and estimates for the location (μ), shape (ξ) and scale (σ) parameters. The logistic model between growth rate of palm oil and soybean oil prices has r estimate equal 0.83, which implies that growth rate of palm oil and soybean oil prices has dependence in extremes but not strong enough. Figure 4 shows some dependence between monthly maxima of growth rate of palm oil and soybean oil prices in which figure 5 confirms this information. And the logistic model between growth rate of palm oil and crude oil prices has r estimate equal 0.90, thus indicating that it has dependence but fairly weak or even independence in extremes between palm oil and crude oil prices. There is a fairly weak dependence or even independence between monthly maxima of growth rate of palm oil and crude oil prices; as shown in figure 6 and confirmed by figure 7.

Table 2. Bivariate Block Maxima Palm oil and Soybean oil prices, Palm oil and Crude oil prices

	BM model	AIC	μ_1	σ_1	ξ_1	μ_2	σ_2	ξ_2	r
Palm-soybean	logistic	1,912.587	2.0922 (0.0768)	1.1316 (0.0595)	0.1464 (0.0482)	2.2733 (0.0681)	1.0217 (0.0496)	0.0183 (0.0419)	0.8325 (0.0379)
Palm-crude	logistic	2,138.662	2.0923 (0.0773)	1.1394 (0.0602)	0.1605 (0.0501)	3.1068 (0.0912)	1.3558 (0.0707)	0.1654 (0.0472)	0.9019 (0.0384)

Note: Terms in parentheses are standard errors of parameter estimates.

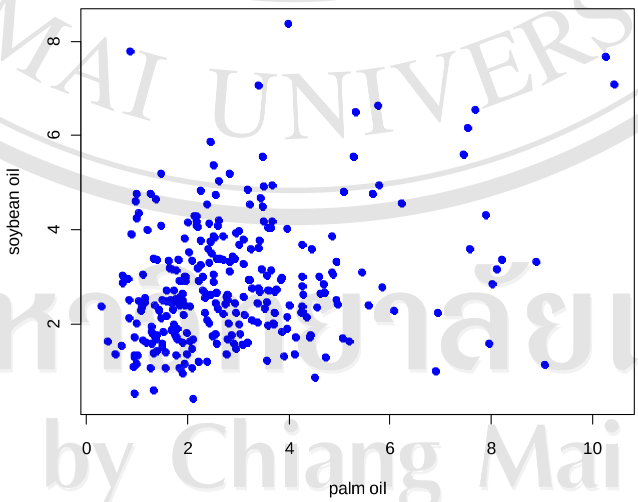

Figure 4. Bivariate monthly maxima of growth rate of palm oil and soybean oil prices

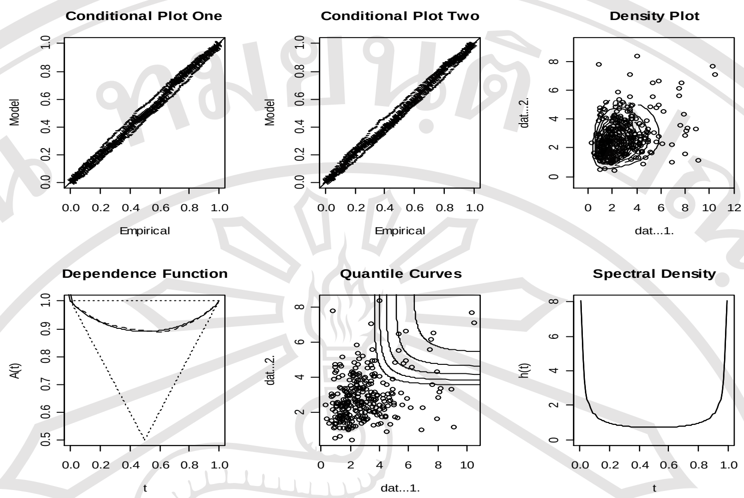

Figure 5. The bivariate logistic distribution function between growth rate of Palm oil and Soybean oil prices.

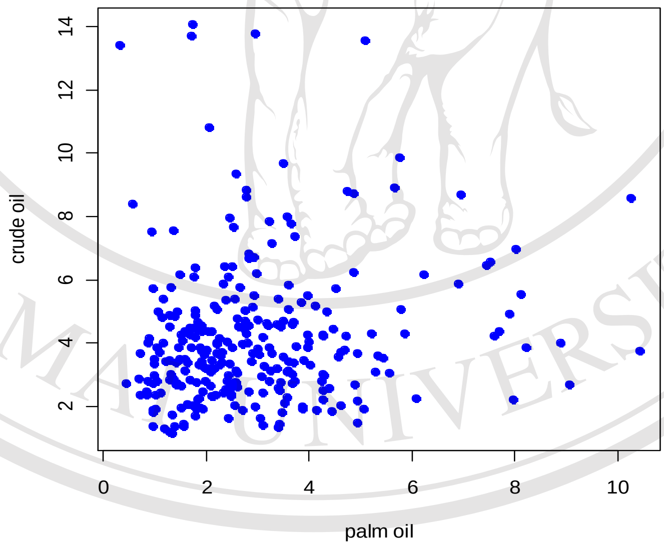

Figure 6. Bivariate monthly maxima of growth rate of palm oil and crude oil prices

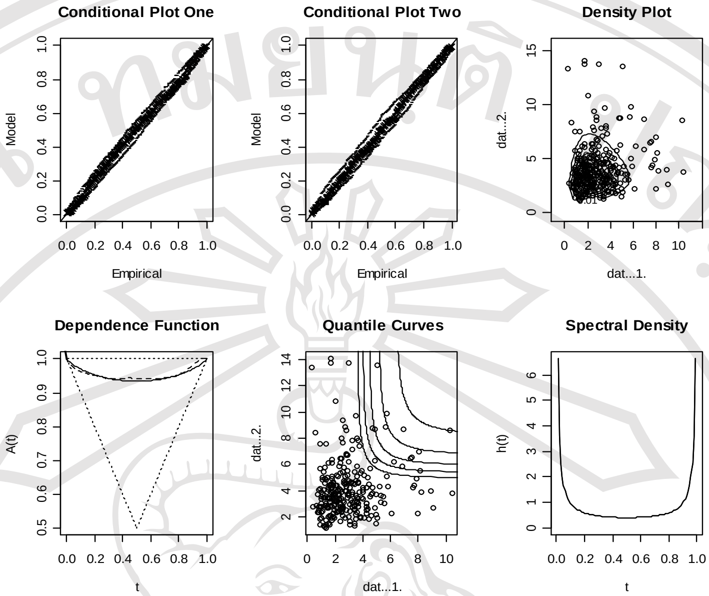

Figure 7. The bivariate logistic distribution function between Growth rate of Palm oil and Crude oil prices.

4.2 Bivariate Threshold Exceedances

We used the growth rate of prices daily data and analyzed the data by modeling exceedances of prices over a threshold. In this case, the dependence in extremes between palm oil and soybean oil prices uses HR models, which minimize AIC from nine models. And the asymmetric negative logistic model is used to find the dependence in extremes between palm oil and crude oil prices.

Table 3 presents the result of the bivariate threshold exceedances analysis of the distribution function parameter (r) and estimates for the shape (ξ) and scale (σ) parameters between growth rate of palm oil and soybean oil prices, growth rate of palm oil and crude oil prices. The HR model has r approach to one that means growth rate of palm oil and soybean oil prices has dependence in extremes. Figure 8 shows dependence in daily growth between palm oil and soybean oil prices and figure 9 provides the information that confirms it. On the other hand, the asymmetric negative logistic model has t_1 , t_2 estimate approach to zero, thus implying that there is independence in daily growth between palm oil and crude oil prices. There is independence in daily growth between palm oil and crude oil prices, where figure 10 presents the data and figure 11 confirms it.

Table 3. Bivariate Threshold Exceedances Palm oil and Soybean oil prices, Palm oil and Crude oil prices

	GPD model	AIC	σ_1	ξ_1	σ_2	ξ_2	t_1	t_2	r
Palm-soybean	HR	6,238.004	1.2265	0.1005	0.9939	0.0437			0.6605
			(0.1070)	(0.0651)	(0.0850)	(0.0636)			(0.0358)
Palm-crude	aneglog	6,602.384	1.2023	0.1037	1.3726	0.1773	0.0256	0.0795	3.411
			(0.1047)	(0.0663)	(0.1218)	(0.0684)	(0.0132)	(0.0477)	(2.1834)

Note: Terms in parentheses are standard errors of parameter estimates.

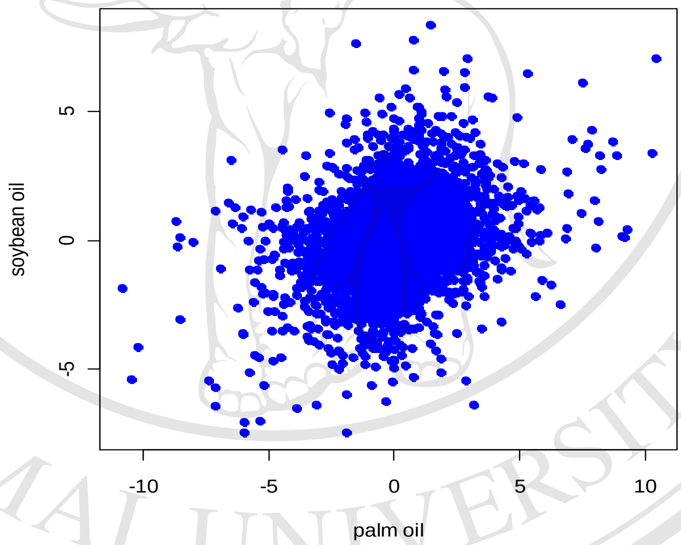

Figure 8. Bivariate threshold exceedances of growth rate of palm oil and soybean oil prices

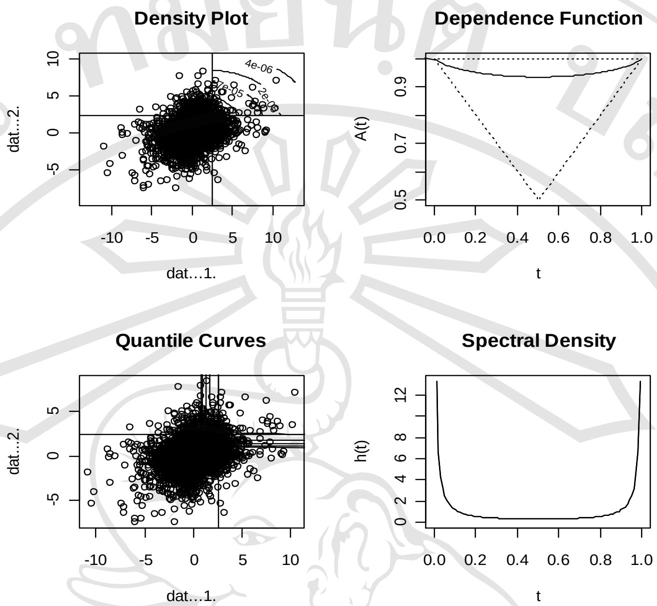

Figure 9. The bivariate HR distribution function between growth rate of Palm oil and Soybean oil prices

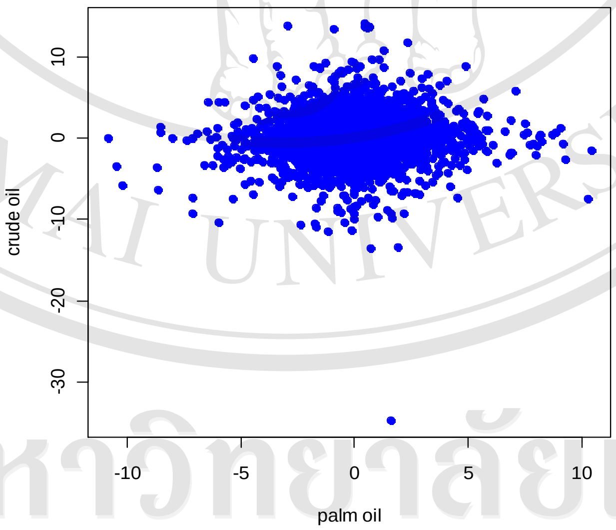

Figure 10. Bivariate threshold exceedances of growth rate of palm oil and crude oil prices

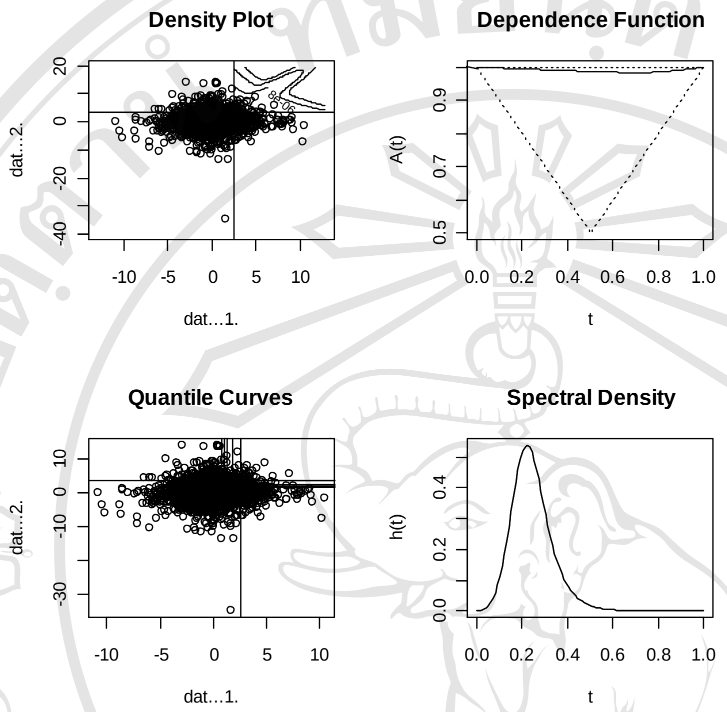

Figure 11. The bivariate asymmetric negative logistic distribution function between growth rate of Palm oil and Crude oil prices

5. Conclusion

This study focuses on the factor affecting palm oil prices. The work attests that there are many factors involved in the movement of palm oil prices. Such a movement has affected the prices of Soybean oil and crude oil as well. The aim of this study is to find the extreme dependence between palm oil and soybean oil prices, palm oil and crude oil prices using the bivariate extreme value. To do this, the paper applies the Bivariate Block Maxima and Bivariate Threshold Exceedances approach to examine the extreme dependence between the growth rate of palm oil and soybean oil prices, and the growth rate of palm oil and crude oil prices. Based upon our application, we see that the results of this paper show that both methods have a similar outcome. The growth rate of palm oil and soybean oil prices has some dependence in extremes. However, in the case of the growth rate of palm oil and crude oil prices, it has fairly weak dependence or even independence in extremes. Therefore, the authors of this study hoped that these findings not only have made a contribution to our understanding of what drives palm oil price movement of soybean oil and change in crude oil prices, but also for the practitioner who want to devise an updated model to enhance a further comprehension of the prices that drive these article of trade.

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Appendix C

Application of Extreme Value Copulas to Palm Oil Prices Analysis

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Abstract

In this paper we study the tail behavior of the palm oil future markets using the Extreme Value Theory and focusing on the dependence structure between the returns on palm oil future price in three palm oil futures markets, namely Malaysian futures markets (KLSE), Dalian Commodity Exchange (DCE) and Singapore Exchange Derivatives Trading Limited (SGX-DT) by using the Extreme Value Copulas. The results demonstrated that the returns on palm oil future price among KLSE and SGX-DT have dependence in extreme, whereas the returns on palm oil future price among KLSE and DCE, SGX-DT and DCE do not have any dependence. The results could be beneficial for any person or company wishing to be engaged in the commerce of trading palm oil.

Key words: Extreme Value Theory, Extreme Value Copulas, Dependence structure, Malaysian futures markets, Dalian Commodity Exchange, Singapore Exchange, Palm

INTRODUCTION

Extreme Value Theory (EVT) is a concept that is concerned with the analysis and modeling of extreme high or low observations. The EVT distributed assumption gives the results for the distribution of the normalized maximum of a high number of observations, or equivalently, the distribution of exceedances of observations over a high threshold (Rakonczai and Tajvidi, 2010). Under EVT assumptions on the underlying distribution of observations, it is often superior to normal distribution in many situations and has been widely used in many fields such as financial, hydrological, insurance and environmental science (Lu et al., 2008). The joint extreme events can have some serious impact on a particular field of study; therefore it needs to be carefully modeled. With a calculation of the probability that there is an observation exceeding a certain benchmark, it requires knowledge of the joint distribution of maximal heights during the forecasting period. This is a typical field of application for EVT (Gudendorf and Segers, 2009).

Copulas method has become rapidly developed and has brought the attention in various fields as a way to overcome the limitations of classical dependence measures as exemplified by the linear correlation. The copulas approach is a statistical tool that is considered as the most general margin-free description of the dependence structure of a multivariate distribution (Segers, 2005). The fact that the theory of multivariate maxima in EVT can be expressed in terms of copulas, its philosophy has been recently acknowledged as a form for application. Copulas is revealed to be a very strong tool in financial risk modeling that deals with different classes of existing risks (Cherubini et al., 2004). Scholars that have implemented the extreme value copulas in their study includes Starica (1999) who had investigated the joint behavior of extreme returns in a foreign exchange rate market, and Lu, Tian and Zhang (2008) who had repeatedly taken up the foreign exchange to analyze the dependence structure between the asset return. The results showed that three copulas are suitable to measure the joint tail risk and tail dependence for markets data. In addition, Longin and Solnik (2001) used EVT to study the dependence structure of international equity markets characterized. An application to the Society of Actuaries medical large claims that the data, in terms of insurance through extreme-value copulas, is the topic of the monograph by Cebrian, Denuit and Lambert (2003)

Palm oil is one of the most important energy-crop in the world (USDA, 2011), its implication as an energy crop is due to being a highly efficient and high yielding source of food and fuel. Palm oil is produced entirely in developing countries. Southeast Asian countries are the largest producing region; palm oil was produced 13.01 million tons in 1992, which increased to 50.26 million tons in 2011, a 286% increase in 19 years (USDA, 2011). Malaysia is one of the world’s biggest palm oil producers. The factors involved in setting palm oil prices are quite interesting. According to the relevance of Malaysia’s palm oil price to the Chinese and Singapore markets, it is important to examine the relationship between the Malaysian futures markets (KLSE) and two palm oil futures markets, namely Dalian Commodity Exchange (DCE) and Singapore Exchange Derivatives Trading Limited (SGX-DT). In this paper, we will deal with the tail behavior of the palm oil future markets using the EVT and focusing on the dependence structure between the returns on palm oil future price in three palm oil futures markets, namely KLSE, DCE and SGX-DT by using the extreme value copulas.

The remainder of the paper is organized as followed: Section 2 presents the univariate EVT and Generalized Extreme Value (GEV) distribution, Section 3 reviews the concept of copulas and extreme value copulas. Section 4 explains the data used in the empirical analysis, Section 5 discusses the empirical results, and finally Section 6 offers a conclusion.

UNIVARIATE EVT AND GEV DISTRIBUTION

The main idea of Extreme Value Theory (EVT) is the concept of modeling and measuring extreme events which occur with a very small probability (Brodin and Kluppelberg, 2008). It provides methods for quantifying such events and their consequences statistically. Generally, there are two principal approaches to identifying extremes in real data. The Block Maxima (BM) and Peaks-Over-Threshold (POT) are central for the statistical analysis of maxima or minima and of exceedances over a higher or lower threshold (Lai and Wu, 2007). The BM studies the statistical behavior of the largest or the smallest value in a sequence of independent random variables (Lei and Qiao, 2010; Lei et al., 2011). The POT approach is based on the Generalized Pareto Distribution (GPD) introduced by Pickands (1975) (cited in Lei and Qiao, 2010). These are models for all large observations that exceed a high threshold. In this paper, we will adopt GEV model of the BM method to study the tail behavior of the tail of palm oil futures markets.

let Zi (i=1,…,n) denote maximum observation in each block. Zn is normalized to obtain a non-degenerated limiting distribution. The BM is closely associated with the use of Generalized Extreme Value (GEV) distribution with c.d.f:

$$H(z) = \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \qquad (1)$$

Where μ, σ > 0 and ξ are location, scale and shape parameter respectively. Note that ξ > 0 is called Frechet distribution, ξ < 0 is called Fisher-Tippet or Weibull distribution and ξ = 0 is called Gumble or double-exponential distribution. Under the assumption that Z1, …, Zn are independent variables having the GEV distribution, the log-likelihood for the GEV parameters when ξ ≠ 0 is given by:

$$\ell(\xi, \mu, \sigma) = -n\log\sigma - (1+1/\xi)\sum_{i=1}^{n}\log\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right] - \sum_{i=1}^{n}\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right]^{-1/\xi} \qquad (2)$$

Provided that $1+\xi\left(\frac{Z_i-\mu}{\sigma}\right) > 0$, for i=1,….,n

The case ξ = 0 requires separate treatment using the Gumbel limit of the GEV distribution. The log-likelihood in that case is:

$$\ell(\mu, \sigma) = -n\log\sigma - \sum_{i=1}^{n}\left(\frac{Z_i-\mu}{\sigma}\right) - \sum_{i=1}^{n}\exp\left\{-\left(\frac{Z_i-\mu}{\sigma}\right)\right\} \tag{3}$$

The maximization of this equation with respect to the parameter vector (μ, σ, ξ) leads to the maximum likelihood estimate with respect to the entire GEV family (see Coles 2001 for detail)

COPULAS AND EXTREME VALUE COPULAS

Copulas have become the attention multivariate modeling in various fields. A copula is a function that links together univariate distribution functions to from a multivariate distribution function (Patton, 2007).

The relevance of copulas stems from a famous result by Sklar (1959) (cited in Segers, 2005). For simplicity, we confined it to the bivariate case. Let X and Y be the stochastic behavior of two random variables with respective marginal cdf's F(x) and G(y) is appropriately described with joint distribution function

$$H(x,y) = P(X \le x, Y \le y) \tag{4}$$

And marginal distribution functions

$$F(x) = P(X \le x), G(y) = P(Y \le y) \tag{5}$$

Since F(x) and G(y) are uniformly distributed between 0 and 1, then the joint distribution function C on [0,1]2 for all (x,y) ϵ R2 such that:

$$H(x,y) = C(F(x), G(y)) \tag{6}$$

Where C is called the copula associated with X and Y which couples the joint distribution H with it margins. Equation (6) is equivalent to H(F-1(u),G-1(v)) = C(u,v) as a consequence of the Sklar's Theorem, where u = F(x), v= G(y) are marginal distributions of X,Y. The implication of the Sklar's Theorem is that, after standardizing the effects of margins, the dependence between X and Y is fully described by the copula (Lu, et al, 2008). A comprehensive overview of the copulas properties can be referred to the work by Nelsen (1999). In this paper, we combine the copula construction with the extreme value theory.

The extreme value copula family is used to represent the Multivariate Extreme Value Distribution (MEVD) by the uniformly distributed margins. Consider a bivariate sample (Xi,Yi), i=1,….,n. Denote component-wise maxima by Mn = max(X1,…,Xn) and Nn = max(Y1,…,Yn). The object of interest is the vector of component-wise block maxima: Mc = (Mn, Nn)´. The bivariate extreme distribution H can be connected by an extreme value copula (EV copula) Co: (Segers, 2005)

$$H(x,y) = C_o(F(x;\mu_1,\sigma_1,\xi_1), G(y;\mu_2,\sigma_2,\xi_2)) \tag{7}$$

Where $\mu_i,\sigma_i\xi_i$ are GEV parameters and F(x) and G(y) are GEV margin. By Sklar's Theorem, the unique copula Co of H is given by

$$C_o(u^t,v^t) = C_o^t(u,v), t>0 \tag{8}$$

The EV copula has more family. In this paper, the two family applied are Gumbel and HuslerRiess. (Cited in Lu et al., 2008)

Gumbel copula:

$$C(u,v) = \exp(-[(-\ln u)^r + (-\ln v)^r]^{\frac{1}{r}}) \tag{9}$$

The independence copula is obtained in the limit as r = 1, and complete dependence is obtained in the limit as r = ∞.

HuslerReiss copula:

$$C(u,v) = \exp\left\{-\tilde{u}\,\Phi\left(\frac{1}{r}+\frac{1}{2}r\ln\left(\frac{\tilde{u}}{\tilde{v}}\right)\right) - \tilde{v}\,\Phi\left(\frac{1}{r}+\frac{1}{2}r\ln\left(\frac{\tilde{v}}{\tilde{u}}\right)\right)\right\} \tag{10}$$

Where $\tilde{u} = -\ln u, \tilde{v} = -\ln v$ and Φ is the standardized normal distribution. The independence copula is obtained in the limit as r = 0, and complete dependence is obtained in the limit as r = ∞. For the estimation of copulas parameters, we used Exact Maximum Likelihood method (EML): the parameters for margins and copula are estimated simultaneously (see Yan 2007 for details)

DATA

This paper used the times series data from DataStream. We work with daily future prices of palm oil data in three markets, namely the Malaysian future markets (KLSE), Dalian Commodity Exchange (DCE) and Singapore Exchange Derivatives Trading Limited (SGX-DT). We took the daily market prices and converted to a return series. Daily prices are computed as return of market i at time t relatives:

$R_{i,t} = \ln(p_{i,t} / p_{i,t-1}) * 100$, where $p_{i,t}$ and $p_{i,t-1}$ are the daily price of futures for days t and t-1respectively. The study period was from December 2007 till June 2012. We have 1196 observations for each market.

EMPIRICAL RESULTS

The parameter estimation of the GEV model

In the GEV model, we focused on the statistical behavior of block maximum data. Therefore, the source data is set of 55 records of monthly maximum in each market. Table1 presents the estimation of three parameters of GEV model based on the maximum likelihood method. The results show that the standard error estimates are relatively low. It implies that the block size of data is appropriate for the parameter estimation. Figure 1, 2, 3 presents the scattered plot of the monthly maximum return on KLSE, SGX-DT and DCE, respectively.

Insert table 1 & figure (1-3) here

The parameter estimation of the extreme value copulas

Insert table 2 here

Table 2 presents the parameter (r) estimation in the Gumbel and HuslerReiss copula analysis. In the Gumbel copula method, the parameter (r) estimation between KLSE and SGX-DT markets is equal to 3.034, which implies that KLSE and SGX-DT markets have dependence in extreme. Whereas the parameter (r) estimation among KLSE and DCE markets, SGX-DT and DCE markets are equal 0.973, 1.065, respectively, thus indicating that KLSE and DCE markets, SGX-DT and DCE markets have neither dependence or even independence in extremes. In the case of HuslerReiss copula, the parameter (r) estimation between KLSE and SGX-DT markets is equal to 2.287. This means that KLSE and SGX-DT markets have dependence in extreme, while the parameter (r) estimation among KLSE and DCE markets, SGX-DT and DCE markets are equal to 0.220, 0.597, respectively. Thus, there is an indication that KLSE and DCE markets, SGX-DT and DCE markets have neither dependence nor even independence in extremes.

CONCLUSION

In this paper, we managed with the tail behavior of return on three palm oil futures prices markets, namely KLSE, DCE and SGX-DT using the univariate EVT and GEV distribution. The study focused on the extreme dependence structure between the returns on palm oil futures prices in three markets using the extreme value copulas. To obtain our results, the paper applied the Gumbel and HuslerReiss copula approach to examine the extreme dependence between KLSE, DCE and SGX-DT markets. The results demonstrated that both methods have a similar outcome. The returns on palm oil future price among KLSE and SGX-DT have dependence in extreme, whereas the returns on palm oil future price among KLSE and DCE, SGX-DT and DCE do not have any dependence. The results could be beneficial for any person or company wishing to be engaged in the commerce of trading palm oil.

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Table1. The parameter estimation results using the ML method based on GEV model

Market	Parameter estimation	ML Method
KLSE	μ	2.491(0.162)
	σ	1.060(0.135)
	ξ	0.281(0.115)
SGX-DT	μ	2.736(0.186)
	σ	1.249(0.158)
	ξ	0.319(0.099)
DCE	μ	2.827(0.333)
	σ	2.186(0.245)
	ξ	0.035(0.104)

Note: Terms in parentheses are standard errors of parameter estimates.

Table2. Estimation of copula parameter

Market	Gumbel copula	HuslerReiss copula
KLSE-SGX-DT	3.034(0.473)	2.287(0.414)
KLSE-DCE	0.973(0.084)	0.220(2.721)
SGX-DT-DCE	1.065(0.079)	0.597(0.156)

Note: Terms in parentheses are standard errors of parameter estimates.

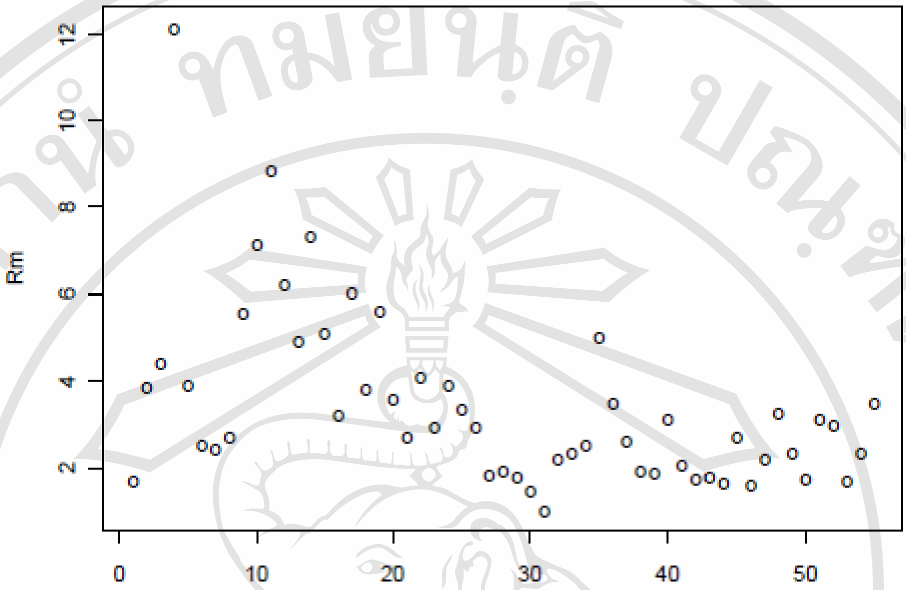

Figure1. The scatter plot of monthly maximum return on KLSE

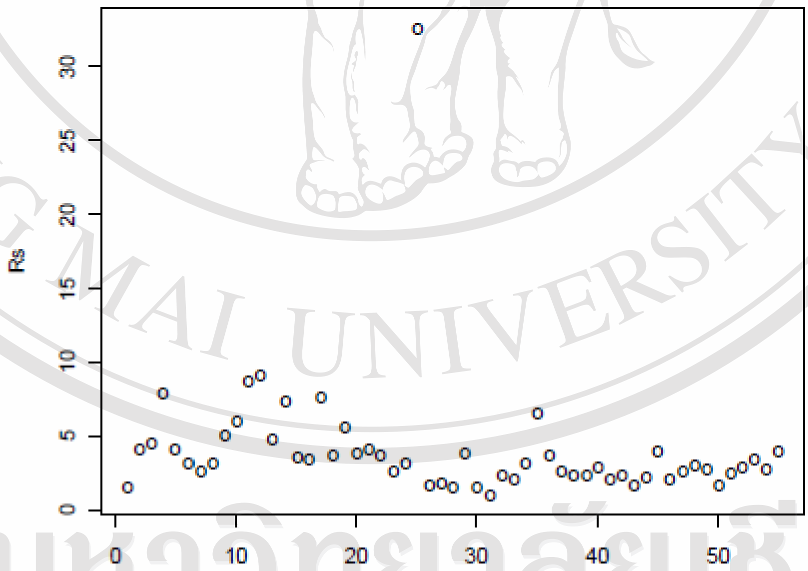

Figure2. The scatter plot of monthly maximum return on SGX-DT

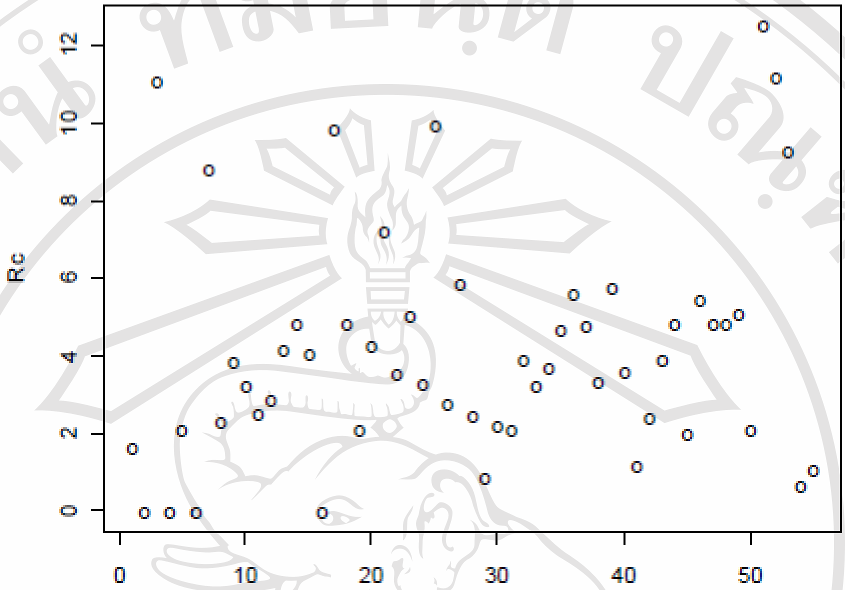

Figure3. The scatter plot of monthly maximum return on DCE

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