Value-at-Risk: Applying Extreme Value Approach to Measuring Financial Markets of the Southeast Asian Countries

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Abstract

This dissertation is generally based on the paper by (Ho et al., 2000) to identify the VaR values in six countries of the Southeast Asia (SEA) during and prior to the recent global financial crisis in 2007-08. The main differences between this dissertation and Ho, et al. (2000) paper are the investigated Asian countries which includes Indonesia, Japan, Korea, Malaysia, Thailand, and Taiwan in the range of time period from 1984 – 1998. However, this dissertation involves countries such as Malaysia, Indonesia, the Philippines, Thailand, Singapore, and Vietnam from the year 2000 – 2011.

Extreme Value Theory (EVT) is applied in both researches to model tail distributions of the market condition and Value-at-Risk (VaR) values were found to be more sensible and satisfactory with EVT approach compared to the traditional approaches, i.e. variance-covariance and historical simulation as the investigated market indexes exhibit leptokurtic returns. The parameter estimates of the maxima and minima series for each index are analyzed and VaR values are obtained based on the componentwise block maxima, i.e. Generalized Extreme Value approach (GEV) of 10-day and 20-day block length.

Furthermore, the 2007-08 financial turmoil is discovered to have rather subtle impact towards the SEA region compare to the Asian financial crisis investigated by (Ho et al., 2000). The Ho, et al. (2000) paper includes back testing analysis on the VaR measures and discovered that EVT approach has the least exceedance or violations. Nevertheless, in this dissertation bivariate extreme value analysis is performed instead of VaR measures evaluations and it suggests that the relationships of extreme events happening within Singapore, Malaysia, Indonesia, and Thailand are rather strong during the financial crisis.
# Table of Contents

Abstract ................................................................................................................................. 2  
Table of Contents .................................................................................................................. 3  
Acknowledgement ................................................................................................................ 4  
Chapter 1 – Introduction ...................................................................................................... 5  
Chapter 2 – Literature Review ............................................................................................ 7  
Chapter 3 – Methodologies ................................................................................................. 15  
  3.1 Extracting and Filtering Data ....................................................................................... 15  
  3.2 Extreme value approach (GEV) .................................................................................. 16  
  3.3 Computing Value – at – Risk (VaR) ............................................................................ 17  
  3.4 Bivariate extreme value distribution .......................................................................... 19  
Chapter 4 – Empirical Analysis ............................................................................................ 21  
  4.1 Data .............................................................................................................................. 21  
  4.2 Extreme Value Theory (EVT) ..................................................................................... 23  
  4.3 Value-at-Risk (VaR) computations using EVT ............................................................. 29  
    4.3.1 Comparison of Extreme Value VaR with Traditional methods......................... 31  
  4.4 Bivariate Extreme Value Distribution ....................................................................... 34  
Chapter 5 – Discussion ........................................................................................................ 38  
Chapter 6 – Conclusion ....................................................................................................... 41  
References ............................................................................................................................ 42  
Appendix 1 – Log-return of all six indices during pre-crisis and whole period ...................... 48  
Appendix 2 – Two methods in identifying extreme data ....................................................... 50  
Appendix 3 – Graphs of index price for all six countries ..................................................... 51  
Appendix 4 – R-Commands ................................................................................................. 52
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Chapter 1 - Introduction

Prior to the last two decades, Value-at-Risk (VaR) has been widely utilized to provide an organization a summary of which it indicates its current risk position and subsequently, be able for the management team to make decisions and perform necessary precautions for risk management purposes. Nevertheless, the recent financial downturn in 2007-08 has disappointed the confidence of users entrusting the infamous measuring tool, despite majority of the banking institutions that strictly adhered to this measure failed. Applying VaR approach in banking institutions could bring abysmal catastrophe if one underestimated the true risk position as they represent the nations’ wealth and significantly affect the economy.

This bring major concern to the countries which also vastly incorporating VaR approaches in their banking sectors but crisis bubbles are yet to burst for instance, the oriental and developing countries. Therefore, precaution steps should be taken to re-evaluate the appropriateness of VaR estimates and a proper modeling method should be applied. More specifically, statistical normal assumptions in the risk management tool are no longer sensible in financial leptokurtic returns and extreme value theory (EVT) that examines rare events should be utilized instead.

The main objectives of this dissertation is to further investigate risk position of six South East Asia (SEA) countries, i.e. Malaysia, Indonesia, the Philippines, Thailand, Singapore, and Vietnam in the current decade (2000 – 2011), following a prior study by Ho, et al. (2000) which examines six Asian markets during the earlier decade (1984 – 1998), both applying EVT. This dissertation is conducted by estimating the VaR values using extreme value approach and comparing them with traditional methods. Furthermore, risk estimates are also contrast against the Ho, et al. (2000) paper to determine if the recent financial turmoil has higher impact towards the Asian markets than the Asian financial crisis in 1997-98.

Finally, the findings of this dissertation also added value with the investigation of connection of extreme value within the researched countries to identify if rare events occur concurrently among these nations located geographically near.
The dissertation is organized in six chapters and the remainder is structured as follows,

- **Chapter 2 Literature review**
  The literature review highlights previous studies of areas included in this particular research, i.e. Value-at-Risk, extreme value approach, and bivariate extreme value.

- **Chapter 3 Methodologies**
  This chapter describes approaches and methodologies utilized for the research including functions of R commands and details on the data.

- **Chapter 4 Empirical analysis**
  This chapter shows the empirical analysis detailing results and outputs of the model estimated.

- **Chapter 5 Discussion**
  This section discusses findings into more detail and illustrates rooms of improvement for this research and some further research could be done in the future.

- **Chapter 6 Conclusion**
  The conclusion will recap and summarize the dissertation as a whole and suggest reasonable statement based on the results computed.
Chapter 2 – Literature Review

The idea of measuring financial risks was first implemented using the parameter of standard deviation established from the pioneering work of Markowitz, H. (1952) that shows the “expected return-variance of return” rule can influence the relationship between beliefs and selection of a portfolio. The variance term or squared of standard deviation, used in the modern portfolio theory, measures the portfolio risk by identifying dispersion of the return from the expectation. However, this mean of calculating portfolio risks was too statistical and considerable unrealistic assumptions (Mandelbrot & Hudson, 2008) are undertaken which could underestimate risk with high fluctuation returns in financial series. Gradually, a new risk measure were introduced in the late 1970s and 1980s i.e. Value-at-Risk (VaR), which gives a notion of probability of losses at firmwide level (Dowd, 2005). According to Hull, J.C. (2011), VaR was originally developed by JP Morgan in one of its system called the RiskMetrics and its reputable ‘4.15 report’ which required his staff to hand in report at 4.15pm on daily basis indicating the latest risk position of the company. This particular risk measuring tool is widely used in the major banking and financial institutions in calculating their various types of risk, typically market risk and credit risk due to the capital requirement enforce by the Basel committee. According to Cuoco and Liu (2006) based on a report of the Basel Committee on Banking Supervision in 1996, daily and a fortnight horizon VaR at 99% confidence level are expected to be disclosed from all the basel-complying financial institutions which would determine their capital requirement as buffer in case of a crisis. Generally, there are three common methods used conventionally in computing the VaR values, i.e. variance-covariance method, historical simulation, and monte-carlo simulations. In his book (Jorion, 2001) carefully describe the three approaches and incorporate other topics that are VaR related. Other studies such as Gencay & Selcuk (2004) and Totić et al. (2011) compare VaR valuse using different approaches of computation.

Attributable to its attractiveness, VaR measure is so extensively in used not only practically but academically as well. Many studies such as Duffie and Pan (1997),
Linsmeier and Pearson (2000), Basak and Shapiro (2001), Giot and Laurent (2003) introduce and incorporate the use of VaR in their research. Campbell et al. (2001) used VaR in their paper as a framework in optimizing portfolio selection i.e. allocating financial assets by maximizing expected return, subject to the constrains set based on VaR limits. Furthermore, empirical evidence by Jorion (2002) suggest that the VaR disclosures from the commercial banks can be used to compare the risk profiles of banks’ trading portfolios since they are well informative in forecasting the variability of bank trading revenues. Nevertheless, criticism on VaR was not lacking either where many doubt its reliability and validity of assumption held in the measuring tool. There are generally two major problems using VaR as the major risk measure, firstly, the mathematical issue proposed by Artzner et al. (1999) and secondly the accuracy risk in using VaR. The first issue regarding its measuring reliability is that, Artzner et al. (1999) suggest all financial risk measure should adhere the ‘coherent’ properties and VaR failed to comply with the most important element – subadditivity. The second problem of this measure is the risk in using the VaR itself, as it is affected by the ‘estimation’ risk and sampling variation (Jorion, 1996). In the similar paper by Jorian (1996), also suggested that it is important to set the confidence level arbitrarily to minimize the error in VaR and confidence intervals should be reported jointly with VaR values in order to improve the accuracy of VaR measures. In another empirical study, Berkowitz and O’Brien (2002) investigated six large commercial banks in the US by examining the accuracy of the VaR estimates and assessing the performance of banks’ trading risk models which they found that the reported VaRs are rather less informative as a measure of actual portfolio risk. This is due to computation and modelling practice used in complex portfolios and regulatory restrictions that might caused VaR inaccuracy. Despite of its criticisms, many researchers and practitionists continue to use VaR as measure of risk but with better improvisations. Some researchers apply different models towards data for better VaR estimation such as, Hull and White (1998a), Hull and Whilte (1998b), Mittnik and Paollela (2000) and, Giot and Laurent (2001), other researchers compute the VaR using different approaches, i.e. Extreme Value approach, for instance Danielsson

Financial academicians tend to use statistical and probabilistic framework in analysing data even from the pioneering work of modern portfolio theory, where the calculation of first and second moment of a return distribution. VaR can also be categorised as one of the probabilistic expression since it is a quantile measure based on certain percentage of confidence level (Hull, 2011). However, over reliance on the central tendency theorem and normality assumptions in financial risk analysis were no longer sensible ever since the occurrence of crises – extreme events that swept trillions off the markets. Therefore, new approach and model revamping need to be implemented to provide more useful statistics about the probability of disastrous or extreme events. Extreme value theory (EVT) is a rather unique in statistical studies as it involves investigating extreme events – events that are unlikely to occur, but catastrophic when happened. Extreme value theory has become one of the most indispensable concept over the past half-century which was used in various disciplines such as, engineering, environmental, in the insurance industry and traffic prediction in telecommunications (Coles, 2001a). Gumbel (1958) and Galambos (1995) give distinct mathematical and statistical presentation and the elements of extreme value approach. Despite the newly generated method of EVT, there are some weakness and limitations that must be considered. Diebold et al. (1998) contend that despite “exciting opportunities and helping to fill some serious gaps in our current capabilities”, cautions are to be taken as “estimation of aspects of very low-frequency events from short historical samples is fraught with pitfalls” when applying EVT.

Similarly in the paper by Embrechts (2000), limitations of EVT in Integrated Risk Management (IRM) are listed as follows:

“In order to estimate way in the tails (beyond or at the limit of available data) one has to make mathematical assumptions on the tail model.
These assumptions are very difficult (if at all) to verify in practice. Hence there is intrinsic model risk.”

“Even for a (standard) EVT-VaR estimation, one has to set the “optimal” threshold above which the data are to be used for tail estimation. There is no canonical “optimal” choice!” (p.p 8)

In short, Embrechts summarized that “if IRM is interested in the analysis of rare events, then EVT will play a small, though important role” and further emphasized that EVT is not the total solution for risk management.

Although undeniably many academic researches found limitations and opportunities EVT could offer, but Normal and t-distribution assumptions are inappropriate in modelling tail distribution. For example, both studies by Gencay & Selcuk (2004) and Ho et al. (2000) found VaR generated using the EVT approach are more accurate at higher quantiles than using the well-known variance-covariance and historical simulation methods. In the following section, parametric framework of this study and the basic theory of EVT will be presented.

There are generally two approaches in identifying extreme data (Gilli & Këllezi, 2006), the first method considers the maximum (or minimum) the variable takes in successive periods, for instance monthly or annually. The second approach involved selecting data that exceeds over a high threshold. Appendix 2 demonstrates the two methods of identifying extremes data. In this dissertation, focus will be given to the first approach although the latter was claimed to be more efficient. There is also a great explanation and demonstration of modelling extreme events using both approaches by Embrechts et al. (1996) which worth referring.

Suppose a statistical model is considered below,

\[ M_n = \max\{X_1, \ldots, X_n\} \]

where \( X_1, \ldots, X_n \) has similar distribution function \( F \) and are independent random variables. If \( n \) is the observation on monthly basis, then \( M_n \) would be a monthly
maxima. According to Coles (2001), $M_n$ can be derived exactly for all values of $n$ in theory as follow,

$$Pr\{M_n \leq z\} = Pr\{X_1 \leq z, ..., X_n \leq z\}$$
$$Pr\{M_n \leq z\} = Pr\{X_1 \leq z\} \times ... \times \{X_n \leq z\}$$
$$Pr\{M_n \leq z\} = \{F(z)\}^n$$

Since the distribution $F$ is unknown, therefore an approximate models for $F^n$ is to be estimated on the extreme data basis. We can look at the behaviour of $F^n$ as $n \to \infty$ by conducting a linear renormalization of the variable $M_n$ as there is a difficulty when $F^n(z) \to 0$ as $n \to \infty$, the distribution of $M_n$ is then degenerated to a point mass on the upper end point of $F$:

$$M_n^* = \frac{M_n - \mu_n}{\beta_n},$$

where appropriate values of $\mu_n$ and $\beta_n$ are chosen to stabilize the location and scale of $M_n^*$ as $n$ increases avoiding the problem arises with the variable $M_n$. When the appropriate values exist such that,

$$Pr\{(M_n - \mu_n)/\beta_n \leq z\} \to G(x) \text{ as } n \to \infty,$$

where $G$ is a non-degenerate distribution function, then $G$ belongs to one of the following families (Coles, 2001b):

I: $G(z) = \exp\{-\exp\left[-\frac{(z - \mu)}{\beta}\right]\}, \ -\infty < z < \infty$

II: $G(z) = \begin{cases} 0, & z \leq \beta \\ \exp\left\{-\frac{(z - \mu)}{\beta}\right\}, & z > \beta \end{cases}$

III: $G(z) = \begin{cases} \exp\left\{-\left(\frac{z - \mu}{\beta}\right)^\alpha\right\}, & z \leq \beta \\ 1, & z \geq \beta \end{cases}$

for parameters $\beta > 0$, $\mu$ and in the case of families II and III, $\alpha > 0$. Collectively, these three classes of distribution label I, II, and III are known as the Gumbel, Frechet and Weibull distributions.
The later development of Generalised Extreme Value (GEV) distribution, where the parameters meet the criteria of $-\infty < \mu < \infty, \beta > 0, -\infty < \xi < \infty$, the three families can be combined into a new expression defined on the set $\{z : 1 + \xi(z - \mu)/\beta > 0\}$ as follow,

$$H_{\xi, \mu, \beta} = \begin{cases} \exp \left[ - \left[ 1 + \xi \left( \frac{z - \mu}{\beta} \right) \right]^{-1/\xi} \right] & ; \xi \neq 0 \\ \exp \left[ - \exp \left( \frac{z - \mu}{\beta} \right) \right] & ; \xi = 0 \end{cases}$$

where $\mu$ represents the location parameter of the limiting distribution, $\beta$ represents the scale parameter of the limiting distribution. The distribution above was also a representation of a unified model from the three classes with single parameter by taking the reparameterization of $\xi = 1/\alpha$ where Frechet and Weibull distributions attain the shape of a Gumbel distribution when the tail index parameter $\alpha$ goes to $\infty$ and $-\infty$, respectively (Gencay & Selcuk, 2004). The $\xi$ which represents the shape parameter, corresponds to the thickness and fatness of the tail distribution where the greater value of $|\xi|$, the fatter is the tail (Ho et al., 2000). In the case when $\xi = 0$, the distribution corresponds to Gumbel (Type I) distribution. When $\xi < 0$, it assembles the Weibull (Type III) distribution and Frechet (Type II) distribution when $\xi > 0$.

The extension of univariate extreme value theory can be motivated to further research on establishing relationship among extreme values of more than one variable, also known as the multivariate extreme value distribution. This further developments “toward extremes of vector rather than scalar random variables, and the joint distribution of several high-order statistics” was suggested by Gnedenko (1992) who provide foundations of asymptotic theory for extremes in his paper. Furthermore, many multivariate extreme value theory related studies stemmed directly from his paper. For example, a study by Embrechts et al. (2000) carefully describe the technical issues of modelling tail events in multivariate case in the field of finance and insurance. On top of that, other researchers modelled the multivariate extremes using different method such as Coles & Tawn (1991) explaining point process theory, and Mikosch (2005) contrasting approaches of multivariate student distribution and copulas. However,
estimating $n$ - dimensional of vectors could be somewhat cumbersome and there is no exact available theory to analyse multivariate extreme value (Embrechts et al., 2000). Moreover, multivariate models are less fully prescribed in general theory and creates computation and validation difficulties (Coles, 2001a). Therefore, in this paper, only two dimensions – bivariate extreme distributions would be considered for simplicity. One of the pioneering work on modeling and estimation of bivariate extreme value theory, was done by Tawn (1988) describing estimation procedure on sea level data while another rather recent paper by Galiatsatou and Prinos (2011), compare the results of bivariate logistic model estimations using three different approaches, i.e. the Maximum Likelihood Estimation (MLE), a Bayesian procedure with flat prior distributions, and L-Moments (LM) procedures.

Another important feature in understanding multivariate or bivariate extreme value distribution is the dependence parameter, which also known as the extremal dependence structure, indicates relationship among extreme variables and gives better comprehension of the tail behaviour of the asset (Poon et al., 2004). Poon et al. (2004) showed parametric and non-parametric estimation of dependence structure in bivariate context and categorised them into four types, i.e. perfect independence, perfect dependence, asymptotic dependence, and asymptotic independence. In the similar paper, two parameters, $\chi$ and $\tilde{\chi}$ are also introduced, to quantify degree of asymptotic dependence and asymptotic independence respectively. The parameter $\chi$ take value between zero when the extremal variables are asymptotically independent and one being perfectly dependent. As for the parameter $\tilde{\chi}$, it further explains the relation when $\chi = 0$ and range from -1 to 1. Values of $\tilde{\chi} > 0$, $\tilde{\chi} = 0$, and $\tilde{\chi} < 0$ correspond, respectively, explain that the bivariate extremes are positively associated, independent, and negatively associated (Poon et al., 2004). Another excellent piece of study by Coles et al. (1999) on environmental data, shows complete modelling procedure for both componentwise block maxima and threshold methods, and generally acknowledges the measure of $\chi$ and $\tilde{\chi}$ being informative and complementary in describing form of extremal dependence in multivariate series. However, estimation of
\( \chi \) and \( \bar{\chi} \) using componentwise block maxima format are not as informative as using threshold method due to insufficient data to overcome the large sampling variation in the empirical estimates (Coles, 2001a). Other researchers involved in modelling and estimating dependence measure to financial area include Hsing et al. (2004) and Brodin & Kluppelberg (2010).
Chapter 3 - Methodologies

The aim of this study is to estimate the VaR values using the extreme value approach which closely follow the paper by Ho et al. (2000) and compare the results to determine whether the emerging asian markets has become worsen, and how they responded in both financial crisis happened in 1997-98 and 2007-08. Furthermore, relationships among extreme events are established to add value to this dissertation. Most of the methodologies used are R software based and the commands to produce the output are presented in the appendices.

3.1 Extracting and Filtering Data

The raw data which obtained from the Bloomberg terminal comprises of six indexes of the South East Asia region. In order to accommodate the key objective of this research, the data is synchronized to similar length for each indexes and filtered accordingly for serial-correlation and heteroskedasticity (ARMA-GARCH). This is to produce independent and identical distribution (iid) which is an essential step to begin with when using EVT. Firstly, data series are transferred into time-series format in R software before differentiating the natural logarithm of price day $t$ with day $t - 1$ to obtain the log returns,

$$r_{i,t} = \log x_{i,t} - \log x_{i,t-1}$$

$$R_{i,t} = r_{i,t} - \bar{r}_i$$

given $r_{i,t}$ is log return for index $i$ and $x_{i,t}$ is the index price at day $t$. Then, the mean of the log returns, $\bar{r}_i$ are removed from the log returns distribution before fitting into the ARMA-GARCH model into two stages. Firstly, the function “auto.arima” under the package “forecast” is utilized to determine the appropriate order of ARMA. Then, GARCH(1,1) model is used to fit for every index in order to correct the heteroskedasticity in the residuals. Next, obtaining volatility adjusted returns would be the subsequent stage suggested by Hull & White (1998) that volatility should reflect today’s trading environment. The function “ugarchforecast” is utilised to predict the
targeted volatility $\sigma_{\text{now}}$ for each log return series and “sigma” to obtain the log return variance $\sigma_t^2$.

Suppose a constant, $s_t$ is multiplied into the demean log-return distribution $R_{l,t}$ at day $t$, then the variance of this product would be $s_t^2 \sigma_t^2$. In order for today's variance, $\sigma_{\text{now}}^2$ to be equivalent to $s_t^2 \sigma_t^2$, the constant would be

$$s_t^2 = \frac{\sigma_{\text{now}}^2}{\sigma_t^2}$$

and the square root of $s_t^2$ will result,

$$s_t = \frac{\sigma_{\text{now}}}{\sigma_t}$$

The end result of volatility adjusted return happens when we add back the mean to the product of the implicit constant $s_t$ with demean log-return $R_{l,t}$, as follow,

$$\text{Adjusted } r_{i,t} = s_t R_{l,t} + \bar{r}_t$$

By obtaining the adjusted log-returns, these distribution are assumed to be independent and identical (iid).

3.2 Extreme value approach (GEV)

Componentwise block maxima method, which explained above, is utilized in this dissertation in extracting the maxima and minima series of the return distribution. A major procedure was reference from Fawcett (2008) which allow both minima and maxima data to be extracted according to the choice of block size from designated distributions. After extracting the required extreme returns, the parameters of $\xi$, $\beta$, and $\mu$ are estimated using the function “gevFit” under the package “fExtremes”.

In estimating the minima series, it is essential to obtain the return distribution in positive form in order for the function “gevFit” to run appropriately. For instance, the JCI minima distribution obtained initially showed in the left hand side of Figure 1 skewed to the left. This is because the minima series are all in negative value and the parameter estimates would be misleading and somewhat wrong if we run the “gevFit” function directly to this distribution. As a result, it would produce right tail estimate with
\(\xi < 0\) which is erroneous. Hence, to obtain the ‘correct’ right tail estimate, minima series are multiply by -1 to mirror the negative return distribution shown in the right hand side of Figure 1. In the subsequent analysis, minima series are treated similarly as maxima series except that they are the negative return distribution to be kept in mind.

**Figure 1**

![Indonesia Minima Series](image)

### 3.3 Computing Value-at-Risk (VaR)

Value-at-risk (VaR) is also a quantile measure of a particular distribution with a certain holding period and confidence level. Gencay and Selcuk (2004) contrasted six different models computing one-period ahead VaR estimates in both tails of the distribution, however, they adopted Generalized Pareto distribution (GPD) approach for their EVT model. The paper from Ho, et al. (2000) which this dissertation is closely obeying, used the following expression to compute the VaR values for minima and maxima series,

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* Figure 1 shows the probability density distribution of minima series for Jakarta Composite Index (JCI) from 20-day block length. The left-hand side plot shows the original signs of the extreme log-return data, while the right-hand side plot shows the mirror image where change of sign from negative to positive by multiplying -1 into the data.
where in their paper $\alpha$, $\beta$, and $\tau$ refer to scale, location parameters and tail index respectively. These expressions are rather different as the tail index does not equal to shape parameter. From a careful distinction between Ho et al. (2000) and Gencay & Selcuk (2004), the two papers denote the shape parameters as $\xi$ and $k$ and tail index as $\alpha$ and $\tau$ respectively. Furthermore, the relationship of these parameters are given as follow,

$$\xi = \frac{1}{\alpha}, \quad \tau = \frac{1}{k}, \quad \xi = -\tau$$

where the third relationship is obtain from the expressions of Frechet type distribution based on the Fisher-Tippett theorem in both the studies, indicates that $k = \alpha$. Hence, we can rewrite the VaR expression using the parameter notation in this dissertation as follow,

$$\text{VaR}\_{\text{long}} = -\mu_n^{\text{min}} - \frac{\beta_n^{\text{min}}}{\xi_n^{\text{min}}} [1 - (-\ln p)^{-\xi_n^{\text{min}}}]$$

$$\text{VaR}\_{\text{short}} = \mu_n^{\text{max}} - \frac{\beta_n^{\text{max}}}{\xi_n^{\text{max}}} [1 - (-\ln p)^{-\xi_n^{\text{max}}}]$$

In another paper by Tsay (2009) shows another method in computing VaR under the extreme value approach by incorporating the block size into the formula. In addition, R commands (see appendix) to computation of VaR function is also available (Tsay, 2012) which will be utilized in this dissertation. As mentioned previously that minima series will be treated similarly as maxima series, we can use one expression for all parameters as such,

$$\text{VaR} = \begin{cases} 
\mu_n - \frac{\beta_n}{\xi_n} [1 - [-n \ln(1 - p)^{-\xi_n}]] & \text{if } \xi_n \neq 0 \\
\mu_n - \beta_n \ln[-n \ln(1 - p)] & \text{if } \xi_n = 0 
\end{cases}$$

where the notation $n$ is the block size and $p$ is the upper probability. In addition to that, comparison of VaR values using traditional methods, i.e. variance-covariance method
and historical simulation is also performed in this dissertation. The function “VaR” is utilised under the package “Performance Analytics” in R software to compute the VaR values using the traditional approaches mentioned previously.

3.4 Bivariate extreme value distribution

To determine a linear relationship between two variables, a conventional statistic measure used was the Pearson correlation $\rho$. However, to establish a relationship between two extreme values is rather cumbersome and the efficiency of the estimate depends much on the type of data.

In this section, modelling of bivariate extreme value is established within the minima series and the dependence parameter estimate, $\hat{\alpha}$ (Coles, 2001a) will be utilised. In addition, the function “fbvevd” under package of “evd” is also incorporated in estimating the dependence parameter using MLE approach. Furthermore, the comparison of dependence estimates between pre-crisis and the whole period will be done to identify their changes and interpretations are done necessarily.

Firstly, the original log-return of minima series is obtained for the six indexes and they are grouped into 15 pairs with one another without replacements. Then, the next step is to obtain common Frechet marginal distributions by renormalizing the pairs of minimum returns according to their extreme value parameters. To illustrate this, assume a pair of minima series denoted as $(x_1, y_1), \ldots, (x_n, y_n)$ with their individual extreme value parameters of $\xi_x, \mu_x, \beta_x$ and $\xi_y, \mu_y, \beta_y$ are renormalized into standard Frechet distribution as follow,

$$ z_{x,i} = \left[1 + \xi_x \left(\frac{x_i - \mu_x}{\beta_x}\right)\right]^{1/\xi_x} \quad \text{and} \quad z_{y,i} = \left[1 + \xi_y \left(\frac{y_i - \mu_y}{\beta_y}\right)\right]^{1/\xi_y} $$

where $(z_{x,1}, z_{y,1}), \ldots, (z_{x,n}, z_{y,n})$ is a pair of transformed vectors that approximately distributed according to the standard Frechet distribution (Coles, 2001a). Subsequently, we fit these 15 pairs of transformed distributions into the “fbvevd” function and obtain the dependence parameter estimates $\hat{\alpha}$ and their standard errors. The major reason minima series were transformed instead of fitting directly into the estimating function in
R, apart from the suggestion made by Coles, S. (2001a), is that the standardised distributions fit successfully with MLE approach of log model and produced different dependence parameters for each pair without error warnings. Furthermore, standard errors are also provided in order to determine the significance of the dependence parameters which is much more sensible. The outputs of the parameter are also cross-checked with their respective pairs of scatter plots and resulted reasonably.
Chapter 4 – Empirical Analysis

4.1 Data

The logarithmic returns are computed from stock market indices, i.e. Malaysia (Kuala Lumpur Composite Index), Indonesia (Jakarta Composite Index), the Philippines (Philippines Stock Exchange), Thailand (Stock Exchange of Thailand), Singapore (Straits Times Index), and Vietnam (Vietnam Ho Chi Minh Stock Index) using data from the Bloomberg terminal. In order to accommodate the extreme value approach, daily returns are obtained from year 2000 to 2011. This study generally mimics the (Ho, L.C. et al., 2000) paper which examines Asian markets during the Asian financial crisis. Nevertheless, the focus given in this dissertation is to examine the extreme events in South East Asia countries during the global financial crisis in 2008 instead. The recent global financial crisis hit almost every part of the financial world including emerging markets. For instance, the study by Shabri Abd Majid, M. and Hj Kassim (2009) shows that the impact of 2007 US financial crisis was somewhat severe towards developing countries, i.e. Malaysia and Indonesia where both indices fell 36.45 percent and 43.39 percent respectively during the investigated period. There are 2248 daily return observations for each indices starting from 31 July 2000 to 31 December 2011. This is due to the establishment of Vietnam Ho Chi Minh Stock Index on 28 July 2000 with base index of 100 (Narayan & Narayan, 2010), therefore observations prior to this date is not considered. We assume and subdivided the data into two stages, the pre-crisis period from 28 July 2000 to 25 July 2007 (Shabri Abd Majid & Hj Kassim, 2009) that consists of 6 years and the overall period of 10.5 years ended in 31 December 2011. By doing this, we are able to investigate if the impact 2007-08 financial crisis was significant affecting the South East Asian countries.

Appendix 1 shows the log-return of all six indices and the red-colored plots are the pre-crisis period defined earlier. By eyeballing the six plots, there are very obvious fluctuations of returns after 25 July 2007, when the global financial crisis occurred. For example, in Malaysia KLCI, the Philippines PCOMP, and Singapore FSSTI indexes, significant negative returns can be seen right after the pre-crisis period. However, huge
fluctuations also occurred during the pre-crisis period especially in Vietnam VN and Thailand SET where a lot of noise can be detected in the beginning of the period. Next, Table 1 and 2 show the summary statistics of all the indices together with the Jarque-Bera normality test for both pre-crisis period (6 years) and the whole period (10.5 years). Of all the cases, Malaysia, Indonesia, Thailand, Singapore and Vietnam are negatively skewed except for the Philippines index with a positive skewness of 1.427 and 0.3798 in the two periods respectively. The Philippines also possess the highest kurtosis of 15.944 (6-year) and second highest of 11.705 (10.5-year) despite all others exhibit high kurtosis value of more than three. Furthermore, all of them are also highly significant in Jarque-Bera statistics which implied that their distributions are not normal. Comparatively, the trend movement of kurtosis value and the level of skewness between pre-crisis and the whole period are mixed for different countries. This is due to the capturing of extreme events that happens at different point of time in different stock exchanges.

Table 1
28/07/2000 – 25/07/2007 (6 years)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Variance</th>
<th>Stdev</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque-Bera statistic</th>
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<td>KLCI</td>
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Table 2
28/07/2000 – 31/12/2011 (10.5 years)

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Table 3 exhibits the summary statistics of filtered daily returns modified for heteroskedasticity and serial-correlation. Empirical studies strongly support that stochastic volatility in financial series are not necessarily independent (McNeil & Frey, 2000) and conditional extreme value theory should be considered by taking into account of the GARCH process. In addition, a study by Fernandez, V. (2003) on calculating Value-at-Risk (VaR) using EVT approach found that using conditional-EVT method is the most suitable way to compute VaR To determine the appropriate order of autoregressive and moving average (ARMA), we used the function “auto.arima” provided in the 'forecast' package from R. Whereas, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model of (1,1) is used to correct for heteroskedasticity in the residuals. After fitting the indexes into the ARMA-GARCH models, Stock Exchange of Thailand (THAI) reveals as the highest kurtosis and negative skewness of 31.86 and -2.216 respectively during the pre-crisis period. The Philippines (0.8402), Malaysia (0.1180) and Vietnam (0.3235) indexes are positively skewed after the ARMA-GARCH fit. However, in all other cases, high kurtosis value can still be observed except for Singapore FSSTI (2.217) and they are statistically significant in Jarque-Bera test indicating abnormality in the distributions even when they are corrected for current volatility during the pre-crisis period.

Table 3
28/07/2000 – 25/07/2007 (6 years)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Variance</th>
<th>Stdev</th>
<th>Skewness</th>
<th>Kurtosis</th>
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4.2 Extreme Value Theory (EVT)

We assume that the data is iid after the ARMA-GARCH fitting and Generalized Extreme Value (GEV) approach is chosen to analyze this data. In addition, we used 10-day and 20-day of blocks maxima and minima to accommodate with the paper (Ho, L.C. et al., 2000) that we are adhering in order for the results to be comparable. Although
the minima series are the main focus in this dissertation, given risk identification tends to investigate adverse loss of an asset. However, in this empirical analysis, maxima series are also included in order to further support the riskiness in pre-crisis period and the whole period rather than sole analysis in the minima series. For example, the fact that maxima series exhibit higher VaR values during the pre-crisis period and lower VaR values in the minima series than the whole 10.5-year period shows that pre-crisis period returns are less risky. Furthermore, investigating extreme values should both tails, i.e. minima and maxima of the distributions since the financial assets possess leptokurtic characteristics.

Table 4 shows the GEV parameter estimates of the shape $\xi$, location $\mu$, and scale $\beta$ together with the Value-at-Risk (VaR) at confidence level of 0.05 and 0.01 during the pre-crisis period. Whereas the whole period of 10.5 years of the similar parameter estimates is represented in Table 5 and their respective standard errors are in parenthesis.

**Figure 2**
The location parameter $\mu$, describes the position of the extreme distribution, deviates further from the origin as the block size increases. This happen for all cases shown in Table 4 and Table 5, for instance in the maxima series as the block size increases from 10-day to 20-day the location parameter increase to becoming more positive. On the other hand, the location parameter become more negative in the minima series as the block size increases from 10-day to 20-day. Next, the scale parameter $\beta$ which represents the dispersion of an extreme distribution has not much of difference between countries for maxima returns where they are all less than 1% except for Vietnam. Similarly for the minima returns, dispersion levels are all below one per cent except for Vietnam which is slightly above 1%. This shows that Vietnam had the highest scale factor during the pre-crisis period and for the 10.5 year period shown in Table 4 and Table 5 respectively. For the block minima returns as a whole, location parameter $\mu$ in the longer period is about 13.3% larger aggregately on average than the pre-crisis period; whereas the scale parameter $\beta$ values were 3.3% greater on average in the 10.5-year period. This means that on average, the pre-crisis period has less fluctuation in the SEA region than the whole period considered.

The most important factor is the shape parameter $\xi$, which has relation with the tail index, tells us the characteristic of the limiting extreme distribution. The shape parameters, in general, are all in positive sign except for Thailand in its maxima series but they are not statistically significant at 0.01. The shape parameter $\xi$ as explain earlier also shows the thickness and fatness of a tail distribution. The higher the value of $\xi$ represents thicker and fatter tails. As shown in Figure 2 above, the tail characteristics of Thailand 20-day block minima series is rather thicker and fatter on the left hand side which has a higher shaper parameter of 0.2564 and thinner on the right hand figure. Furthermore, the positive sign of shape parameters in minima and maxima returns indicate the characteristics of Frechet type distribution (Coles, 2001b).

The shape parameters are mostly decreasing for both maxima and minima series in comparison of the 6-year period (Table 4) with period ending December 2011 (Table 5). This indicates that most of them have fatter tails during the pre-crisis period. For
the maxima series, the shape parameter values for Indonesia, the Philippines and Vietnam are modestly more positive, while Singapore’s tail estimates in the reverse case are closer to zero. However, it experienced the greatest rise from 0.0250 to 0.0718 which is about 2.87 times greater. The estimate for Malaysia lies in between Singapore and the modestly positive countries. Nevertheless, Thailand’s tail index (-0.0958), the special case with negative sign, estimated from the 6-year period is about double the size of the 10.5-year period (-0.0454). Therefore, we can say that Thailand Stock Exchange exhibits a Weibull type distribution statistically based on the shape parameter in the maxima series. For the minima series in 20-day block length, shape parameters for all the countries fell from pre-crisis period (6-year) to the 10.5-year period. The ξ parameter for Malaysia, Indonesia, and the Philippines decline about 19.7%, 8.2%, and 1.9% respectively; while Thailand and Singapore slumped considerably at 39.0% and 62.0% respectively. However, Vietnam, the highest fall shape parameter, dropped almost 6 times from 0.3122 to 0.0527 in the longer period analysis.
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4.3 Value-at-Risk (VaR) computations using EVT

Using the asymptotic distribution of extreme value returns, we can compute the Value-at-Risk (VaR) which is the quantile risk measure of the parent distribution instead of the extreme distribution. This is because, we are interested in the portfolio value loss that we would incurred investing in the index as a whole and not losses in the tail distribution itself. There are various computation methods used in many different studies such as McNeil, A.J. (1999), Longin, F.M. (2000), Gencay and Selcuk (2004), and Dowd, K. (2005) to calculate VaR under extreme value analysis. We found that the method suggested by Ho, et al. (2000) make more sensible quantile measure. The computation of VaR from Ho, et al. (2000) for different confidence levels or probability values that can be written as,

\[
VaR_{\text{long}} = -\mu_n^{\text{min}} - \frac{\beta_n^{\text{min}}}{\xi_n^{\text{min}}}[1 - (-\ln p)^{-\xi_n^{\text{min}}}] 
\]

for long position, and similarly short position can then be defined as,

\[
VaR_{\text{short}} = \mu_n^{\text{max}} - \frac{\beta_n^{\text{max}}}{\xi_n^{\text{max}}}[1 - (-\ln p)^{-\xi_n^{\text{max}}}] 
\]

where \(\xi_n^{\text{max}}\) and \(\xi_n^{\text{min}}\) are the shape parameter in \(n\)-block size for maxima and minima series respectively. This goes similar with the scale parameter \(\beta_n^{\text{max}}\) and \(\beta_n^{\text{min}}\); location parameter \(\mu_n^{\text{max}}\) and \(\mu_n^{\text{min}}\) as well. However, we used the VaR function created in R commands (refer Appendix) based on the teaching material by Tsay, R.S. (2012) which is slightly different from the expression above. To calculate the 95% and 99% VaR values presented in Table 4 for the pre-crisis period and in Table 5 for the 10.5-year period, the expression used in the R command was based on the paper by Tsay, R.S. (2009) as follows,

\[
VaR = \begin{cases} 
\mu_n - \frac{\beta_n}{\xi_n}[1 - (-n \ln(1-p)^{-\xi_n})] & \text{if } \xi_n \neq 0 \\
\mu_n - \beta_n \ln[-n \ln(1-p)] & \text{if } \xi_n = 0 
\end{cases}
\]
The reported VaR returns will be expressed in terms of profit or loss as if an investment portfolio is held. Thus, for the maxima series of log returns of KLCI 20-day block length during pre-crisis period, the 95% confidence level VaR is 0.027904 and an investor who holds along position of £10,000,000 would have a five percent chance of getting a profit not more than £279,040 a day. Else in the minima series, the 1-day horizon VaR of 95% quantile for the similar asset is 0.020935. Hence, with the same amount of investment, an investor would incur losses of not more than £209,350 a day. Using the same asset of KLCI for 10-day block length minima series, the VaR value for 5% significance level is 0.014297 which gives an investor who holds £10,000,000 in the investment a maximum loss of £142,970 in a day. In this particular case, the bigger block sizes of \( n = 20 \) gives a higher VaR value. Nevertheless, in general, 95% VaR values for six countries in maxima series and 20-day block length is 47.8% on average greater than the 10-day block length, while it is about 25.6% larger on average for the 95% VaR values in minima series. Moreover, the longer period (10.5 years) VaR values for minima series are on average 15.5% larger than the pre-crisis period (6-year). This is reverse for the case of maxima series, where the average VaR value is about 30.1% lower in the 10.5-year period.

This analysis starts by reporting the pre-crisis VaR values shown in Table 4. An investor is assumed to hold £10,000,000 long position portfolio for any single index and VaR values are described in terms of portfolio gains and losses. From the 20-day block length for 95% VaR in the minima series of pre-crisis period, the lowest maximum loss an investor could expect is about £209,350 a day investing in Malaysia. However, the highest maximum VaR an investor could expect from is investing in Indonesia with maximum loss of £387,280 in a day. This figure does not vary much among other countries which the VaR values range between £330,000 and £386,000 of loss a day.

On the other hand, the maxima series in Table 4 shows the profit an investor who holds long position could expect with a particular confidence level. For example, the highest maximum profit an investor could expect is about £647,450 a day, if invest in Thailand with 5% significance level. With 95% confidence level, investing in Indonesia index and Singapore index could gain an investor a maximum profit of
£370,000 and £394,010 a day. The Philippines and Vietnam possess rather modestly high VaR values of £430,510 and £501,140 gain in a day respectively while the lowest maximum gain an investor could expect is investing in Malaysia with VaR values only about £279,040.

Next, the analysis continues with 10.5-year period represented in Table 5, focusing on the 20-day block length for the 95% VaR in the minima series. The 95% VaR for Malaysia is the lowest among the six countries where an investor who invest similarly, £10,000,000 would expect about £242,100 of maximum loss in a day, while the highest 95% VaR goes to Vietnam which is about £616,300 a day. The Philippines, Thailand and Indonesia are nearly the same where investors would expect maximum loss ranging from £300,000 to £400,000 in a day. However, Singapore is somewhat riskier with VaR value of £424,400 loss in a day. On the contrary, the maxima series basically exhibits the maximum gain an investor could make in a day with certain level of confidence investing in any one of the indexes. For the longer period investment (10.5 years), an investor who holds £10,000,000 long position would expect to gain the highest maximum profit of £493,600 a day if invest in Vietnam index with 5% chance. However, if invest in Malaysia index, it would be the lowest maximum gain of £283,000 a day and investing in the remaining countries, i.e. Indonesia, the Philippines, Thailand, and Singapore, the maximum VaR range between £348,200 and £481,800 a day.

4.3.1 Comparison of Extreme Value VaR with Traditional methods

The comparison of extreme value approach VaR with traditional methods, i.e. variance-covariance (Var-Cov) and historical simulation is presented in Table 6. It shows only the minima return series for both pre-crisis and the whole period since losses caused by the financial turmoil is the main interest. The VaRs using the Var-Cov method for 95% confidence level are generally greater than estimations using historical simulation. Their values differ from a low of 1% for Singapore during the whole period to a high of 13.9% greater for Thailand during the pre-crisis period. However, almost all the 99% confidence level VaR using the historical simulation method is greater than Var-Cov approach and they range from 2% greater (the Philippines) to 36.7%
(Vietnam). This situation is similar to the Ho, et al. (2000) paper where the estimation of VaR using the variance-covariance method is higher than historical simulation at 95% confidence level and the reversed at 99% confidence level.

In Table 6, values of VaR using the extreme value approach show that they are generally larger than the VaR computed using the Var-Cov and historical simulation. This is true for all 95% confidence level cases of VaR, both pre-crisis and the whole 10.5-year period, which is about 20% to 90% greater. For the case of Vietnam, the value is almost doubled compared to traditional methods. As for the 99% confidence level of VaR, the extreme value approach also shows significantly larger VaR values compared to variance-covariance and historical simulation method for the whole 10.5-year period, while most of them during pre-crisis period. In general, these results support the view that variance-covariance method (normal distribution assumptions) underestimates VaR of financial returns with fat-tails and suggests that extreme value approach is rather appropriate for banking institutions to apply in their internal VaR models in evaluating market risk positions and capital adequacy.
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*VaR values in Table 6 are expressed as x% of the position.*
4.4 **Bivariate Extreme Value Distribution**

In this section, we investigate the extreme events of two stock indexes jointly in order to establish their relationships during the examined period. This is known as the bivariate extreme value that only focus on two extreme variables at any point of time instead of multivariate extreme which consider two or more factors and can be very complicated. Studies on multivariate extremes has been given attention in modeling rare events such as, sea levels (Tawn, 1988), wave and storm surge events (Galiatsatou & Prinos, 2011), and in financial area (Brodin & Kluppelberg, 2010). In another study by (Poon, S.H. et al., 2004) paper, it demonstrates how joint-tail distribution can be modeled using parametric approach for calculating Value-at-Risk (VaR). A relationship among the extreme components, which is known as the extremal dependence structure in the extreme value literature, explains the tail behavior of two risk factors that we are interested in. Conventionally, evaluating risk of two financial assets jointly using the normal assumptions is done by applying Markowitz modern portfolio theory of portfolio variance (Reilly & Brown, 2006) which can be computed as follows,

\[
\sigma_{\text{port}}^2 = w_a^2 \sigma_a^2 + w_b^2 \sigma_b^2 + 2w_a w_b \sigma_a \sigma_b \rho_{ab}
\]

where \(w_a\) and \(w_b\) are the weightage of asset \(a\) and \(b\) in the portfolio, \(\sigma_a\) and \(\sigma_b\) are the standard deviation of the risk in asset \(a\) and \(b\), while \(\rho_{ab}\) is the correlation between asset \(a\) and \(b\). Hence, to achieve at the minimum portfolio risk, the most common way is to identify the lowest correlation value between asset \(a\) and \(b\).

Table 7 below shows the maximum likelihood estimates (MLE) and standard errors for logistic model fitted to bivariate series of minima returns for both the pre-crisis and 10.5-year period. The higher value of \(\hat{\alpha}\) shows the weaker relationship of extremal events between the two countries (Coles, 2001a). According to the results, Vietnam has very weak dependence measure across all other SEA countries with \(\hat{\alpha} > 0.9\). This generally indicates that rare events hardly occur in Vietnam given that when extremal events happened in other countries. Stronger relationship can be seen when the 2007/2008 financial crisis took place are countries like KLCI-FSSTI, JCI-THAI, JCI-
FSSTI, and THAI-FSSTI with dependence parameter of about 0.60 to 0.668. In short, extreme loss events are more likely for Singapore, Malaysia, Thailand, and Indonesia to happen concurrently in any two of these countries.

Figure 3 below illustrates the scatter plots of series of minima returns contrasting stronger and weaker $\hat{\alpha}$ estimates which give better graphical view of the bivariate extreme events. The left figure shows scatter plot of Indonesia and Singapore extreme minima returns series with the highest dependence estimate (0.605), tend to trend towards the lower-left corner of the plot. This shows that Indonesia index is likely to incur higher losses given when it is also happen to Singapore index. On the right figure, the plot illustrates the lowest alpha estimate of 0.999, which scarcely indicate any dependency in the series.

*Figure 3*

Next, Table 8 shows the comparisons of dependence estimates $\hat{\alpha}$ between pre-crisis period and the whole period shown in Table 7. Apparently, most of them with $\hat{\alpha}$ less than 0.9 dropped at the range from 5% to 17.4% in the whole period. As mentioned above that lower value of dependence estimates indicates stronger relationships of extreme events between two variables, all indexes except Vietnam move in tandem to our expectations. For example, the dependence estimates for...
Indonesia and Thailand dropped about 15.8% to $\hat{\alpha} = 0.668$. This indicates that during the period with crisis events, both countries happened to suffer the impact concurrently, i.e. Indonesia would most likely experience extreme losses given that Thailand correspondingly suffered a loss from extreme events. Generally, almost all the dependence parameter slumped during the whole period which include financial crisis, i.e. extreme events, additively supports the analysis of VaR values in the previous chapter that most of the indexes have higher VaR values during crisis.

Nevertheless, it is not possible for this analysis to conclude that there is a direct relationship between the change of dependence estimates and the change in VaR values from pre-crisis to the whole period. For example, it is not true to infer that if the dependence estimates fell during the crisis period, i.e. stronger relationships among extreme events, then it reflects higher VaR values in both of the indexes. This is because for the case of the Philippines and Thailand, their dependence estimates dropped 10.8% which shows stronger relationship yet their VaR values become lower in the crisis period (10.5-year). Another example is the pair of Malaysia and the Philippines where stronger dependence estimate was shown but change in VaR values were mixed. Therefore, it is sensible to conclude that from this analysis, the VaR measure has little or no direct influence to the changes of $\hat{\alpha}$ as both measures interpret different point of views in risks.
### Table 7
*Dependence parameter estimate, $\hat{\alpha}$ and standard error*

<table>
<thead>
<tr>
<th>Pre-crisis</th>
<th>Whole period</th>
</tr>
</thead>
<tbody>
<tr>
<td>JCI</td>
<td>JCI</td>
</tr>
<tr>
<td>KLCI</td>
<td>0.7867</td>
</tr>
<tr>
<td></td>
<td>(0.0768)</td>
</tr>
<tr>
<td>JCI</td>
<td>0.7138</td>
</tr>
<tr>
<td></td>
<td>(0.0672)</td>
</tr>
<tr>
<td>PCOMP</td>
<td>0.8616</td>
</tr>
<tr>
<td></td>
<td>(0.0672)</td>
</tr>
<tr>
<td>THAI</td>
<td>0.8187</td>
</tr>
<tr>
<td></td>
<td>(0.0818)</td>
</tr>
<tr>
<td>FSSTI</td>
<td>0.6847</td>
</tr>
<tr>
<td></td>
<td>(0.0767)</td>
</tr>
<tr>
<td>VN</td>
<td>0.9993</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
</tr>
</tbody>
</table>

### Table 8
*Comparison of dependence parameter estimate $\hat{\alpha}$ from pre-crisis period (6 years) to whole period (10.5 years)*

<table>
<thead>
<tr>
<th></th>
<th>KLCI</th>
<th>JCI</th>
<th>PCOMP</th>
<th>THAI</th>
<th>FSSTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>JCI</td>
<td>-9.7%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PCOMP</td>
<td>-15.6%</td>
<td>-16.5%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>THAI</td>
<td>-4.6%</td>
<td>-15.8%</td>
<td>-10.8%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FSSTI</td>
<td>-10.2%</td>
<td>-9.9%</td>
<td>-10.2%</td>
<td>-17.4%</td>
<td></td>
</tr>
<tr>
<td>VN</td>
<td>0.1%</td>
<td>-1.9%</td>
<td>-0.2%</td>
<td>1.4%</td>
<td>-5.0%</td>
</tr>
</tbody>
</table>
Chapter 5 - Discussion

In this section, findings of the research will be discuss in more detail by comparing results with published papers, mainly from Ho, et al. (2000). Furthermore, this section will also incorporates room of improvements for this dissertations and motivations of further researching area.

The empirical analysis conducted in this dissertation mimics closely to Ho, et al (2000) as the main objective is to establish differences of impact between financial crisis in the late 1990s and the one in 2007-08 towards almost similar region of markets. As both research found that Asian countries are all characterized with fat tail return distributions, extreme value approach is utilized. Moreover, analyses show that traditional methods irrelevantly underestimate the VaR values. As a result, this research is executed by analyzing two different periods, i.e. pre-crisis period from year 2000 to mid-2007 and the whole period of 2000 to year end 2011.

From the results in this dissertation solely, the 2007-08 financial turmoil that hits the global financial markets has definite impact towards the South East Asia region. This could be observed from the VaR values of the minima series in pre-crisis period and the whole period. VaR values during the whole period for all the countries researched are generally higher and indicates that SEA financial markets suffer a certain weight of losses compare to lower VaR values in the pre-crisis period. The statement above is further supported by the opposite effect of the VaR values in maxima series that the VaR values are higher in general for all countries during the pre-crisis period. This indicates that profits in the whole period are torn down lower when accounting for return data involving crisis effects. These analysis outcomes generally met the initial expectations of this research and bivariate extreme value analysis was also conducted to see the relationship of extreme minima returns between pair of countries. It is found that stronger relationship within countries like Singapore, Malaysia, Thailand, and Indonesia infer that the 2007-08 financial turmoil affects these markets somewhat concurrently. Apart from the status of country developments itself, it might be the
factor of geographical locations, i.e. these four countries which are more neighboring to each other than the Philippines and Vietnam. This gives a possible explanation for stronger relationship in rare events and the suffering the impact of the crisis.

Next, the results in this study suggest that South East Asia markets are more resilient against the 2007-08 financial crises than the one happened a decade ago. This is shown graphically in Appendix 3 through the plots of the raw data indexes where most of them are able to restore their normal position and continue to accelerate upwards after the crisis. Statistically, by comparing the results in the published paper of Ho, et al. (2000), it is very noticeable from the VaR values that the 1998 Asian financial crisis researched by Ho et al. has higher impact towards the Asian countries. The fluctuations are also greater during the investigated year from 1984 to 1998 as their maxima series exhibit significantly higher VaR values. Therefore, in short, financial markets in the SEA region are said to be affected but with lower impact in the recent global financial catastrophe compared to the financial crisis in the late 1990s.

There are definitely rooms for improvements in this dissertation; one of them is back-testing VaR values. The VaR quantile measure used excessively in various studies should be evaluated to test its reliability and accuracy in the estimated model. Ho, et al. (2000) presented an evaluation on the VaR estimations by identifying number of exceedance based on frequency test. The objective is to test whether the observed frequency of returns that exceed VaR is consistent with the frequency of tail returns estimated by the model (Dowd, 2005). Therefore, in this dissertation, there is generally no empirical basis indicating that the VaR measures are accurate or reliable.

A minor conflict in this study comparing to Ho, et al. (2000) might arise in the range of period considered as the whole period, i.e. from 2000 to 2011, where there is three extra years of data after the global 2007-08 financial crisis. In Ho, et al. (2000) paper, the data considered that inclusive of Asian crisis period was from 1984 to 1998 which ended slightly after the crisis subsided. This might raise concerns that VaR values in this dissertation might underestimate the loss return due to buffering of three extra
years from year 2009 to 2011, and not limiting the data up to year 2008. Nevertheless, there is another major problem if data is constrained up to year 2008. Since going backward of time, prior year 2000, will not only overlap with the Asian financial crisis effect, data for Vietnam is not available then, but also data scarcity for extreme value approach. Therefore, going forward in time would be the most sensible way to overcome these problems.

The next improvement this dissertation could make is to adopt the other method of estimating extreme value approach which claimed to be more efficient, i.e. Generalized Pareto distribution method (GPD) (Gencay & Selcuk, 2004). This technique would extract different format of data distribution based on a pre-determined threshold and assured with more abundant data compare to GEV method. Furthermore, using the GPD would allow the further added value topic in this dissertation, i.e. bivariate extreme value analysis, to extend its content more into detail. Moreover, a more appropriate estimation of extremal dependence structure proposed by Coles et al. (1999) and Poon et al. (2004) can be conducted applying threshold data format. This is especially shown in the study by Galiatsatou & Prinos (2011) mentioned in the literature review in modeling bivariate extreme value distribution.

Future researches could be done based on the emerging idea from this dissertation is multivariate or bivariate extreme value analysis focusing on Asian financial markets. As the oriental countries are rapidly emerging and positioning significant feature on the globe, more specialize researches should be done to grasp better understanding of the developments of financial theme in these countries. Moreover, research on multivariate or bivariate extreme value analysis is rather new in the financial area and potential researching in these areas would definitely benefit both the academia and practical world.
Chapter 6 - Conclusion

The recent financial turmoil in 2007-08 assertively brought disastrous effect to the whole financial globe due to the complex risk involved in subprime-mortgage, credit crunch, and short-term derivative securities to name a few. The more complicated understanding of risks will result tougher quantifying methods to estimate them. Risk management is all about being conservative and precautionary where misjudged should never be lower, i.e. overstating risks is always better than the opposite in terms of preventing disastrous events.

Therefore, the traditional methods and normal assumptions in computing the VaR values are no doubt underestimated the relevant and ‘true’ risk position in the financial markets. Instead, emphasis on the tail distributions analysis should be performed and has much more satisfactory sense. This is supported in this study that volatile fluctuations during financial turmoil should be accommodated with extreme value analysis rather than relying on unrealistic traditional methods.

Eventually, VaR measures shown in this dissertation also concludes that Asian markets are more resilient against the recent financial downturn which might indicates that certain precautious steps were taken in these countries and that they are able to buffer the crisis impact. Furthermore, the close and stronger relationship of extreme values within most of the Southeast Asia countries might indicate similar financial strategies are used that caused them to pick up virtually similar impacts during crisis. Hence, this research suggests that risk position in the Southeast Asia are much better of compare to the past decades when the 1997-98 Asian financial crisis outburst in the region.
References


Appendix 1 – Log-return of all six indices during pre-crisis and whole period
Appendix 2 – Two methods in identifying extreme data

Adapted from (Gilli & Këllezi, 2006), “An Application of Extreme Value Theory for Measuring Risk”

The left figure shows the first method mentioned in the research i.e. block maxima, and in this case, the observations $X_2, X_5, X_7$, and $X_{11}$ are the extreme events for the four sub-periods.

Meanwhile the right figure represents the threshold method which observations are retrieved beyond a determined threshold $u$. Here, observations $X_1, X_2, X_7, X_8, X_9$ and $X_{11}$ exceed the threshold and constitute extreme events.
Appendix 3 – Graphs of index price for all six countries
Appendix 4 – R-Commands

The R commands would be lengthy and repetitious to show all six indexes, therefore only one index of commands and output will be presented. The remaining five indexes exhibit similar results. However, the overall analysis of bivariate extreme value distribution will show for all indexes.

#loading raw data into R

```r
> library(zoo)
> library(quantmod)
> library(timeSeries)
> library(tseries)
> library(fBasics)
> myformat="%e/%m/%Y"
> klci=read.zoo("KLCI.csv",header=T,format=myformat,sep=" ","
> klci=as.timeSeries(klci)
> klci=klci[,1]
> head(klci)
GMT     KLCI
2000-01-03 833.89
2000-01-04 832.80
2000-01-05 815.80
2000-01-06 818.43
2000-01-11 846.74
2000-01-12 869.62
```

#Rename indexes

```r
> names(klci)="KLCI"
```

#Combine all the indexes

```r
> allse=cbind(klci,jci,pcomp,thai,sti,vn)
```

#Removing the NAs

```r
> allse=allse[complete.cases(allse),]
> tail(allse)
GMT     KLCI JCI   PCOMP THAI FSSTI VN
2011-12-27 1484.98 3794.27 4368.88 1043.75 2673.32 367.72
2011-12-28 1491.46 3795.44 4370.46 1042.52 2664.80 360.37
2011-12-29 1496.15 3797.15 4372.24 1037.37 2676.47 356.21
2011-12-30 1500.91 3789.43 4361.43 1028.38 2673.62 347.80
2011-12-31 1504.11 3769.21 4336.63 1028.19 2666.25 350.66
2011-12-31 1506.69 3808.77 4371.96 1023.91 2672.78 350.51
```

#Computing log-returns

```r
> l.dse <- diff(log(allse))
> dse=l.dse[-1,]
```
> head(dse)

<table>
<thead>
<tr>
<th></th>
<th>GMT</th>
<th>KLCI</th>
<th>JCI</th>
<th>PCOMP</th>
<th>THAI</th>
<th>FSSTI</th>
<th>VN</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>0.0003254231</td>
<td>-0.013342317</td>
<td>-0.013951352</td>
<td>-0.02405239</td>
<td>0.006941671</td>
<td>0.01538110</td>
<td>0.007711011</td>
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<tr>
<td>2000</td>
<td>0.0046210803</td>
<td>-0.003574086</td>
<td>-0.003109609</td>
<td>0.05651028</td>
<td>0.0007109449</td>
<td>0.01745178</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.0154066057</td>
<td>0.007562521</td>
<td>0.026824702</td>
<td>0.03330159</td>
<td>0.007109449</td>
<td>0.01745178</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.0008961179</td>
<td>-0.007344372</td>
<td>-0.000744499</td>
<td>0.01520720</td>
<td>0.002042607</td>
<td>0.01621759</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.0145104878</td>
<td>0.030608561</td>
<td>0.016930550</td>
<td>0.03170387</td>
<td>0.020580877</td>
<td>0.03166686</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.0098450888</td>
<td>-0.018741487</td>
<td>-0.001214412</td>
<td>0.03372676</td>
<td>0.039996297</td>
<td>0.03069477</td>
<td></td>
</tr>
</tbody>
</table>

#The Jarque-Bera test
> jarqueberaTest(dse[,1])
Title: Jarque - Bera Normality Test
Test Results:
STATISTIC:
  X-squared: 13671.8656
P VALUE:
  Asymptotic p Value: < 2.2e-16

#Fitting into ARMA-GARCH model
> library(fGarch)
> library(rugarch)
> library(forecast)

#Removing the mean
> dser=dse-colMeans(dse)
> head(dser)

<table>
<thead>
<tr>
<th></th>
<th>GMT</th>
<th>KLCI</th>
<th>JCI</th>
<th>PCOMP</th>
<th>THAI</th>
<th>FSSTI</th>
<th>VN</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>0.006075391</td>
<td>-0.013457527</td>
<td>-0.014446280</td>
<td>-0.02433450</td>
<td>0.000826461</td>
<td>0.01488617</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.0037167881</td>
<td>-0.004132012</td>
<td>-0.003668328</td>
<td>0.05560599</td>
<td>0.007153084</td>
<td>0.01730151</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.0149116777</td>
<td>0.007280405</td>
<td>0.026709492</td>
<td>0.03280666</td>
<td>-0.007391565</td>
<td>0.01733657</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.014548372</td>
<td>-0.008248664</td>
<td>-0.001302426</td>
<td>0.01576592</td>
<td>0.001138315</td>
<td>0.01565966</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.0146256977</td>
<td>0.030113633</td>
<td>0.016984343</td>
<td>0.03158656</td>
<td>0.020085949</td>
<td>0.03138474</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>0.0098271622</td>
<td>-0.019300206</td>
<td>-0.002118704</td>
<td>0.03316884</td>
<td>0.039437577</td>
<td>0.02979048</td>
<td></td>
</tr>
</tbody>
</table>

#Retrieve appropriate ARMA order
#KLCI
> auto.arima(dser[,1])
Series: dser[, 1]
ARIMA(0,0,1) with zero mean
Coefficients:
  ma1
  0.1091
s.e.  0.0206
sigma^2 estimated as 0.0001059:  log likelihood=7098.34
AIC=-14192.67  AICC=-14192.67  BIC=-14181.24
> uspeck <- ugarchspec(variance.model=list(garchOrder=c(1,1)),
mean.model=list(armaOrder=c(0,1), include.mean=TRUE),distribution.model = 'ged')
> ugfk <- ugarchfit(uspeck,data=dser[,1])
> ugfk

*-----------------------------------------------------*
*          GARCH Model Fit                             *
*-----------------------------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model : sGARCH(1,1)
Mean Model    : ARFIMA(0,0,1)
Distribution : ged

Optimal Parameters
------------------------------------
| Estimate | Std. Error | t value | Pr(>|t|) |
|-----------|------------|---------|---------|
| mu        | 0.000050   | 0.000125| 0.40038 | 0.688875|
| ma1       | 0.076122   | 0.022881| 3.32685 | 0.000878|
| omega     | 0.000001   | 0.000000| 2.52726 | 0.011496|
| alpha1    | 0.086391   | 0.019307| 4.47459 | 0.000008|
| beta1     | 0.905861   | 0.019609| 46.19667| 0.000000|
| shape     | 1.121836   | 0.041085| 27.30549| 0.000000|

Robust Standard Errors:
------------------------------------
| Estimate | Std. Error | t value | Pr(>|t|) |
|-----------|------------|---------|---------|
| mu        | 0.000050   | 0.000124| 0.4043  | 0.685995|
| ma1       | 0.076122   | 0.026985| 2.8208  | 0.004790|
| omega     | 0.000001   | 0.000001| 1.7321  | 0.083257|
| alpha1    | 0.086391   | 0.029272| 2.9513  | 0.003165|
| beta1     | 0.905861   | 0.031352| 28.8935 | 0.000000|
| shape     | 1.121836   | 0.053513| 20.9640 | 0.000000|

LogLikelihood : 7566.571

Information Criteria
------------------------------------
| Akaike     | -6.7265    |
| Bayes      | -6.7112    |
| Shibata    | -6.7265    |
| Hannan-Quinn | -6.7209    |

Q-Statistics on Standardized Residuals
------------------------------------
| statistic | p-value   |
Lag10     27.45  0.001177
Lag15     30.38  0.006772
Lag20     37.37  0.007122

H0: No serial correlation

Q-Statistics on Standardized Squared Residuals
---------------------------------------------
          statistic   p-value
Lag10     2.563   0.9791
Lag15     5.417   0.9791
Lag20     7.769   0.9888

ARCH LM Tests
---------------------------------------------

<table>
<thead>
<tr>
<th>Statistic</th>
<th>DoF</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARCH Lag[2]</td>
<td>2</td>
<td>0.6339</td>
</tr>
<tr>
<td>ARCH Lag[5]</td>
<td>5</td>
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</tr>
<tr>
<td>ARCH Lag[10]</td>
<td>10</td>
<td>0.9905</td>
</tr>
</tbody>
</table>

Nyblom stability test
---------------------------------------------

Joint Statistic:  95.462
Individual Statistics:
mu  0.29400
ma1 0.04333
omega 20.26483
alpha1 0.11301
beta1 0.14877
shape 0.07267

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic: 1.49 1.68 2.12
Individual Statistic: 0.35 0.47 0.75

Sign Bias Test
---------------------------------------------

<table>
<thead>
<tr>
<th>t-value</th>
<th>prob</th>
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<tbody>
<tr>
<td>Sign Bias</td>
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<tr>
<td>Negative Sign Bias</td>
<td>0.8943</td>
<td>0.3712</td>
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<tr>
<td>Positive Sign Bias</td>
<td>0.8420</td>
<td>0.3999</td>
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<tr>
<td>Joint Effect</td>
<td>1.5875</td>
<td>0.6622</td>
</tr>
</tbody>
</table>

Adjusted Pearson Goodness-of-Fit Test:
---------------------------------------------

<table>
<thead>
<tr>
<th>group statistic</th>
<th>p-value(g-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 20</td>
<td>29.06 0.064984</td>
</tr>
</tbody>
</table>
> ugarchforecast(ugfk)

*------------------------------------*
*       GARCH Model Forecast       *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast:

<table>
<thead>
<tr>
<th></th>
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<th>series</th>
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<tr>
<td>2012-01-12</td>
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<td>5.015e-05</td>
</tr>
</tbody>
</table>

#Estimating volatilities for demean KLCI
> volk <- sigma(ugfk)
> head(volk)
[1] 0.010296997 0.009858560 0.009504852 0.010065072 0.009667812 0.010192174
> fc=ugarchforecast(ugfk)
> vol.p=as.data.frame(fc)[1,1]
#Obtaining the constant
> st=vol.p/volk
> head(st)
[1] 0.7440391 0.7771285 0.8060481 0.7611836 0.7924614 0.7516913
> dser1.adj=dse[,1]*st
> dser1=dser1.adj+mean(dse[,1])
# Volatility adjusted KLCI index

```r
> head(dser1)

<table>
<thead>
<tr>
<th>GMT</th>
<th>KLCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-07-31</td>
<td>3.998858e-05</td>
</tr>
<tr>
<td>2000-08-02</td>
<td>3.873289e-03</td>
</tr>
<tr>
<td>2000-08-04</td>
<td>1.270058e-02</td>
</tr>
<tr>
<td>2000-08-07</td>
<td>-3.999942e-04</td>
</tr>
<tr>
<td>2000-08-11</td>
<td>-1.121689e-02</td>
</tr>
<tr>
<td>2000-08-16</td>
<td>7.682584e-03</td>
</tr>
</tbody>
</table>
```

# ARMA-GARCH fitted distribution

```r
> dse.fit2=cbind(dser1,dser2,dser3,dser4,dser5,dser6)

# Extracting maxima and minima series
# 10-day block maxima
```r
```r
> for(i in 1:dim(max.return)[1]){  
+   max.return[,]=apply(dse.fit2[((i-1)*10+1):(i*10),],2,max)
+ }
```
```r
> max.return=matrix(ncol=6,nrow=floor(dim(dse.fit2)[1]/10))
> for(i in 1:dim(max.return)[1]){  
+   max.return[,]=apply(dse.fit2[((i-1)*10+1):(i*10),],2,max)
+ }
```

# 10-day block minima

```r
> min.return=matrix(ncol=6,nrow=floor(dim(dse.fit2)[1]/10))
> for(i in 1:dim(min.return)[1]){  
+   min.return[,]=apply(dse.fit2[((i-1)*10+1):(i*10),],2,min)
+ }
```

# Flipping the minima return to positive sign

```r
> min.return=-min.return
```

# Fitting extreme values into 'fExtremes' package for function gevFit

```r
> fitkl.max=gevFit(max.return[,1])
> fitkl.max

Title:
GEV Parameter Estimation
Call:
  gevFit(x = max.return[, 1])
Estimation Type:
  gev mle
Estimated Parameters:
  xi  mu  beta
  0.117683613  0.009013239  0.004753373
```
> fitkl.min=gevFit(min.return[,1])
> fitkl.min

Title:
GEV Parameter Estimation
Call:
gevFit(x = min.return[, 1])
Estimation Type:
gev mle
Estimated Parameters:

<table>
<thead>
<tr>
<th>xi</th>
<th>mu</th>
<th>beta</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.182369225</td>
<td>0.007459078</td>
<td>0.004609729</td>
</tr>
</tbody>
</table>

#Extracting all parameter estimates
> cbind(fitkl.max@fit$par.est,fitjc.max@fit$par.est,fitpc.max@fit$par.est,fitth.max@fit$par.est,fitsti.max@fit$par.est,fitvn.max@fit$par.est)

<table>
<thead>
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<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>xi</td>
<td>0.117683613</td>
<td>0.208283185</td>
<td>0.257315270</td>
<td>-0.095803665</td>
<td>0.025039039</td>
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<tr>
<td>mu</td>
<td>0.009013239</td>
<td>0.020713508</td>
<td>0.020980193</td>
<td>0.022284623</td>
<td>0.017043309</td>
</tr>
<tr>
<td>beta</td>
<td>0.004753373</td>
<td>0.005913265</td>
<td>0.008721529</td>
<td>0.008472684</td>
<td>0.005747287</td>
</tr>
</tbody>
</table>

# Computing VaR estimates
#VaR formula obtain from Dr. Lee Fawcett
>`"evtVaR" <- function(xi,mu,sigma,n=20,prob=0.01){
  +  # Comput VaR using the block maximum.
  +  # sigma: scale parameter (It is the alpha_n in the textbook)
  +  # mu: location parameter (It is the beat_n in the textbook)
  +  # For long position: mu = -beta_n
  +  # For short position: mu = beta_n
  +  # xi: shape parameter (It is the -k_n of the textbook)
  +  # n: block size
  +  # p: tail probability
  +  if (abs(xi) < 0.00000001)
  +    VaR = mu + sigma*log((-n)*log(1-prob))
  +  else if (abs(xi) >= 0.00000001){
  +    v1=1.0-(-n*log(1.0-prob))^{|-xi|}
  +    VaR = mu - (sigma/|x|)*v1
  +  }
  +  print(VaR)
  +  evtVaR<-list(VaR = VaR)
  + }`
# Build matrix \( y \) of EVT parameter estimates
\[
> y = \text{cbind}(\text{fitkl.max@fit$par.est}, \text{fitjc.max@fit$par.est}, \text{fitpc.max@fit$par.est}, \text{fitth.max@fit$par.est}, \text{fitsti.max@fit$par.est}, \text{fitvn.max@fit$par.est})
\]
\[
> y = t(as.data.frame(y))
\]
\[
> y[1,]
\]
\[
\begin{array}{ccc}
V1 & 0.11768361 & 0.009013239 & 0.004753373 \\
\end{array}
\]

# VaR value for whole period 10-day block maxima series
\[
> \text{evtVaR}(y[1,1], y[1,2], y[1,3], n=10, \text{prob} = c(0.05, 0.01))
\]
\[
[1] 0.01231463 0.02155346
\]

# VaR values for whole period 10-day block minima series
# according to the formula, long position \( \mu \) is negative in value
\[
> u = y[,2] - 1
\]
\[
> y = \text{cbind}(y[,1], u, y[,3])
\]
\[
> y[1,]
\]
\[
\begin{array}{ccc}
V1 & 0.182369225 & -0.007459078 & 0.004609729 \\
\end{array}
\]
\[
> \text{evtVaR}(y[1,1], y[1,2], y[1,3], n=10, \text{prob} = c(0.95, 0.99)) # n=10,
\]
\[
[1] -0.01913860 -0.02016413
\]

# Extracting 20-day block maxima and minima
\[
> \text{max.return} = \text{matrix}(\text{ncol}=6, \text{nrow} = \text{floor}(\text{dim(dse.fit2)[1]/20}))
\]
\[
> \text{for(i in 1:dim(max.return)[1])}{
+ \text{max.return}[i,] = \text{apply}(\text{dse.fit2}[((i-1)*20+1):(i*20),],2, \text{max})
+ }
\]
\[
> \text{min.return} = \text{matrix}(\text{ncol}=6, \text{nrow} = \text{floor}(\text{dim(dse.fit2)[1]/20}))
\]
\[
> \text{for(i in 1:dim(min.return)[1])}{
+ \text{min.return}[i,] = \text{apply}(\text{dse.fit2}[((i-1)*20+1):(i*20),],2, \text{min})
+ }
\]
\[
> \text{min.return} = \text{min.return}
\]

# Fitting into `fExtremes` of function `gevFit` to obtain parameter estimates
# Maxima
\[
> \text{fitkl.max = gevFit(max.return[,1])}
\]
\[
> \text{fitkl.max}
\]
\[
\begin{array}{l}
\text{Title:} \\
\text{GEV Parameter Estimation} \\
\text{Call:} \\
\text{gevFit(x = max.return[, 1])} \\
\text{Estimation Type:}
\end{array}
\]
gev mle
Estimated Parameters:
\[
x_i \hspace{1cm} \mu \hspace{1cm} \beta
\]
0.136832753 0.012628017 0.004989277

#Minima
> fitkl.min=gevFit(min.return[,1])
> fitkl.min
  Title: GEV Parameter Estimation
  Call: gevFit(x = min.return[, 1])
  Estimation Type: gev mle
  Estimated Parameters:
\[
x_i \hspace{1cm} \mu \hspace{1cm} \beta
\]
0.216732865 0.010697549 0.004977897

#Combining all parameter estimates
> y=cbind(fitkl.max@fit$par.ests,fitjc.max@fit$par.ests,fitpc.max@fit$par.ests,fith.max@fit$par.ests,fitth.max@fit$par.ests,fitth.max@fit$par.ests,fitth.max@fit$par.ests)
> y=t(as.data.frame(y))
> y[1,]
\[
x_i \hspace{1cm} \mu \hspace{1cm} \beta
\]
0.13683275 0.01262802 0.004989277

#VaR for whole period 20-day block maxima series
> evtVaR(y[1,1],y[1,2],y[1,3],n=20,prob=c(0.05,0.01))
[1] 0.0282638 0.02945383

#VaR for whole period of 20-day block minima series
> u=y[,2]*-1
> y=cbind(y[,1],u,y[,3])
> y[1,]
\[
x_i \hspace{1cm} \mu \hspace{1cm} \beta
\]
0.13683275 -0.01069755 0.004977897
> evtVaR(y[1,1],y[1,2],y[1,3],n=20,prob=c(0.95,0.99))
[1] -0.02420587 -0.02504761

# Extracting data for pre-crisis period
The fitting of ARMA GARCH fit, extracting extreme maxima and minima values, estimating of EVT parameters and VaR values are generally repetitive steps similar with the whole period analysis except with different set of data. Here, R commands shows the initial log-return data extracted for the 6-year period up to 25 July 2007.
> fse=dse[1:1327,]
> head(fse)

GMT

<table>
<thead>
<tr>
<th>KLCI</th>
<th>JCI</th>
<th>PCOMP</th>
<th>THAI</th>
<th>FSSTI</th>
<th>VN</th>
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</thead>
<tbody>
<tr>
<td>2000-07-31</td>
<td>0.003254231</td>
<td>-0.013342317</td>
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<td>0.0046210803</td>
<td>-0.003574086</td>
<td>-0.003109609</td>
<td>0.05651028</td>
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<tr>
<td>2000-08-04</td>
<td>0.0154066057</td>
<td>0.007562521</td>
<td>0.026824702</td>
<td>0.03330159</td>
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<tr>
<td>2000-08-07</td>
<td>-0.0008961179</td>
<td>-0.007344372</td>
<td>-0.000744499</td>
<td>-0.01520720</td>
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<tr>
<td>2000-08-11</td>
<td>-0.0145104878</td>
<td>0.030608561</td>
<td>0.016930550</td>
<td>0.03170387</td>
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<tr>
<td>2000-08-16</td>
<td>0.0098450888</td>
<td>-0.018741487</td>
<td>-0.001214412</td>
<td>0.03372676</td>
<td>0.039996297</td>
</tr>
</tbody>
</table>

> tail(fse)

GMT

<table>
<thead>
<tr>
<th>KLCI</th>
<th>JCI</th>
<th>PCOMP</th>
<th>THAI</th>
<th>FSSTI</th>
<th>VN</th>
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</thead>
<tbody>
<tr>
<td>2007-07-18</td>
<td>-0.0060072048</td>
<td>-0.002937817</td>
<td>0.0013718305</td>
<td>-0.008614327</td>
<td>-0.017587708</td>
</tr>
<tr>
<td>2007-07-19</td>
<td>0.0052228569</td>
<td>0.016893092</td>
<td>-0.0085752726</td>
<td>-0.002710955</td>
<td>0.007462742</td>
</tr>
<tr>
<td>2007-07-20</td>
<td>0.0043207885</td>
<td>0.013920416</td>
<td>0.0095066156</td>
<td>0.003863829</td>
<td>0.013887532</td>
</tr>
<tr>
<td>2007-07-23</td>
<td>-0.000600628</td>
<td>0.005820596</td>
<td>-0.0001310849</td>
<td>0.014102828</td>
<td>-0.00400648</td>
</tr>
<tr>
<td>2007-07-24</td>
<td>0.0076792832</td>
<td>0.008756571</td>
<td>-0.0084766421</td>
<td>0.021026601</td>
<td>0.00887587</td>
</tr>
<tr>
<td>2007-07-25</td>
<td>-0.008983060</td>
<td>-0.002743704</td>
<td>-0.0165216122</td>
<td>0.003060186</td>
<td>-0.008409479</td>
</tr>
</tbody>
</table>

#VaR methods comparison
#Using the 'PerformanceAnalytics' package
#Pre-crisis period

> VaR(fse.fit2[,c(1:6)],p=.95,method="historical")

KLCI JCI PCOMP THAI FSSTI VN
VaR -0.009916425 -0.0159813 -0.01840015 -0.0182408 -0.0147082 -0.01829792

> VaR(fse.fit2[,c(1:6)],p=.99,method="historical")

KLCI JCI PCOMP THAI FSSTI VN
VaR -0.01747219 -0.03131618 -0.02975223 -0.02773677 -0.02408726 -0.05153356

> VaR(fse.fit2[,c(1:6)],p=.95,method="gaussian")

KLCI JCI PCOMP THAI FSSTI VN
VaR -0.01118716 -0.01757568 -0.02015677 -0.02097563 -0.01514323 -0.02421484

> VaR(fse.fit2[,c(1:6)],p=.99,method="gaussian")

KLCI JCI PCOMP THAI FSSTI VN
VaR -0.01615303 -0.02580546 -0.02906075 -0.03030855 -0.02174683 -0.03566915

#Whole period

> VaR(dse.fit2[,c(1:6)],p=.95,method="historical")

KLCI JCI PCOMP THAI FSSTI VN
VaR -0.01161281 -0.01744079 -0.01553668 -0.01602946 -0.01814919 -0.02069463

> VaR(dse.fit2[,c(1:6)],p=.99,method="historical")

KLCI JCI PCOMP THAI FSSTI VN
VaR -0.02110237 -0.03198493 -0.02542269 -0.0252749 -0.02834736 -0.03798381

> VaR(dse.fit2[,c(1:6)],p=.95,method="gaussian")
# Bivariate Extreme Value Analysis

# Pre-crisis period

# Extracting minimum returns for 20-day block

```r
> min.return=matrix(ncol=6,nrow=floor(dim(fse.fit2)[1]/20))
> for(i in 1:dim(min.return)[1]){
+   min.return[i,]=apply(fse.fit2[((i-1)*20+1):(i*20),],2,min)
+}
> min.return=-min.return
```

# Obtain parameter estimate in the form of matrix y

```r
>y=cbind(fitkl.min@fit$par.est,fitjc.min@fit$par.est,fitpc.min@fit$par.est,fitth.min@fit$par.est,fitsti.min@fit$par.est,fitvn.min@fit$par.est)
>y=
```

### Transform the log-returns of minima series to common marginal Frechet distribution

```r
> std.k=(1+y[1,1]*((min.return[,1]-y[1,2])/y[1,3]))^(1/y[1,1])
> std.j=(1+y[2,1]*((min.return[,2]-y[2,2])/y[2,3]))^(1/y[2,1])
> std.p=(1+y[3,1]*((min.return[,3]-y[3,2])/y[3,3]))^(1/y[3,1])
> std.t=(1+y[4,1]*((min.return[,4]-y[4,2])/y[4,3]))^(1/y[4,1])
> std.f=(1+y[5,1]*((min.return[,5]-y[5,2])/y[5,3]))^(1/y[5,1])
> std.v=(1+y[6,1]*((min.return[,6]-y[6,2])/y[6,3]))^(1/y[6,1])
```

# Combining into 15 pairs of bivariate data series

```r
> kj=cbind(std.k,std.j)
> kp=cbind(std.k,std.p)
> kt=cbind(std.k,std.t)
> kf=cbind(std.k,std.f)
> kv=cbind(std.k,std.v)
> jp=cbind(std.j,std.p)
```
\begin{verbatim}
> jt=cbind(std.j,std.t)
>jf=cbind(std.j,std.f)
> jv=cbind(std.j,std.v)
> pt=cbind(std.p,std.t)
> pf=cbind(std.p,std.f)
> pv=cbind(std.p,std.v)
> tf=cbind(std.t,std.f)
> tv=cbind(std.t,std.v)
> fv=cbind(std.f,std.v)

#Fitting into function 'fbvevd' of package 'evd' to obtain dependence parameter
> kj2=fbvevd(kj,model="log")
> kp2=fbvevd(kp,model="log")
> kt2=fbvevd(kt,model="log")
> kf2=fbvevd(kf,model="log")
> kv2=fbvevd(kv,model="log")
> jp2=fbvevd(jp,model="log")
> jt2=fbvevd(jt,model="log")
> jf2=fbvevd(jf,model="log")
> jv2=fbvevd(jv,model="log")
> pt2=fbvevd(pt,model="log")
> pf2=fbvevd(pf,model="log")
> pv2=fbvevd(pv,model="log")
> tf2=fbvevd(tf,model="log")
> tv2=fbvevd(tv,model="log")
> fv2=fbvevd(fv,model="log")

#Combining the dependence parameter estimates and standard errors
> cbind(kj2$est[7],kp2$est[7],kt2$est[7],kf2$est[7],kv2$est[7],jp2$est[7],jt2$est[7],jf2$est[7],jv2$est[7],pt2$est[7],pf2$est[7],pv2$est[7],tf2$est[7],tv2$est[7],fv2$est[7])

0.78672 0.86673 0.81870 0.68472 0.99932 0.86157 0.78159
0.66800 0.89743 0.78209 0.78385 0.99980 0.73870 0.98592 0.95721

> cbind(kj2$std.err[7],kp2$std.err[7],kt2$std.err[7],kf2$std.err[7],kv2$std.err[7],jp2$std.err[7],jt2$std.err[7],jf2$std.err[7],jv2$std.err[7],pt2$std.err[7],pf2$std.err[7],pv2$std.err[7],tf2$std.err[7],tv2$std.err[7],fv2$std.err[7])

0.07682 0.08109 0.08178 0.07674 0.00000 0.08278 0.07968
0.07343 0.06515 0.08036 0.08076 0.00000 0.08104 0.06067 0.06356
\end{verbatim}
# Whole period of 10.5 years has the repetitive steps as above
# the dependence parameter and standard errors are shown below

```r
cbind(kj2$est[7], kp2$est[7], kt2$est[7], kf2$est[7], kv2$est[7], jp2$est[7], jt2$est[7],jf2$est[7], jv2$est[7], pt2$est[7], pf2$est[7], pv2$est[7], tf2$est[7], tv2$est[7], fv2$est[7])
```

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<td>0.99987</td>
<td>0.73031</td>
<td>0.66760</td>
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</table>

```r
cbind(kj2$std.err[7], kp2$std.err[7], kt2$std.err[7], kf2$std.err[7], kv2$std.err[7], jp2$std.err[7], jt2$std.err[7],jf2$std.err[7], jv2$std.err[7], pt2$std.err[7], pf2$std.err[7], pv2$std.err[7], tf2$std.err[7], tv2$std.err[7], fv2$std.err[7])
```

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<td>0.0638</td>
<td>0.0536</td>
<td>0.0000</td>
<td>0.0650</td>
<td>0.0586</td>
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</tbody>
</table>

```r
cbind(kj2$std.err[7], kp2$std.err[7], kt2$std.err[7], kf2$std.err[7], kv2$std.err[7], jp2$std.err[7], jt2$std.err[7],jf2$std.err[7], jv2$std.err[7], pt2$std.err[7], pf2$std.err[7], pv2$std.err[7], tf2$std.err[7], tv2$std.err[7], fv2$std.err[7])
```

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<td>0.0641</td>
<td>0.0586</td>
<td>0.0000</td>
<td>0.0541</td>
<td>0.0000</td>
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</table>