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Empirical Comparison of Extreme Value Theory Vis-À-Vis Other Methods of VaR Estimation Using ASEAN+3 Exchange Rates

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This study applies Extreme Value Theory in calculating Value-at-Risk (VaR) of portfolios consisting of foreign exchange exposures of ASEAN+3 countries. This paper addresses the issue that traditional VaR models assume normality of the return distribution. Empirical evidence confirms the stylized facts that financial asset returns are typically negatively skewed and fat-tailed. Moreover, risk management concerns itself with the distribution of the tails, or events in the extremes of the distribution. Estimation of magnitude and the likelihood of extreme events should be given greater attention than central tendency characteristics. Thus, this paper proposes the application of Extreme Value Theory in computing an "Extreme VaR" to directly focus on the behavior of the tail of return distribution. The modeling is done on daily exchange rates returns of ASEAN+3 countries from January 24, 2004 to January 31, 2010.

Keywords: Extreme Value Theory, Value-at-Risk, ASEAN+3, foreign exchange

The main attraction of Value-at-Risk (VaR) as a risk indicator is that it is able to compress all market risk factors into a single number. In its simplicity, it generates a lot of intuitive appeal to risk managers and other finance practitioners as it succinctly describes the risk of holding a portfolio of assets.

VaR is widely accepted as the modern measure of market risk that indicates the maximum potential loss in the value of a portfolio with a given probability over a given time horizon. It has become a key risk metric since the Basel Committee required banks to cover losses in their trading portfolios over a 10-day horizon, 99 percent of the time. Mathematically, VaR is given by:

$$(1)\quad \Pr[\Delta V \leq VaR(\alpha)] = 1 - \alpha$$

where ΔV is the change in the Portfolio's value, and $1 - \alpha$ is the probability level. Under the Basel II Risk-Based Capital Adequacy Framework (Basel Committee on Banking Supervision Publication, 2006), banks and other financial institutions are required to calculate VaR for market risk with $\alpha = 0.05$ (95% confidence) or $\alpha = 0.01$ (99% confidence), and N = 1 day or N = 10 days.

There are different approaches of calculating VaR, but the initial step is always the same – fitting a probability distribution of portfolio returns. In this paper, VaR is estimated using the following approaches:

1. **Parametric** - assumes that returns have a normal or Gaussian distribution (Longerstaey 1996);
2. **Nonparametric** - employs the empirical distribution of returns from the historical sample (Acerbi & Tasche, 2002); and
3. **Semiparametric** - specifically applying Extreme Value Theory (Danielsson & deVries, 1998; McNeil & Frey, 2000)

Engle and Manganelli (2001) critique the first approach arguing that financial time series data are hardly normally distributed. In fact, the seminal works of Mandelbrot (1963) and Fama (1965) provide evidence that financial data have the following empirical peculiarities: (1) returns have negative skewness, in which there is a disproportionately large amount of outliers that fall below the left tail; (2) financial return distributions are leptokurtic, with heaver tails than the normal distribution. Because of aforementioned characteristics, it should be the function of risk management to impute these departures from the normal distribution (Rachev, Menn & Fabozzi, 2005). The historical approach in calculating Value-at-Risk provides the advantages of simplicity, and does not assume any particular distribution (Nieto & Ruiz, 2008). By using historically-informed samples, the fat-tailed attribute of returns becomes built-in.

Risk management deals with the distribution of outcomes that deviate from their expected value. Rather than focusing on the center of the distribution, risk management directs its attention in describing the behavior in the extremes (Jorion, 2007). According to Dowd (2005), the extreme events are generally classified into two:

1. High Frequency Low Severity (HFLS) – risky events that occur frequently but have a minimal impact, and
2. Low Frequency High Severity (LFHS) – extreme events that occur infrequently but have a high severity

The latter category poses a greater problem, since the high impact on the firm is hidden under the guise of a low probability. The recent financial crisis and unexpected natural catastrophes are examples of these LFHS events (Dowd, 2005).

As a result, modern risk management tools have started to incorporate statistical techniques developed for analyzing extreme realizations of random variables, which is Extreme Value Theory (EVT). Through EVT, the distribution of the tails of a random variable is obtained by modeling the extreme observations. Since the VaR metric attempts to measure the economic impact of extreme events, application of EVT is argued to provide better estimates by modeling the tails directly. Thus, a tail (child) distribution is modeled from the original (parent) distribution

Empirical studies in various financial markets have been made to test the efficacy of integrating EVT in VaR estimation. A number of articles have focused on the stock market (Ho, Burridge, Cadle & Theobald, 2000; Gencay, Selcuk & Ulugulyagci,, 2003; Gencay & Selcuk, 2004; Bekiros & Georgoutsos, 2005; Magadia, 2010). With the development of alternative financial instruments, recent publications have also employed Value-at-Risk estimation on Treasury Yields (Bali, 2003), Futures Contracts (Brooks, Clare, Molle & Persand, 2005) and even Electricity Spot Prices (Chan & Gray, 2006). These articles find that Extreme VaR dominates the other approaches in forecasting Value-at-Risk, especially in estimating quantiles at the extreme tails.

There are two main branches of univariate Extreme Value Theory that pertains to the approach in modeling extremes of a single time series: the Blocks Maxima approach (MAX), and the Peaks Over Threshold (POTS) approach.

The Blocks Maxima Approach

Since Value-at-Risk is concerned about the maximum loss in value of a portfolio, the Blocks Maxima method looks into maximum values of the distribution of losses. The sample is first divided into *m* blocks, and then the maximum value of each block is denoted by $M_n = \max\{X_1, ..., X_n\}$ where $\{X_t\}$ is a sequence of random variables (Reiss & Thomas, 2001). Fisher and Tippet (1928) showed that under certain conditions, the distribution of extremes converges to a Generalized Extreme Value (GEV) Distribution of the following form:

$$(2)\ H(x) = \begin{cases} \exp[-(1 + \xi(\frac{x-\mu}{\sigma}))^{-1/x}]\ if\ \xi \neq 0 \\ \exp[-\exp(\frac{x-\mu}{\sigma})]\ if\ \xi = 0 \end{cases}$$

where μ is known as the *location* parameter, σ is known as the *scale* parameter, ξ is known as the *shape* parameter, satisfying the condition that $1 + \xi(\frac{x-\mu}{\sigma}) > 0$.

The location and scale parameters are akin to the mean and variance that measures respectively the central tendency and dispersion of M_n. The shape parameter ξ, on the hand, also called the tail index gives an indication of the shape or heaviness of the tails of the distribution. Depending upon the value of ξ, the GEV gives rise to different families of distributions.

1. If $\xi < 0$, the distribution becomes known as a **Weibull** distribution, which has lighter than normal tails
2. If $\xi = 0$, the distribution becomes known as a **Gumbel** distribution, which has exponential tails
3. If $\xi > 0$, the distribution becomes known as a **Frechet** distribution, which has heavier than normal tails. The Frechet distribution is particularly useful for financial returns because they are typically heavy-tailed.

Value-at-Risk[1] for a given confidence level 1 - α, can be computed by first obtaining the quantile associated with the GEV distribution.

$$(3)\ VaR(\alpha) = \begin{cases} \mu - \frac{\sigma}{\xi}[1 - \ln(\alpha)]^{-\xi}]\ if\ \xi > 0 \\ \mu - \sigma \ln[-\ln(\alpha)]\ if\ \xi = 0 \end{cases}$$

where the parameters μ, σ, and ξ are replaced by their maximum likelihood estimates.

The Peaks Over Threshold (POTS) Approach

The more modern POTS approach provides an alternative way in modeling extreme values by fixing a high threshold u, and obtaining the distribution function of the exceedances from u. Let *F(x)* represent the distribution function of the random variable *X*, then the distribution of the excess losses over a threshold u is given by:

$$(4)\ F_u(x) = \Pr[(X-u) \leq x \mid X > u] \quad \text{for } x > 0$$

This provides the probability that a loss exceeds the threshold by at most x, conditional to the event that the random variable X exceeded the threshold (Dowd, 2005). Balkema and de Haan (1974) and Pickands (1975) state that for large enough u, the conditional excess distribution function $F_u(x)$ converges to Generalized Pareto Distribution (GPD) of the following form:

$$(5)\ G(x) = \begin{cases} 1 - (1 + \xi(x/\beta))^{-1/\xi}]\ if\ \xi \neq 0 \\ 1 - \exp(-x/\beta)\ if\ \xi = 0 \end{cases}$$

where $\beta > 0$ is referred to as the *scale* parameter, and ξ represents the *shape* parameter or tail index. Because financial data are typically heavy-tailed, we are interested in cases where the tail index is positive (i.e. $\xi > 0$).

The key issue in implementing the POTS approach is the selection of an appropriate threshold u, which effectively determines the number of observations in excess of the threshold value. Choosing u involves a trade-off between variance and bias. A high threshold will reduce the number of observations that exceed it, thereby inflating the variance of the parameter estimates.

On the other hand, selecting a low threshold increases the number of observations, but biases may ensue since data included may no longer consistent as being in the tails.

Threshold selection may be implemented through the following graphical technique. If the GPD has a parameter $\xi > 0$, the mean excess function (MEF) associated with it is given by:

$$(6) \qquad e(u) = E[X - u \mid X > u] = \frac{\sigma + \xi u}{1 - \xi}$$

Dowd (2005) prescribes plotting the mean excess function, and choosing a threshold where the MEF becomes relatively stable or horizontal. If a GPD model provides a good approximation of the tail distribution, the plot should become increasingly linear as u increases (McNeil, Frey & Embrechts, 2005).

When the appropriate threshold is set, the child (tail) distribution then, consists of the exceedances over u. The Value-at-Risk associated with confidence level 1 - α, can then be obtained by solving for the 1 – α quantile.

$$(7) \quad VaR(\alpha) = \mu + \frac{\sigma}{\xi}\{(\frac{n(1-\alpha)}{N_u})^{-\xi} - 1\}$$

where n is number of observations in the original distribution, N_u is the number of observations in the tail, and the parameters μ, σ, and ξ, are substituted with their maximum likelihood estimates.

Description of the Data

In this paper, the POTS approach is applied to daily (interbank) exchange rate data obtained from www.oanda.com. Foreign Exchange data is used primarily because of the immediate adjustment of prices to events in the real economy and financial markets. Fama (1970) argues that the efficiency of the market should be considered, so that prices fully reflect information available to the public. Moreover, foreign exchange markets operate on a daily basis with readily observable quotes, which promotes continuity in price movements and reduces data gaps.

The countries of interest belong to the ASEAN+3, which is currently the most active regional grouping pursuing financial integration and adoption of a unified currency. These countries are - Brunei, Cambodia, China, Indonesia, Japan, Laos, Malaysia, Myanmar, Philippines, Singapore, South Korea, Thailand and Vietnam. However, few of these countries have adopted a fixed exchange rate regime where the state's monetary authority has the explicit power to set and adjust their exchange rate according to their objectives (as shown in Appendix A). For apparent reasons, we are only interested in the nine countries with flexible exchange rate regimes, specifically Cambodia, Indonesia, Japan, Laos, Myanmar, Philippines, Singapore, South Korea and Thailand. The full sample period extends from the period January 24, 2004 to January 31, 2010, consisting of 2,200 daily observations of both the exchange rates and their continuously compounded returns. The time frame May 26, 2009 to January 31, 2010 has been reserved as the out-of-sample period for backtesting purposes in assessing the predictive performance of the alternative models.

This paper adopts the market convention for foreign exchange rates, wherein rates are expressed in amount of US Dollars per unit of Foreign Currency (e.g. KHR|USD is the amount of US Dollars needed to purchase 1 Cambodian Riel). From the exchange rate data, the continuously compounded rate of return is computed as $\ln \frac{x_t}{x_{t-1}}$ x 100% where x_t is the exchange rate at time t.

Evidently, the empirical peculiarities of financial data documented by Mandelbrot (1963) and Fama (1965) are obvious in the descriptive measures of the exchange rate returns in Table 1. Only five out of nine are negatively skewed, but all exhibit fat-tails with values of a kurtosis greater than that of the normal distribution.

Statistical tests of normality such as the Jarque Bera, Anderson Darling and Kolmogorov-Smirnov are implemented on the data, as shown in Table 2. According to Gencay and Salcuk (2004), a visual inspection of the

Table 1
Summary Statistics of Exchange Rates and Returns

	Exchange Rates				Returns			
	MEAN	STDEV	SKEW	KURT	MEAN	STDEV	SKEW	KURT
KHR|USD	0.00026	0.00001	0.40730	-0.12502	-0.00127	0.19283	-0.57566	26.20625
IDR|USD	0.00011	0.00001	-1.54634	2.32547	-0.00428	0.27023	-0.60977	21.56177
JPY|USD	0.00011	0.00001	0.45973	-1.24361	0.00567	0.16937	0.81597	17.22806
LAK|USD	0.00914	0.00068	0.95589	0.72517	0.00248	0.21979	0.36335	4.50182
MMK|USD	0.16019	0.00186	0.42418	-0.99805	-0.00020	0.12156	-0.36064	21.60646
PHP|USD	0.02013	0.00204	0.58283	-0.68040	0.00376	0.17143	-0.57676	31.74620
SGD|USD	0.64154	0.04407	0.52272	-0.72086	0.00351	0.10981	0.30979	7.20071
KRW|USD	0.00097	0.00012	-0.91380	-0.04992	-0.00104	0.45398	-0.01490	12.02231
THB|USD	0.02772	0.00289	0.42119	-1.13365	0.00286	0.21331	0.50651	50.73664

Table 2
Normality Tests of Returns (H_0: Normal)

	Jarque Bera	Anderson Darling	Watson	Cravon-von Mises	Kolmogorov-Smirnov
KHR	55608.70**	143.91260**	28.90008**	28.90340**	8.15676**
IDR	37690.53**	88.29966**	17.05535**	17.06150**	6.64265**
JPY	24199.54**	30.79061**	6.07434**	6.12669**	4.47289**
LAK	1678.82**	126.47610**	25.74227**	25.75836**	8.62505**
MMK	37767.96**	221.60600**	47.39007**	47.40108**	11.99579**
PHP	81558.51**	64.08009**	12.18118**	12.19633**	5.82632**
SGD	4218.82**	46.60741**	9.32198**	9.32331**	4.76935**
KRW	11677.52**	113.77490**	22.26655**	22.27050**	7.26078**
THB	208141.80**	97.00643**	17.98165**	17.98542**	6.14427**

*, ** indicates significance at the 5% and 1% levels respectively

Quantile-Quantile (Q-Q) plot can also be used to inspect the normality of the data. In Appendix B, the empirical distribution is plotted against the normal distribution. Indeed, both graphical and statistical methods prove that the data is far from being normal, which makes the parametric (Gaussian) approach of estimating VaR inapplicable.

The data is also subjected to Unit Root testing procedures to assess Stationarity within a Panel

Table 3
Tests of Panel Unit Roots (H_0: Unit Root exists)

	Common Unit Root		Individual Unit Root	
	Exchange Rates	Returns	Exchange Rates	Returns
Levin, Lin and Chu t*	-0.02368	6.32889		
Breitung t-stat	-1.30488	-6.56985**		
Hadri Z-stat	12.3723**	1.59548*		
Im, Pesaran and Shin W-stat			-1.07716	-7.73093**
ADF – Fisher Chi-square			4.13208	62.5987**
PP – Fisher Chi-square			4.14684	18.4207**

*, ** indicates significance at the 5% and 1% levels respectively

Table 4
Tests of Individual Stationarity (H_0: Unit Root exists)

Currency	Exchange Rates			
	Augmented Dickey-Fuller		Philips –Perron	
	Level	First Difference	Level	First Difference
KHR	-1.973192	-28.25547**	-2.257751	-61.34314**
IDR	-2.112602	-45.45309**	-2.002386	-45.58517**
JPY	-1.253478	-37.96225**	-1.063609	-37.68924**
LAK	-0.178434	-27.29135**	-0.306565	-61.06489**
MMK	-1.830651	-27.58218**	-3.816898**	-96.03209**
PHP	-0.970857	-35.64676**	-1.007792	-50.28162**
SGD	-0.894374	-31.24061**	-0.944779	-38.70978**
KRW	-0.867176	-18.37985**	-1.071980	-57.14026**
THB	-1.099831	-34.39888**	-1.095304	-42.47546**
	Returns			
	Augmented Dickey-Fuller		Philips -Perron	
	Level	First Difference	Level	First Difference
KHR	-28.26209**	-17.16120**	-61.48482**	-512.1283**
IDR	-44.73700**	-23.80484**	-44.77647**	-553.1853**
JPY	-38.17341**	-19.95744**	-37.92876**	-1133.069**
LAK	-26.91549**	-18.30447**	-59.94385**	-704.3553**
MMK	-27.63105**	-17.53878**	-96.65437**	-284.8015**
PHP	-36.04725**	-18.51990**	-50.83324**	-387.2705**
SGD	-31.45223**	-19.76506**	-39.30301**	-423.2274**
KRW	-37.02713**	-19.54586**	-52.90297**	-324.0272**
THB	-34.57279**	-18.67415**	-42.46124**	-214.4076**

*, ** indicates significance at the 5% and 1% levels respectively

Table 5
Threshold Selection and MLE Parameter Estimates

Currency	Exchange Rates Returns				
	Threshold (u)	N_u	μ^*	σ^*	ξ^*
KHR	0.16	181	0.155241	0.072268	0.465520
IDR	0.28	169	0.212612	0.096924	0.455872
JPY	0.22	223	0.124045	0.051118	0.412091
LAK	0.13	198	0.124689	0.058270	0.467323
MMK	0.28	32	0.936851	0.203176	0.216872
PHP	0.16	198	0.521175	0.045035	0.086410
SGD	0.10	235	0.067482	0.040004	0.592818
KRW	0.11	519	0.089669	0.030327	0.338206
THB	0.15	221	0.391585	0.146478	0.374064

*Maximum Likelihood Estimates of GPD Parameters

data structure, as well as Individual Stationarity, which are displayed in Table 3. For exchange rate series, most of the tests are in agreement that the data is non-stationary with both common and individual unit roots. On the other hand, in order to verify the time series properties of the return distribution, further tests of stationarity were conducted both at Level and First Difference (Table 4). The Augmented Dickey-Fuller and Philips-Perron test statistics are significant at 1% level, indicating that the returns series are stationary with no unit root.

The primary method for threshold selection in this paper is the graphical approach, which uses the MEF plot. An arbitrary selection of the threshold of the return series is made (as shown in Appendix C), and the results are presented in Table 5. Maximum Likelihood estimation is implemented on the exceedances over the threshold also shown in Table 5.

VaR Estimates

With regards to the three approaches to VaR estimation considered in this paper, the computational formulas for each are provided below:

1. **Gaussian VaR**

$$VaR\,(\alpha) = \mu + (N^{-1}(1-\alpha))\,\sigma$$

2. **Historical VaR**

$VaR\,(\alpha) = ((1-\alpha)\,x1950)^{th}$ observation of the historical sample

3. **Extreme VaR**

$$VaR(\alpha) = \mu + \frac{\sigma}{\xi}\{(\frac{n(1-\alpha)}{N_u})^{-\xi} - 1\}$$

Where n = number of observations in the parent distribution, N_u = number of tail observations with the parameters μ, σ and ξ are substituted with their maximum likelihood estimates. The VaR estimates are displayed in Table 6.

After computing VaR estimates, the predictive performance of each approach is backtested using the period May 26, 2009 to January 31, 2010. The number of violations and the empirical failure rate are presented in Table 7.

Table 6
Value-at Risk estimates at α = 5% and α = 1%

Currency	VaR(5%)			VaR(1%)		
	Gaussian	Historical	Extreme VaR	Gaussian	Historical	Extreme VaR
KHR	-0.3184	-0.2636	-0.2826	-0.4499	-0.5861	-0.5977
IDR	-0.4488	-0.3668	-0.3704	-0.6329	-0.8712	-0.7715
JPY	-0.3591	-0.3294	-0.2297	-0.5088	-0.5525	-0.4459
LAK	-0.2806	-0.2330	-0.2372	-0.3960	-0.4885	-0.5033
MMK	-0.6461	-0.4294	-1.1388	-0.9146	-1.3040	-1.6145
PHP	-0.2001	-0.1645	-0.5015	-0.2830	-0.3952	-0.5763
SGD	-0.2782	-0.2438	-0.1526	-0.3951	-0.4266	-0.3962
KRW	-0.1771	-0.1767	-0.1513	-0.2519	-0.3043	-0.2608
THB	-0.7478	-0.6853	-0.9396	-1.0572	-1.6024	-1.7156

Table 7
Predictive Performance of Alternative Models

Currency	VaR Violations at α = 5%			VaR Violations at α = 1%		
	Gaussian	Historical	Extreme VaR	Gaussian	Historical	Extreme VaR
KHR	23 (9.20%)	30 (12.00%)	28 (11.20%)	13 (5.20%)	6 (2.40%)	5 (2.00%)
IDR	9 (3.60%)	14 (5.60%)	13 (5.20%)	5 (2.00%)	0 (0.00%)	1 (0.40%)
JPY	11 (4.40%)	13 (5.20%)	28 (11.20%)	4 (1.60%)	4 (1.60%)	5 (2.00%)
LAK	7 (2.80%)	9 (3.60%)	9 (3.60%)	3 (1.20%)	3 (1.20%)	3 (1.20%)
MMK	5 (2.00%)	17 (6.80%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
PHP	27 (10.80%)	33 (13.20%)	3 (1.20%)	17 (6.80%)	8 (3.20%)	3 (1.20%)
SGD	6 (2.40%)	8 (3.20%)	29 (11.60%)	2 (0.80%)	2 (0.80%)	2 (0.80%)
KRW	44 (17.60%)	44 (17.60%)	45 (18.00%)	33 (13.20%)	27 (10.80%)	30 (12.00%)
THB	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)

Percentages in parentheses represents empirical failure rate in the Backtesting Window

Extreme VaR at $\alpha = 5\%$ tends to provide more cautious estimates only for MMK, PHP, THB. At extreme quantiles, Extreme VaR estimates dominate most of exchange rate markets beating Gaussian and Historical estimates.

The backtesting procedure employed in this paper is Likelihood Ratio of Unconditional Coverage (LR_{UC}), which measures the statistical significance of the empirical failure rate. More robust backtesting procedures may also be applied (Beronilla & Mapa, 2008; Christoffersen, 1998) to test for clustering of violations and model misspecification.

CONCLUSION

This study applies Extreme Value Theory in calculating Value-at-Risk (VaR) of portfolios consisting of foreign exchange exposures of ASEAN+3 countries, currently the most active regional grouping pursuing financial integration and adoption of a unified currency. This paper addresses the issue that traditional VaR models assume normality of the return distribution. Empirical evidence confirms the stylized facts that financial asset returns are typically leptokurtic and fat-tailed. Moreover, risk management concerns itself with the distribution of the tails, or events in the extremes of the distribution. Estimation of the magnitude and likelihood of extreme events should be given greater attention than central tendency characteristics. Thus, this paper proposes the application of Extreme Value Theory in computing an "Extreme VaR" to directly focus on the behavior of the tail of return distribution of ASEAN+3 currencies.

NOTE

1 Value at Risk estimates are for a one-day period unless otherwise specified.

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Appendix A

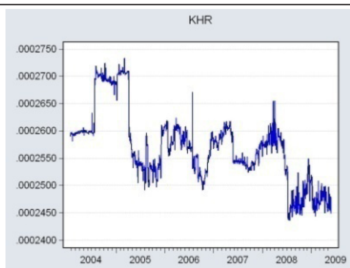
ASEAN+3 Countries, Local Currency and Exchange Rate Regime

Country		Local Currency	Exchange Rate Regime[2]
Brunei	BND	Brunei Dollar	Currency Board Arrangement
Cambodia	KHR	Cambodian Riel	Managed Float
China	CNY	Chinese Yuan Renminbi	Fixed Peg Arrangement (against a single currency)
Indonesia	IDR	Indonesian Rupiah	Managed Float
Japan	JPY	Japanese Yen	Independently Floating
Laos	LAK	Laos Kip	Managed Float
Malaysia	MYR	Malaysian Ringgit	Fixed Peg Arrangement (against a single currency)
Myanmar	MMK	Myanmar Kyat	Managed Float
Philippines	PHP	Philippine Peso	Independently Floating
Singapore	SGD	Singapore Dollar	Managed Float
South Korea	KRW	South Korean Won	Independently Floating
Thailand	THB	Thai Baht	Managed Float
Vietnam	VND	Vietnamese Dong	Fixed Peg Arrangement

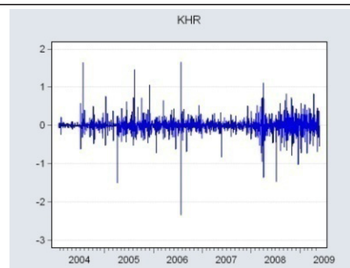
[2]Source: International Monetary Fund – Classification of Exchange Rate Arrangements

Appendix B
Graph of ASEAN+3 Exchange Rates from 1/24/2004 – 1/31/2010:

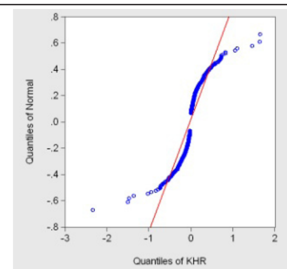
(a) Exchange Rates at Level, (b) Daily Returns, (c) QQ Plot of Empirical Distribution fitted with Normal



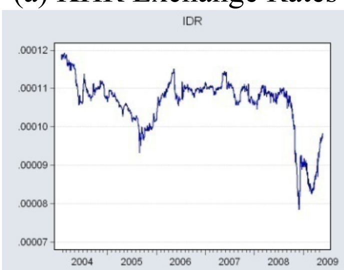
(a) KHR Exchange Rates



(b) KHR Returns



(c) KHR QQ Plot



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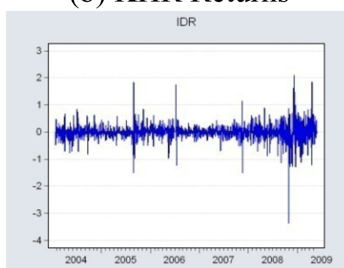

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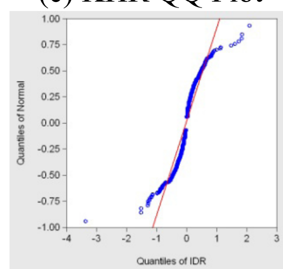
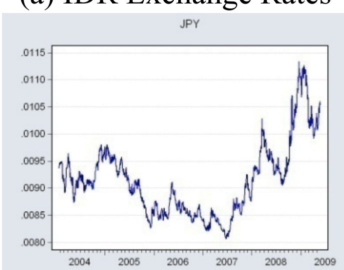
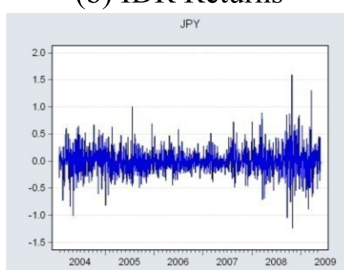


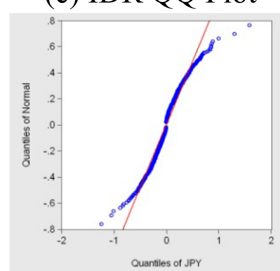
(c) IDR QQ Plot



(a) JPY Exchange Rates

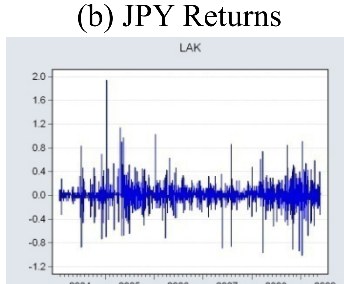


(b) JPY Returns



(c) JPY QQ Plot

(a) LAK Exchange Rates



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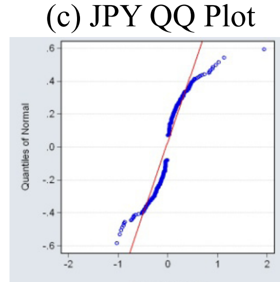

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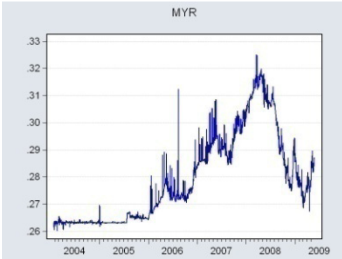

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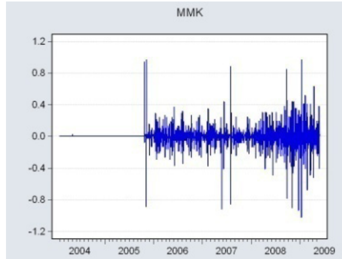

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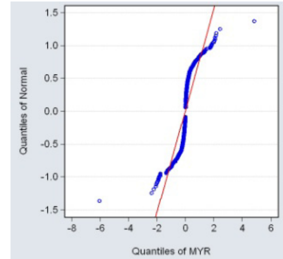
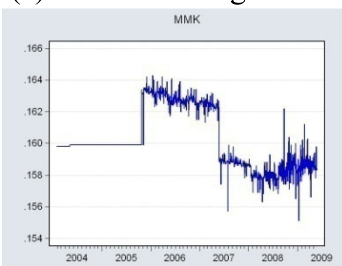


(c) MYR QQ Plot



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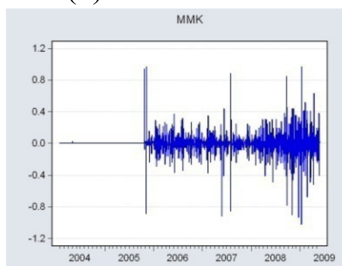

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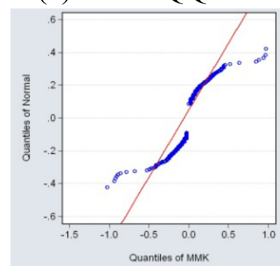

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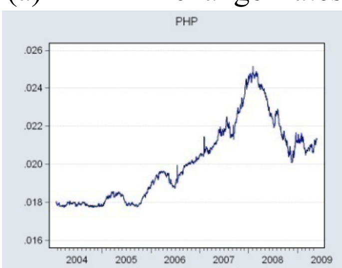

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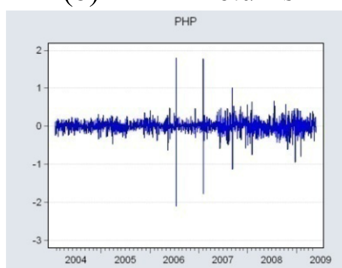

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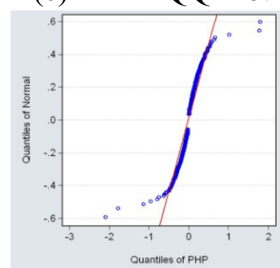
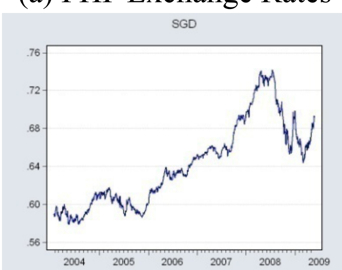


(c) PHP QQ Plot



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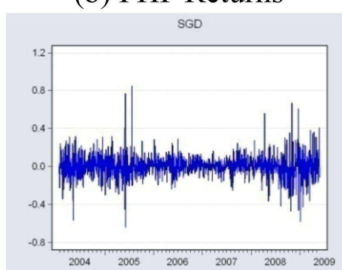

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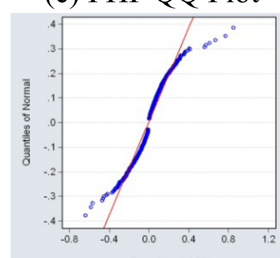
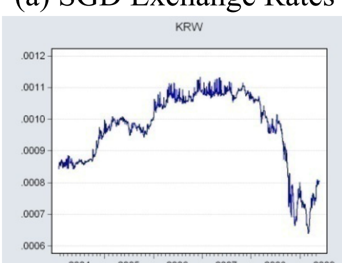


(c) SGD QQ Plot



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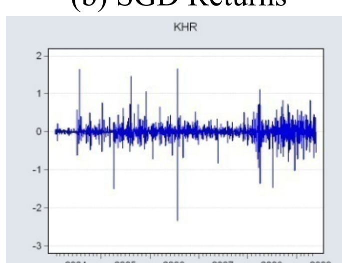

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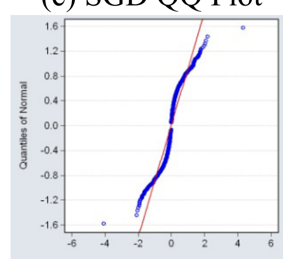
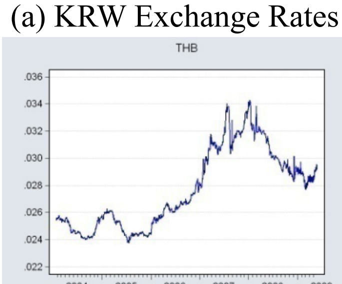


(c) KRW QQ Plot



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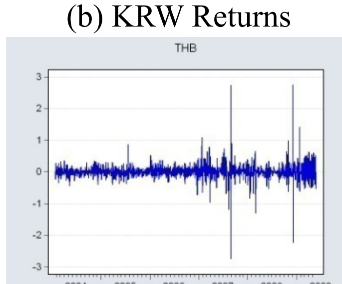

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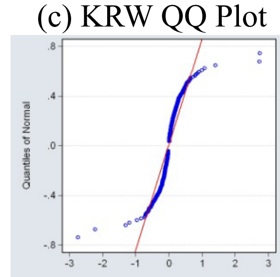
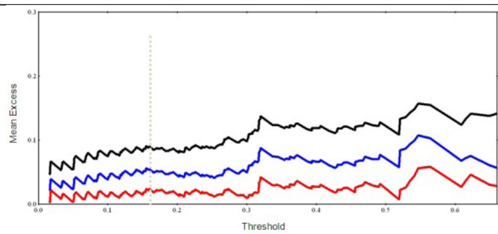
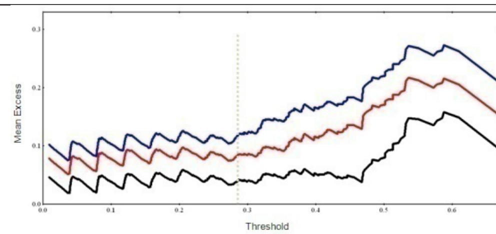


(c) THB QQ Plot

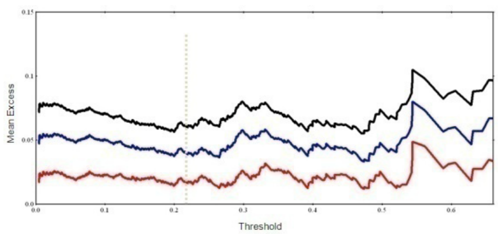
Appendix C
Mean Excess Plots



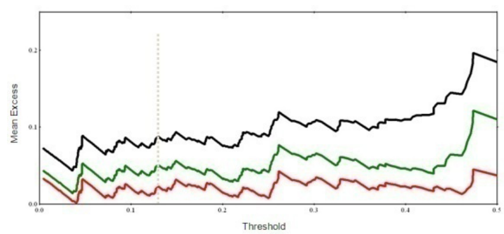
KHR Mean Excess Function



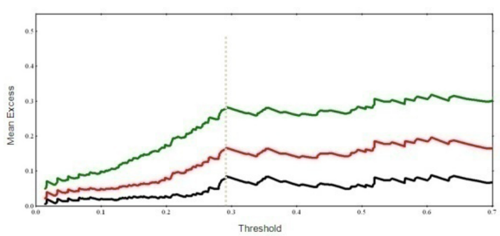
IDR Mean Excess Function



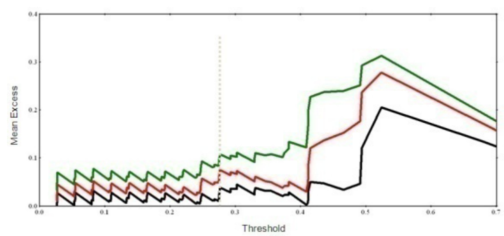
JPY Mean Excess Function



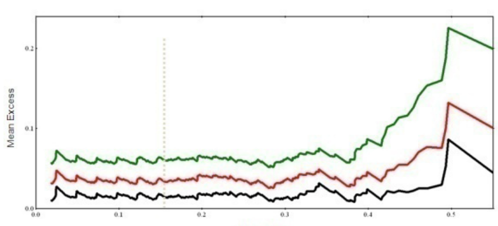
LAK Mean Excess Function



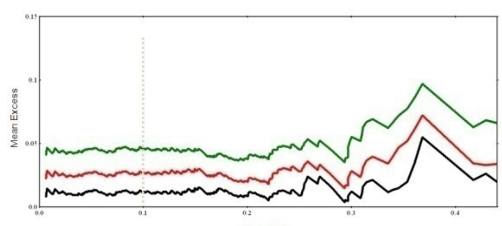
MYR Mean Excess Function



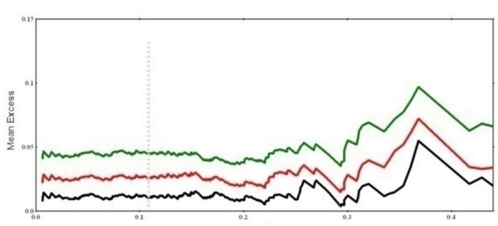
MMK Mean Excess Function



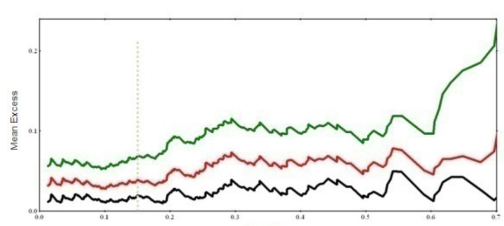
PHP Mean Excess Function



SGD Mean Excess Function



KRW Mean Excess Function



THB Mean Excess Function