Chapter 3

Predicting Malaysian palm oil price using Extreme Value Theory

This chapter provides the first objective which is on the application of both univariate BM and POT to predict the extreme events of palm oil prices in the future. The data is downloaded from the website of the Indexmuldi Company. The univariate models used 300 pieces of observation data on Malaysia Palm Oil Futures price. In the case of BM model, this thesis focuses on the statistical behavior of block maximum data. This analysis is based on the series of annual maximum palm oil price growth rate (PPGR) covering a 25-year period (July 1986 to July 2011). In the case of POT model, this thesis uses the same data but analyze the data by modeling exceedances of individual observations over a threshold according to the following method.

This chapter is an original paper that was presented at the 5th International Conference of the Thailand Econometric Society held at Faculty of Economics, Chiang Mai University, Chiang Mai, Thailand during January 12-13, 2012 and a revised version of the original paper was accepted for publication in the International Journal of Agricultural Management (IJAM) Vol. 2(3), March 2013.

Predicting Malaysian palm oil price using Extreme Value Theory

Kantaporn Chuangchid, Sanzidur Rahman, Aree Wiboonpongse & Songsak Sriboonchitta

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 to be highly informed for making strategic planning for the future.

3.1 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 et al., 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 a small share of palm oil in food as well as a decline in the usage for biofuels. Therefore, the price of palm oil remains uncertain in the future. Figure 3.1 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; this is 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).

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. However, we believe 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 by 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 the following: 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.

3.2 Literature Review

3.2.1 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, thus resulting into a 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; it was producing about 15 million tons of palm oil a year. Therefore, Malaysia has played an important role in 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. The major importers of palm oil 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).

3.2.2 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 the ARMA family approach assumes 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.

3.2.3 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, thus 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 quite severe within a 100-year scenario and thus expected to recur.

3.3 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 3.1). 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.

3.3.1 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).

3.3.2 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 $Z_1, \ldots, Z_n$ 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)

3.3.3 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).

3.4 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 3.1). 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.

3.4.1 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 3.2 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 3.3 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.

Table 3.2 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.

3.4.2 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 3.4 and the mean residual life plot is presented in Figure 3.5. 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 3.6 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 3.7 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.

In Table 3.3, 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 3.3 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.

3.4.3 Discussion

The previous sections have explained that the Malaysian PPGR has a non-normal distribution, shown in Table 3.1. Past studies (e.g., Arshad and Ghaffar, 1986; Nochai, 2006; Karia and Bujang, 2011) that predicted palm oil price using ARMA family methods and assuming normal distribution of the data have utterly 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 3.2 and 3.3). The results presented in Tables 3.2 and 3.3 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).

3.5 Conclusion

This paper applied the 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 that was 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 risk as well as instability.

Table 3.1: 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 3.2: 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 3.3: 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)

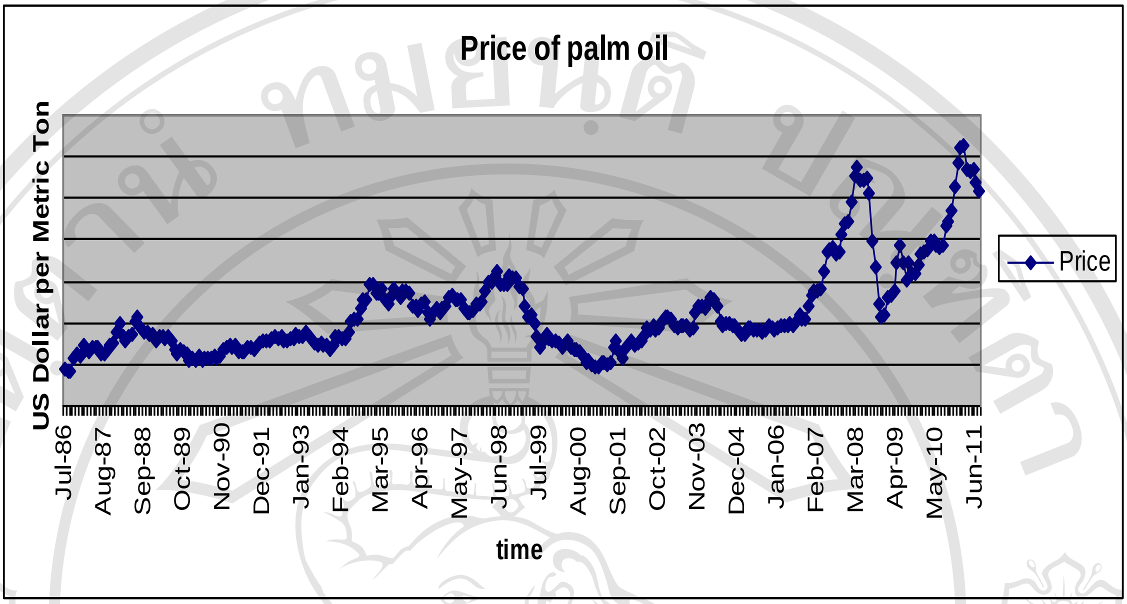

Figure 3.1: Palm oil monthly price, Jul 1986 - Jul 2011

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.

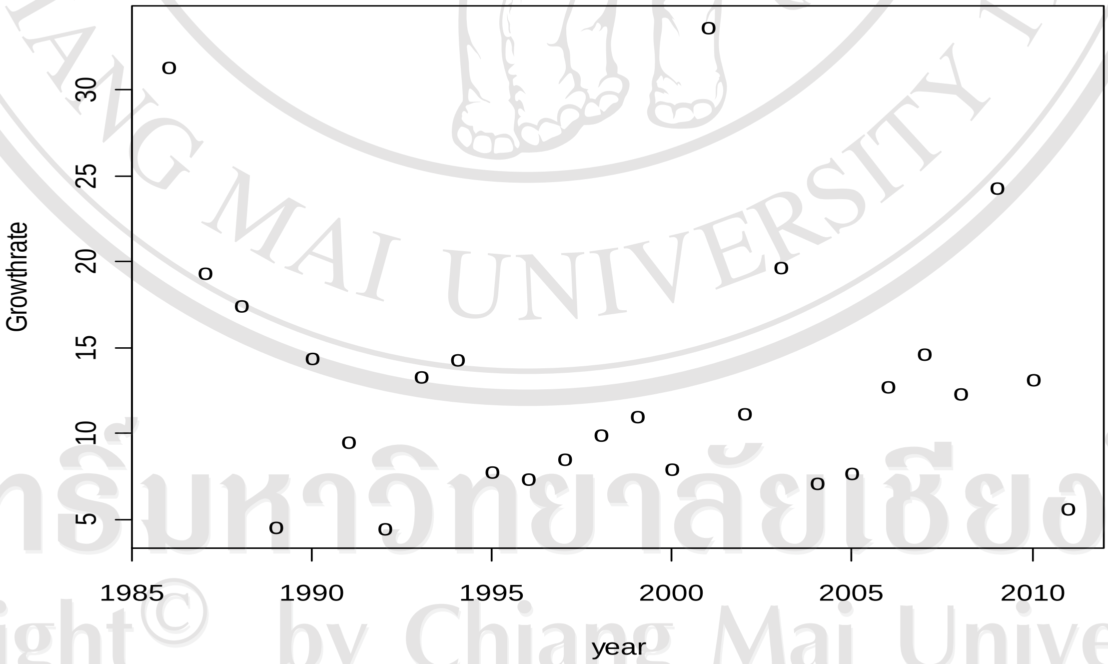

Figure 3.2: The scatter plot of annual maximum palm oil price growth rate (PPGR)

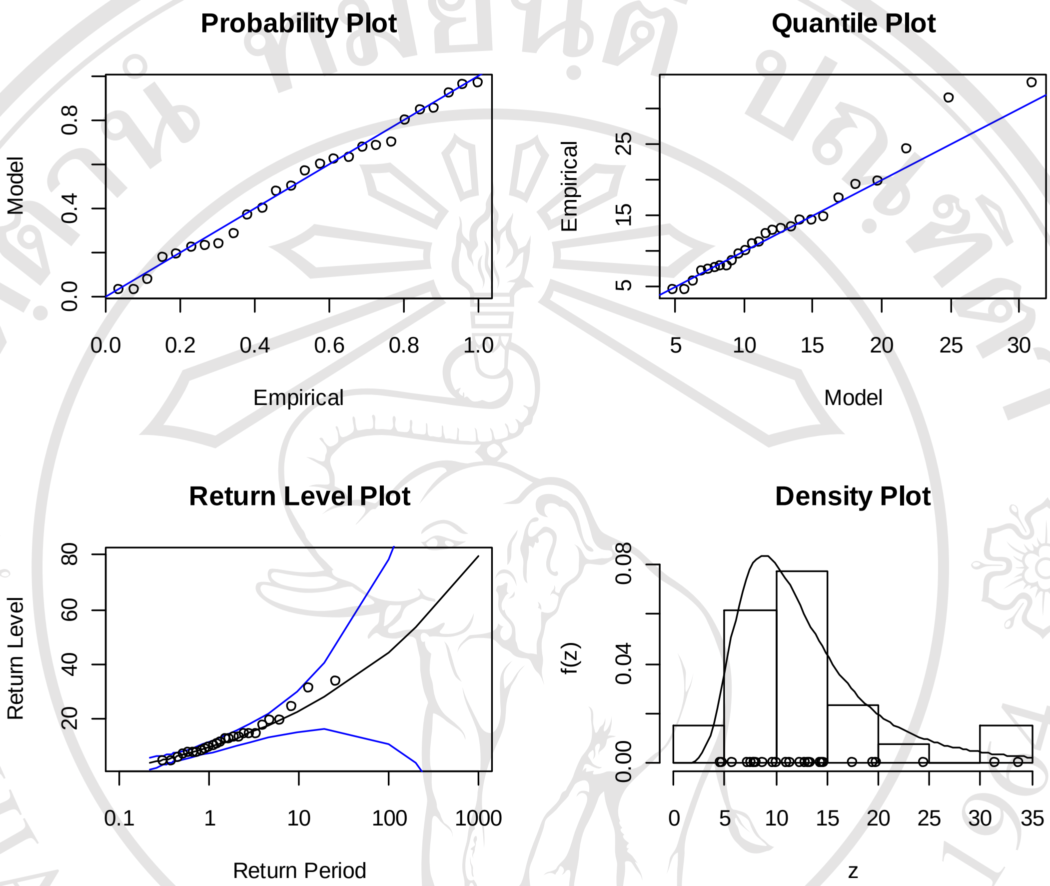

Figure 3.3: Diagnostic plots for GEV fit to the annual maximum PPGR

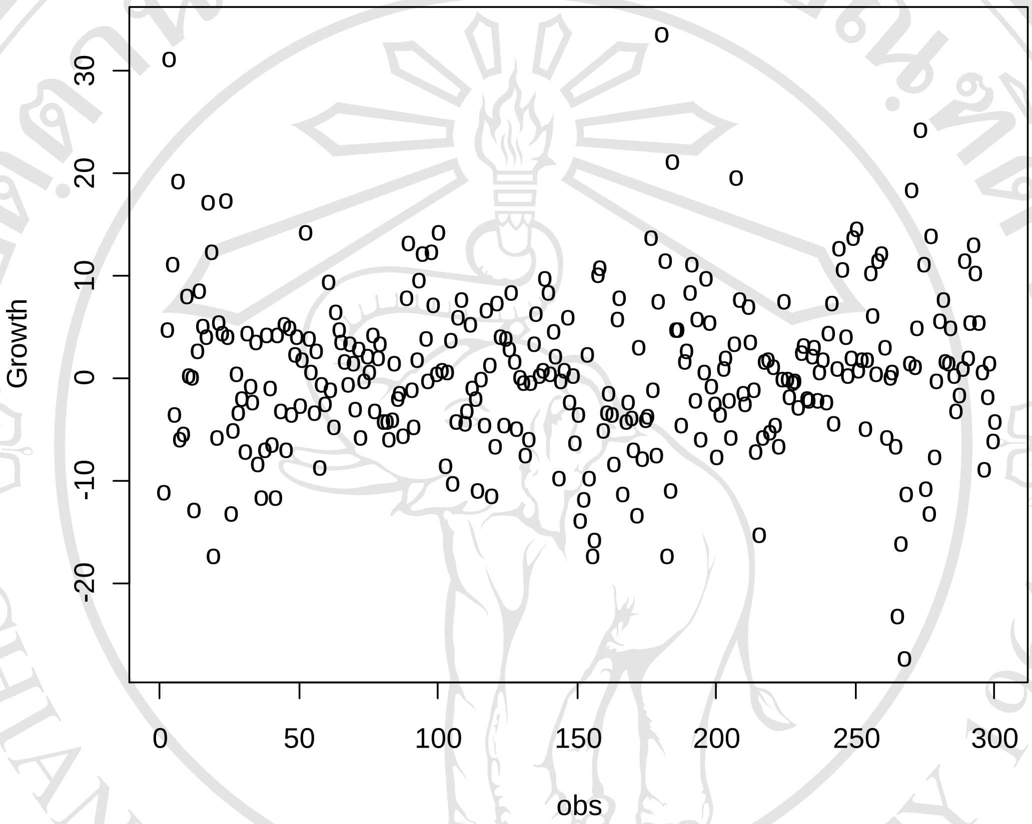

Figure 3.4: The scatter plot of monthly PPGR

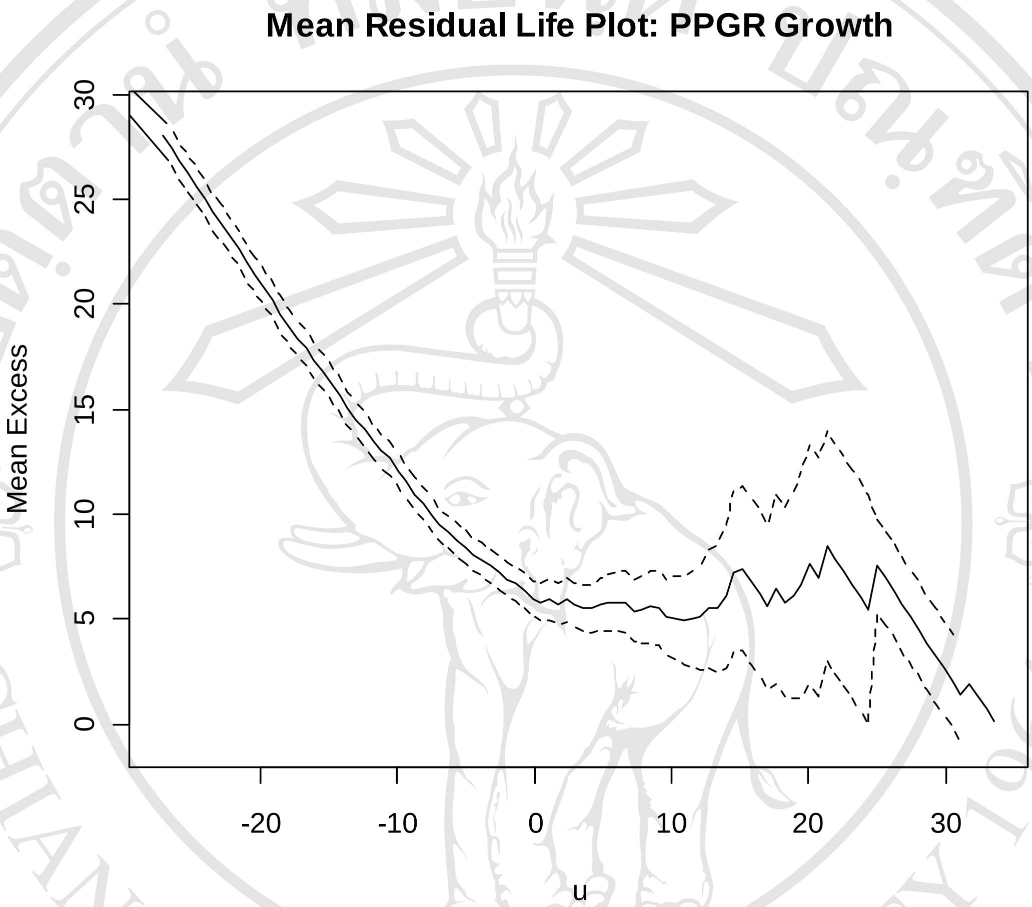

Figure 3.5: Mean Residual Life Plot of PPGR

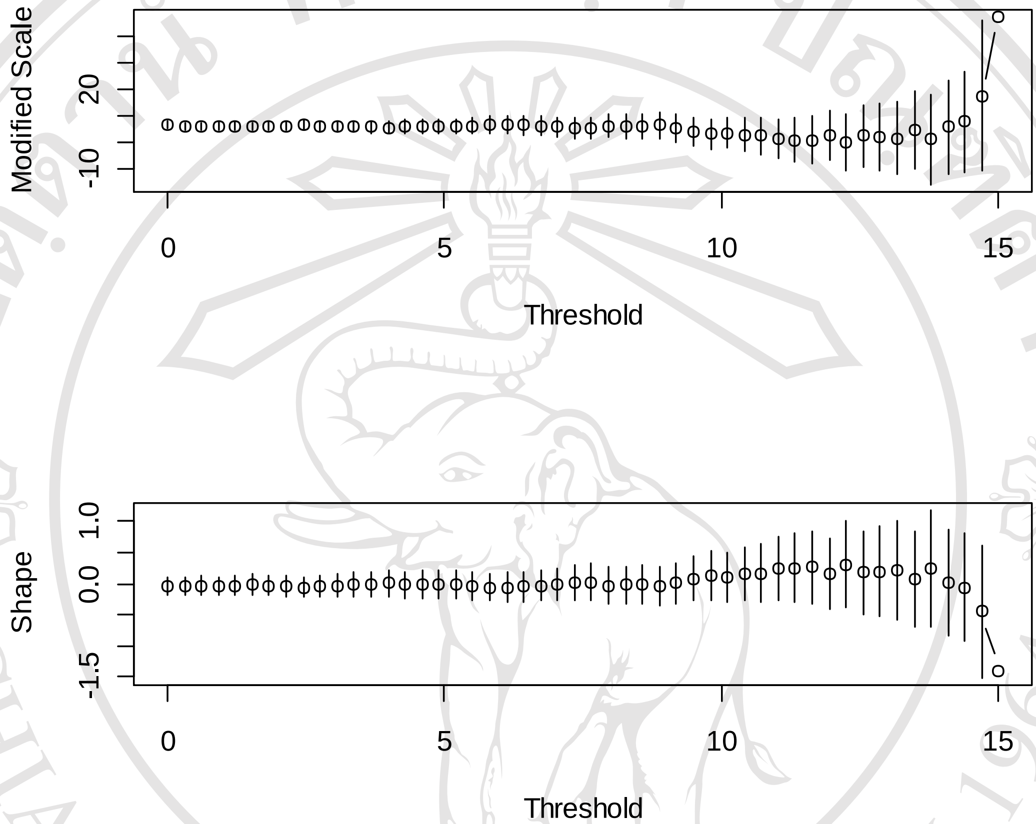

Figure 3.6: Parameter stability plots for PPGR

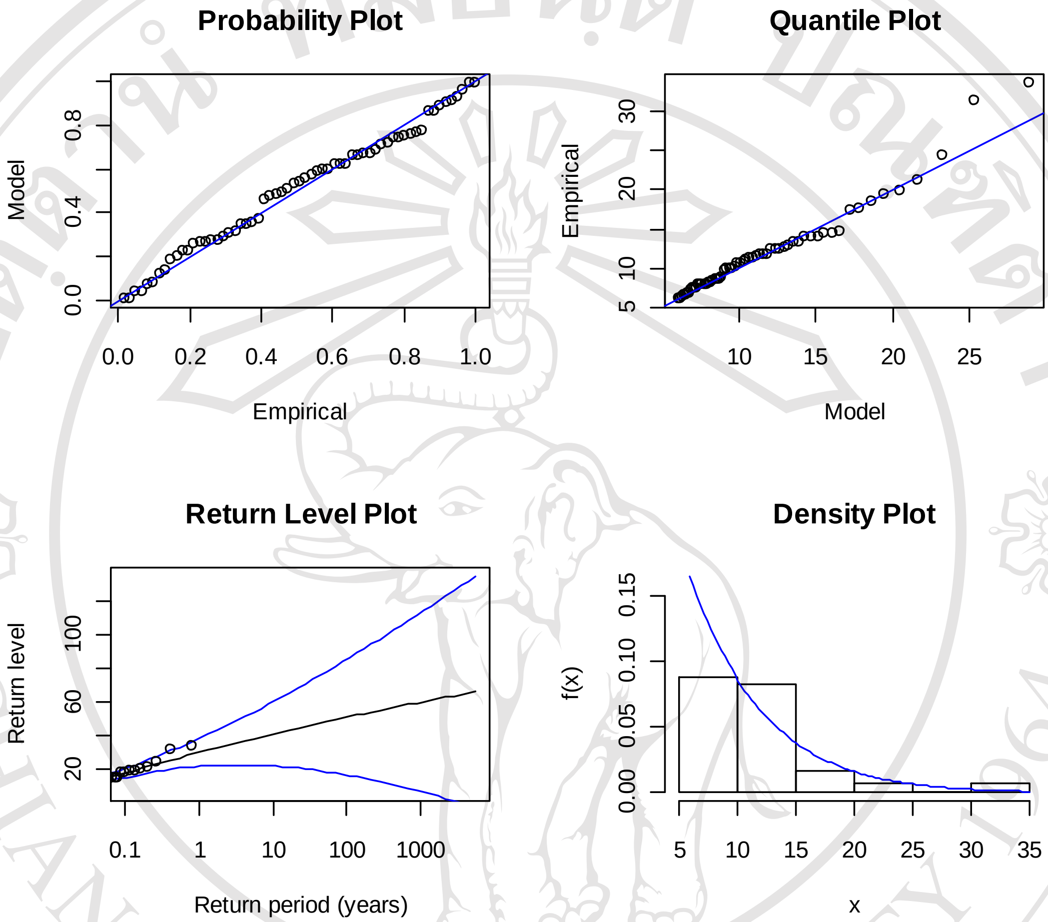

Figure 3.7: Diagnostic plots for GPD fit to PPGR