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Extreme tails behavior in Asian currency markets

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Abstract This study examines extreme tail behavior in Asian currency markets for the period of 2005-2018. Value-at-Risk (VaR) is estimated through Extreme Value Theory (EVT) approach to forecast losses incurred in a day in Asian currencies. Initially EVT approach is used to estimate extreme losses on the left tail of the distribution. Then, the VaR estimation of this approach is back tested through traditional and advance back testing methods to ascertain the accuracy of the models used. Results indicate that the estimation of GPD static model is relevant for extreme risk forecasting in EVT approach at both 95% and 99% confidence intervals. The used method is recommended for use by market players.

Keywords Value-at-Risk (VaR) · Extreme value theory (EVT) · Generalized Pareto distribution (GPD) · Back testing · Risk forecasting

1 Introduction

Risk management is an integral part of the decision making process. VaR is a common method for risk measurement. For the estimation of VaR, various methods are used. One model may not be suitable for all currency portfolios in the world because the behavior of each currency market is different. Sometimes variations in currencies are higher, somewhere currency rates are constant or big shocks exist in some currencies, therefore an appropriate model is required for each currency market according to its currency's behavior. Confidence interval does matter for the selection of the model because level of significance affects

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the quality of the results. At higher confidence intervals, the performance of the model becomes weaker.

To estimate the risk behavior of the extreme left tail of the Asian currency market, Extreme Value Theory (EVT) is used. Investors are more concerned about extreme losses than average. EVT helps to cover all events which are extreme in nature. The outcome of EVT application is different from the common outcome of traditional methods for risk forecast like VaR. Risk measurement through EVT approach is based on two methods, GEV follows block maxima approach and GPD follows static and dynamic approaches.

Bloomberg analyzed 13 Asian currencies in the current year and reported that the Pakistani Rupee performed worst in Asia in 2018. The Pakistani Rupee devalued approximately 20% in this year, followed by Indian Rupee about 11%, Russian Ruble 15%, Venezuelan Bolivar 99%, Argentine Peso 53% and Turkish Lira 38%. However, Brazilian Real decreased by 20%, Swedish Krona 10%, and the Philippines Peso 8%. Chinese Yuan Renminbi also experienced 5% devaluation and Euro declined by 3%. (Official Forex Rate).

Currency devaluation and instability leads us to the choice of risk measurement. After 1990, Value-at-Risk (VaR) is a method which is mostly used for the measurement of risk in financial sectors. "Value-at-Risk is generally defined as the capital sufficient to cover, in most instances, losses from a portfolio over a holding period of a fixed number of days" (Gilli et al 2006).

The main purpose for VAR estimation is to quantify market risk and economic capital allocation, most commonly helping the regulators, investors and the firm itself. Previously different approaches are used to estimate VaR for one day to forecast the risk and return of exchange rates for a portfolio (Omari et al 2017).

With time in worldwide financial markets, evaluating the extreme events probability, has become the main concern in the management of financial risks. These market conditions require the quantication of worst losses in all types of financial markets. EVT provides a wide theoretical base on which the statistical models explaining extreme situations can be formed. The EVT has unique features of stochastic behavior quantication process at abnormally large or small levels. However, EVT generally requires the probability estimation of more extreme events than any other method (Singh et al 2013).

Extreme value theory (EVT) has developed as one of the most important statistical approach for applied sciences for almost the last fifty years and is now being used in other fields like finance. EVT provides more accurate estimation of VaR than other traditional methods, tail dependence decreases when filtering out heteroscedasticity and serial correlation by multivariate GARCH models (Fernandez 2005).

The generalized Pareto distribution (GPD) is another EVT approach which is mostly used to estimate extreme tails behavior. This method does not only take a maximum value but also captures all extreme values above the threshold.

2 Literature review

EVT theory is applied to calculate VaR of each group through parametric method to capture the extreme values. Kolmogorov-Smirnov and Anderson-Darling adhesion tests are then performed to find the actual historical distribution more correctly. The results of these VaR estimates are more effective within a given confidence interval after back testing other than one sample. The result of the study shows that -1.45% is average daily VaR against USD and 65% risk is higher than the other twelve currencies. There were 5% chances that the loss will increase more than 1.45% in a day.

The currencies of emerging markets are less risky with average -0.78% VaR as compared to other studied currency markets in relation to the USD. Argentine Peso has the lowest VaR (0.16%) so this currency is less risky. However, the exchange rates of developed markets are riskier with average -1.15% VaR. Argentine Peso exhibits resistance from external shocks because this currency was not connected to international market during this period. Results indicate that economies at same stage and near to maturity also show similar behavior of exchange rate. The results provide that least risky currencies are Argentine Peso (ARG), Indian Rupee (INR), New Peruvian Sol (PEN) and Chinese Yuan (CNY).

According to Omari et al (2017) study on the daily average currency exchange rates of US Dollar vs Kenya Shillings (USD/KES), UK Sterling Pound vs Kenya Shillings (UKP/KES), European Union Euro vs Kenya Shillings (EUR/ KES) and South African Rand vs Kenya Shillings (SAR/KES), the threshold value required to fit the GPD model is obtained using the graphical approach, which uses the Mean Excess Function (MEF) plot of the return series. Maximum likelihood estimation technique is used on the exceedances over the threshold. The study reports the estimated parameters of the generalized Pareto distribution (GPD) as well as their estimated asymptotic standard errors resulting from applying the POT approach to the filtered standardized innovations. For all the returns series, the shape parameter is found to be positive and significantly different from zero, indicating heavy-tailed distributions of the innovation process characterized by the Fréchet distribution.

This study has tackled two key issues in risk management: computation of value at risk (VaR) and stock market dependence using the new approach of EVT. First, this study analyzed different ways to compute value at risk for stock markets across the United States, Latin America, Europe, and Asia and concluded that quantile estimates based on EVT are best. Secondly, this study tested the degree of extremal dependence across different financial markets in the United States. It concludes that bond markets do not exhibit extremal dependence of stock markets, and much of the extremal dependence across stock markets disappears when controlling for both serial correlation and heteroscedasticity (Fernandez 2005).

McNeil (1997) illustrates, how extreme value theory can be used to model tail related risk measures such as Value-at-Risk, expected shortfall, applying it to daily log-returns on six market indices. The conclusion is that EVT can be useful for assessing the size of extreme events. From a practical point of view this problem can be approached in dierent ways, depending on data availability and frequency, the desired time horizon and the level of complexity one is willing to introduce in the model. The findings of the study provide that the POT method appear superior as it better exploits the information in the data sample (Gilli et al 2006).

The study also describes that the GEVD percentile method is most suitable risk evaluation method for VaR analysis which produces more information than other methods e.g historical simulation and delta normal distribution, at 99 percent and 99.9 percent confidence interval in short position. The estimation based upon empirical distribution tends to create more conservative outcomes than EVT for VaR measures for the long position at 99 percent confidence interval which is triggered by high volatility resulting from returns' discrete behavior outside the tails. The results of EVT for VaR calculation are more accurate at 99.9% than other conventional methods. The reason behind this fact is that GEVD measure exhibits more precise and accurate behavior related to the size of extreme events calculated at the probability distribution tails. The research concludes that there is advantage for the investor to gain more accurate information of actual risk for risk measurement in their portfolio returns during the period of financial crunch.

3 VaR estimation through Extreme Value Theory (EVT)

EVT is a type of modelling used to measure the extreme tails and risk in a distribution by using parametric models. For the measurement of EVT, there are two methods: first method is Generalized Extreme Value Distribution (GEV) which follows Block Maxima/Minima (BMM) Approach and the second method is Generalized Pareto Distribution (GPD) currently known as the Peak Over Threshold (POT) approach. In GPD method, this study uses static and dynamic approach. Three parameters are estimated in these methods: location parameter, scale parameter and shape parameter.

The BMM approach is usually used to calculate EVT. The BMM approach selects the maximum or minimum values in a financial data series that contain, extreme events (Gilli et al 2006). A block of extreme event maxima/minima is an independent data series and identically distributed observations (iid) to GEV using a statistical and tradition method which is maximum likelihood estimation (MLE) (Singh et al 2013). Mn represents the block maxima limit law and n shows the subsample (block) size and is given by the following theorem:

Theorem of Fisher Tippett Gnedenko: "If there are constants ($an > 0$, $bn \in R$) as well as some non-degenerate distribution function H such that:"

$$\frac{Mn - bn}{an} \xrightarrow{d} H$$

However, H represents one of the 3 standard extreme value distributions:

$$Fr\acute{e}chet : \phi_{\vartheta}(x) = \begin{cases} 0 \\ exp(-x^{-\vartheta}) \end{cases}$$

if x $\leq$ 0 and ϑ >0
if x>0 and ϑ >0

$$Weibull : \psi_{\vartheta}(x) = \begin{cases} exp(-(-x^{-\vartheta})) \\ 1 \end{cases}$$

if x$\leq$0 and $\vartheta > 0$
if x>0 and $\vartheta > 0$

$$Gumbel : \Lambda(x) = exp(-exp(-x)) \; if \; x \in R$$

This theorem recommends that the asymptotic distribution of the maxima value is related to the above three distributions, irrespective of the actual distribution of observed data. Generally, limiting distribution type and norming constants cannot be identified at early stage. For identification, this study uses, one parametric distribution projected by Von Mises (1954) and Jenkinson (1955) which includes extreme value distribution of the above three types as a special case. Generalized Extreme Value Distribution (GEVD) can be formed as:

$$H_{\xi,y,\delta}(x) = \begin{cases} exp(-(1+\xi\frac{x-y}{\delta})^{-1/\xi}) \; if \xi \neq 0 \\ exp(-exp(\frac{-x-y}{\delta})) \quad if \xi = 0 \end{cases}$$

For, $1+\xi\frac{(x-y)}{\delta} > 0$ where γ represents location parameter and δ denote scale parameter representing constants of the unknown (Embrechts et al 1999). This is unnormalised maxima limiting distribution which is more useful when we calculate the maximum likelihood. VaR can be estimated as:

$$VaR^{BM}_{T+1,\alpha} = \begin{cases} \gamma - \frac{\delta}{\xi}(1-(-\ln(1-\alpha))^{-\xi}) \; if \xi \neq 0 \\ \gamma - \delta \ln(-\ln(1-\alpha)) \quad if \xi = 0 \end{cases}$$

where, γ is the location parameter, δ is the scale parameter and ξ represents shape parameter. These are the parameters which are used to estimate maximum likelihood ratio. In this equation α represents the given level of significance (5% or 1%) for tails estimation. There is inequality in the tail distribution which can produce the conditional VaR for a fat tailed distribution placed at the maximum domain of attraction of the GEV distribution (Ortiz, 2011). Expected shortfall of block maxima is calculated through:

$$ES^{BM}_{t+1} = (\frac{\alpha}{\alpha-1})VAR_c(X)$$

where $\alpha = 1/\xi$ and ξ is the shape parameter.

GPD is one of the methods to calculate VaR of EVT by using exceedance over threshold. This EVT method takes all the values over a threshold and models the collection of the maximum random variable (Zargar and Kumar 2018). The VaR estimates are more efficient in GPD than GEV because GPD (POT) takes values over a certain threshold while GEV (BMM) only have a maximum value from a financial series for distribution estimation (Singh et al 2013).

Consider X is a random variable, u is a fixed threshold and focus on $X - u$ positive part. The $F_u(x)$ represents the distribution as:

$$F_u(x) = Pr(X - u \leq x | X > u)$$

Many studies claim that any financial market returns show the infinite fourth moment of distribution. The main issue is that the normal distribution cannot capture these phenomena while the GPD method can model this behavior. Generalized Pareto distribution (GPD) given by:

$$G_{\xi,\alpha}(x) = \begin{cases} (1+\frac{\xi}{\sigma}x)^{-1/\xi} & if \xi \neq 0 \\ 1-e^{-x/\sigma} & if \xi = 0 \end{cases}$$

where $x \in [0,(x-u)]$ if $\xi \geq 0$ and $x \in [0,(-\sigma/\xi)]$ if $\xi < 0$. Here ξ represents the shape parameter and σ denotes the scale parameter.

GPD requires, both shape parameter ξ and scale parameter σ. If the shape $\xi = 0$ then distribution will be Gumbel, if $\xi < 0$ then it will be Weibull and when $\xi > 0$ then distribution will be Fréchet. To examine the behavior of extreme tails, one of the GPD method is static in which a user-supplied uniform random number generator is used to create a random sample. The parameters of distribution are same location, scale and shape. In the estimation of GPD static VaR, the study use α as a threshold. The probability function of GPD-Static is:

$$VaR^s_{t+1} = u + \frac{\hat{\sigma}}{\hat{\xi}}\lfloor[\frac{n}{N_u}(1-p)]^{-\xi} - 1\rfloor$$

The location parameter μ of the Pareto distribution indicates to the minimum possible value of that variable, scale parameter σ and shape parameter ξ which must be greater than 0. Expected shortfall is actually the expected potential loss that exceeds VaR at the given confidence interval. Expected shortfall of GPD-Static related to its VaR is calculated through:

$$ES^s_{\hat{q}} = VaR_{\hat{q}}\frac{\sigma+\xi(VaR_{\hat{q}}-u)}{1-\xi} = \frac{VaR_{\hat{q}}}{1-\xi} + \frac{\sigma-\xi u}{1-\xi}$$

McNeil (1997) proposed a dynamic VaR forecasting method based on using EVT. Their method makes use of GARCH modelling to model the current market volatility background which is further fed into VaR estimates obtained from the POT model fitted to residuals of a GARCH model. By the use of GARCH models to forecast the estimates of conditional volatility the model provides dynamic 1 day ahead forecasts for VaR and ES for the financial time series.

$$VaR^d_{t+1} = \mu_{t+1} + \sigma_{t+1} * VaR^s_{t+1}$$

Expected shortfall is the average of the negative values in any financial series beyond a given confidence interval e. g 95% or 99%. It is another tool of risk measurements the expected shortfall (ES) or conditional expectation of the tails which measure the potential loss exceeding VaR. The distribution function of the expected shortfall is:

$$ES^d_{t+1} = \mu_{t+1} + \sigma_{t+1} * VaR^d_{t+1}$$

Back testing is a statistical procedure designed to assess the accuracy of all risk forecasting models by comparing the realized trading losses with the VaR predicted losses (Omari et al 2017). This study also tests two issues, violation exceptions tested through unconditional coverage and exception clustering through the independence test.

Violation ratio compares expected violations with observed values. In VR (violation ratio), for better model selection, value should be equal to 1 or closer. According to literature, generally values between 0.80-1.20 are acceptable. If value > 1 then it means observed violations are high so returns are forecasting at lower end therefore model is weaker. If value < 1 then it is under estimated and model is not forecasting correct values.

Kupiec back testing (1995) is a proportion of failures (POF) test. The POF test works with the binomial distribution approach. Measurement of this test is through likelihood ratio to check that the probability of exceptions between observed and expected violations are synchronized or not at the given confidence level. If results show that the observed and expected violations are different then this model is rejected. The POF test is measured through:

$$LR_{POF} = -2\log\left(\frac{(1-p)^{N-x}p^{x}}{(1-\frac{x}{N})^{N-x}(\frac{x}{N})^{x}}\right)$$

where x represents the number of failures, N represents the number of observations and $p = 1 - VaR$ level. Null hypothesis of Kupiec test is that the observed violations are equal to expected violations. Measurement of this method is through likelihood ratio, if $LR < x^2$ (1) then null hypothesis will be accepted for 95% and 99% significance level.

Christoffersen method to test whether the probability of observing an exception on a particular day depends on whether an exception occurred. Instead of unconditional probability of observing an exception, Christoffersen's test helps us to check the consecutive days dependency in risk and return forecasting. The statistic independence test in Christoffersen's interval forecast (IF) is estimated through:

$$LR_{CCI} = -2\log\left(\frac{(1-\Pi)^{n00+n10}\Pi^{n10+n11}}{(1-\Pi_0)^{n00}\Pi_0^{n01}(1-\Pi)^{n10}\Pi_1^{n11}}\right)$$

$n00$ is the not failed number of periods followed by a not failed period. $n10$ is the failed number of periods followed by a not failed period. $n01$ is the not failed number of periods followed by a failed period. $n11$ is the failed number of periods followed by a failed period. Π_0 denotes the probability of failure on period t, given that no failure occurred on period $t-1 = n01/(n00+n01)$. Π_1 represents the probability of failure on period t, given that a failure occurred on period $t-1 = n11/(n10+n11)$. Π showing the probability of failure on period $t = (n01 + n11/(n00 + n01 + n10 + n11)$.

The null hypothesis assumes that there is no clustering in the financial time series, means the probability of today's loss does not follow the past pattern. The null hypothesis is rejected if $LR > x^2$ (1) for violations identified.

4 Data analysis and discussion

The sample forming the basis of analysis for this study is the daily exchange rate of 25 selected Asian currencies with the US dollar. The sample period is 2005-2018. The extreme tail behavior is also examined for the following sample:

China, Japan, India, Korea, Indonesia, Turkey, Saudi Arabia, Taiwan, Thailand, Iran, United Arab Emirates (UAE), Israel, Hong Kong, Singapore, Malaysia, Philippines, Pakistan, Bangladesh, Vietnam, Iraq, Qatar, Kazakhstan, Kuwait, Sri Lanka, Oman. The data is collected from investing.com

Table 1 shows descriptive analysis of daily returns of Asian currency markets over the period of Jan 2005- Dec 2018. Mean values are the average daily return of the currency. China, Singapore and Thailand report higher mean so their average daily returns are higher than other countries. Kazakhstan, Turkey and Iran are the countries that report highest losses. Moreover, some countries like Oman, Qatar, Saudi Arabia and UAE report no return. Iran, Thailand and Korean currency markets report maximum average return within a day. Whereas, Hong Kong, UAE and Oman report maximum average loss within a day. Standard deviation explains the risk of currency markets. Iran, Turkey and Kazakhstan currency markets are riskier as compared to other Asian currency markets. Hong Kong, Oman and UAE's currency markets are less risky. Currency market returns of Saudi Arabia, Hong Kong and Qatar are positively skewed. Return of currency of Pakistan, Vietnam and Kazakhstan are more negativity skewed.

Table 1: Descriptive analysis

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
Bangladesh	-0.000086	0	0.0459	-0.0506	0.0037	-0.8189	45.74
China	0.00005	0	0.0203	-0.0184	0.0015	0.2166	26.58
Hong Kong	-0.000002	0	0.0043	-0.0028	0.0003	1.0919	24.3
India	-0.000128	0	0.0355	-0.0369	0.0046	-0.1383	9.716
Indonesia	-0.000122	0	0.0647	-0.0762	0.0046	-0.7645	42.34
Iran	-0.000397	0	0.7069	-0.7069	0.0342	-2.1813	413.1
Iraq	0.000046	0	0.0366	-0.0829	0.005	-1.1751	37.67
Israel	0.00004	0.00003	0.0276	-0.0414	0.0049	-0.1889	7.759
Japan	-0.000019	-0.00008	0.0377	-0.0522	0.0065	0.1083	7.402
Kazakhstan	-0.000292	0	0.0714	-0.2464	0.0073	-19.321	579
Korea	-0.000021	0.00002	0.1095	-0.1022	0.0071	0.0639	37.83
Kuwait	-0.000007	0	0.0239	-0.0232	0.0016	-0.6519	52.48
Malaysia	-0.000024	0	0.036	-0.0203	0.004	0.378	8.486
Oman	0	0	0.0039	-0.0063	0.0003	-1.598	93.57
Pakistan	-0.000211	0	0.0541	-0.0796	0.0034	-3.5568	114.8
Philippines	0.000018	0	0.0225	-0.0177	0.0037	0.0259	5.424
Qatar	0	0	0.0593	-0.0593	0.0027	1.0593	283.8
Saudi Arabia	0	0	0.0159	-0.0129	0.0005	3.9885	501.7
Singapore	0.00005	0.00008	0.0218	-0.0212	0.0035	0.038	6.577
Sri Lanka	-0.000155	0	0.0251	-0.0401	0.0025	-1.6962	50.37
Taiwan	0.000011	0	0.0175	-0.0182	0.003	0.1909	6.787
Thailand	0.000049	0	0.1103	-0.1095	0.0047	-0.2302	173.2
Turkey	-0.000371	0.00009	0.08	-0.1476	0.0097	-1.3955	24.4
UAE	0	0	0.0035	-0.0043	0.0002	0.2589	297.1
Vietnam	-0.000105	0	0.0436	-0.0651	0.0023	-8.4808	286.7

Kurtosis of all Asian currency markets is more than 3 which report leptokurtic behavior and indicate non-normal distribution in currency returns. Kazakhstan, Saudi Arabia and Iran have more fat tails while Taiwan, Singapore and Philippines have less fat tails. This explains that data is non-normal emphasis on fat tails is desired. According to this descriptive analysis, risk and return relationship in these 25 Asian currency markets are inefficient. Ideally if risk is high then return should also high which is not true for these currency markets.

4.1 VaR estimation through EVT approach

In financial markets, the movements in currency price are extreme in nature so individual investors/institutions are not concerned about the whole distribution but only with the extreme tails which can cause the great losses. For tail shape forecasting, there are 2 types of distributions:

- GEV (Block Maxima Approach)
- GPD (Static and Dynamic Approaches)

Table 2 shows the results of VaR under EVT (Extreme Value Theory) Approach. At 95% confidence interval in 1st column GEV (Block Maxima) Approach, there are 95% chances that loss of Irani Rial will not exceed 8.11% in a day followed by Iraqi Dinar (6.1%) and Turkish Lira (4.53%). Least risky currencies are UAE Dirham (0.06%), Saudi Riyal (0.14%) and Hong Kong Dollar (0.16%). Accord-

Table 2: VaR estimation through EVT approach

	Block Maxima		GPD (Static)		GPD (Dynamic)	
	0.95	0.99	0.95	0.99	0.95	0.99
	VaR	VaR	VaR	VaR	VaR	VaR
Bangladesh	-0.0232841	-0.0546006	-0.0043546	-0.01185	-0.000008	-0.0000145
China	-0.0077069	-0.014584	-0.0020552	-0.00457	-0.0000855	-0.0000881
Hong Kong	-0.001584	-0.0028093	-0.0004745	-0.00091	-0.0000015	-0.000002
India	-0.0197131	-0.0304406	-0.0074387	-0.01318	-0.0000081	-0.0000141
Indonesia	-0.023821	-0.0448701	-0.0062877	-0.01239	-0.0000018	-0.000037
Iran	-0.0810785	-0.6392229	-0.0020104	-0.01009	-0.0003226	-0.0000544
Iraq	-0.0610006	-0.4467558	-0.0029014	-0.02172	-0.0000707	-0.0001604
Israel	-0.0217178	-0.0352658	-0.0075875	-0.01409	-0.0000865	-0.0001078
Japan	-0.0265097	-0.0405208	-0.0098363	-0.01756	-0.0000699	-0.0000346
Kazakhstan	-0.0321235	-0.1333019	-0.0044084	-0.01362	-0.0001431	-0.0000475
Korea	-0.030149	-0.0540435	-0.0095002	-0.02094	-0.0001963	-0.0002501
Kuwait	-0.0077513	-0.0148541	-0.0020768	-0.0044	-0.000004	-0.0000008
Malaysia	-0.0153369	-0.0207374	-0.0065813	-0.01119	-0.0000682	-0.0000849
Oman	-0.0053787	-0.0268494	-0.0000351	-0.00077	-0.0000041	-0.0000042
Pakistan	-0.0212579	-0.0588988	-0.0037185	-0.01107	-0.0002493	-0.00023
Philippines	-0.0135106	-0.0194716	-0.0058301	-0.00991	-0.0000485	-0.0000615
Qatar	-0.0030329	-0.01396	-0.0003022	-0.00211	-0.000013	-0.0000202
Saudi Arabia	-0.0014154	-0.005123	-0.0001606	-0.00084	-0.0000003	-0.0000009
Singapore	-0.0131401	-0.0188694	-0.0054697	-0.00923	-0.0001034	-0.0001147
Sri Lanka	-0.0168498	-0.0462982	-0.0030017	-0.00761	-0.0000207	-0.0000071
Taiwan	-0.0123837	-0.0176505	-0.0048144	-0.00774	-0.0000368	-0.000046
Thailand	-0.0202103	-0.0396765	-0.0053612	-0.01009	-0.000084	-0.0001102
Turkey	-0.0452667	-0.0767911	-0.0149199	-0.0294	-0.0000075	-0.0001378
UAE	-0.0005836	-0.0016744	-0.0001084	-0.00035	-0.0000001	-0.0000001
Vietnam	-0.0184145	-0.0750634	-0.0016326	-0.00537	-0.0001837	-0.0001307

ing to the GPD Static calculation in the 3rd column, there are 95% chances that Turkish Lira will not suffer more than 1.49% loss in a day followed by Japanese Yen with 0.98% and Korean Won with 0.95% loss. Lower risk reported currencies are Omani Rial with 0%, UAE Dirham with 0.01%, and Saudi Riyal with 0.02% during this period.

According to GPD Dynamic analysis in the 5th column, results show that there are 95% chances that loss of Irani Rial will not exceed by 0.03% followed by Pakistani Rupee, Korean Won and Vietnam's Dong that report 0.02% loss. Lowest loss reporting currencies are Hong Kong Dollar, UAE Dirham, Saudi Riyal, Indonesian Rupiah, Kuwaiti Dinar, Omani Rial, Turkish Lira, Bangladeshi Taka, Indian Rupee Qatari Riyal, Sri Lankan Rupee, Taiwans Dollar and Philip Peso that are almost 0.

At 99% confidence interval in the 2nd column GEV (Block Maxima), there are 99% chances that loss of Irani Rial will not increase 63.92% followed by Iraqi Dinar with 44.68% and Kazakhstani Tenge with 13.33% loss in a day. However, loss trend in Irani Rial and Iraqi Dinar currency is abnormally high at 99% confidence level. Less loss bearing currencies are UAE Dirham with 0.17% loss, Hong Kong Dollar with 0.28% loss and Saudi Riyal with 0.51% loss.

According to GPD Static calculation in the 4th column, there are 99% chances that the loss of Turkish Lira will not be higher than 2.94% in a day followed by Iraqi Dinar with 2.17% risk and Korean Won with 2.09% loss. Lower loss reporting currencies are UAE Dirham with 0.03%, Omani Rial and Saudi Riyal with 0.08% during this period.

According to GPD Dynamic analysis in the 6th column, there are 99% chances that Irani Rial will not suffer more than 0.03% loss followed by Irani Rial, Pakistani Rupee, Korean Won and Vietnam's Dong report 0.02% loss. However, lower risky currencies are Hong Kong Dollar, UAE Dirham, Kuwaiti Dinar, Saudi Riyal, Omani Rial, Sri Lankan Rupee, Indian Rupee, Bangladeshi Taka, Qatari Riyal, Japanese Yen, Indonesian Rupiah, Taiwans Dollar and Kazakhstani Tenge that are almost 0.

After estimation of VaR under extreme conditions, back testing is used to examine the accuracy of the model. Initial violation ratio is estimated that compares the actual violation with expected violations. Table 3 shows the violation ratio for EVT based VaR estimation during 2005-2018 period at 95% and 99% confidence intervals. At 95% and 99% confidence intervals, the VR reported that 96% of the estimated results are closer to 1, as its not violated by GPD static whereas, the other forecasting models like Block Maxima and GPD dynamic indicate weak VaR estimates. EVT violation ratio trend is same at 95% and 99% confidence intervals. However, performance at 95% level models is better than 99% level.

Table 4 explains the results of kupiec back testing at 95% and 99% level of significance. At 95% results show that null hypothesis is accepted in 96% cases when GPD static EVT approach is used which is higher than Block Maxima and GPD dynamic with 0% acceptance level. However, only Omani Rial results report insignificant likelihood ratio 186.82 > 3.84 out of 25 Asian currencies. For the results at 99% confidence interval, null hypothesis is accepted for 100% currencies when VaR is estimated by using GPD static because all values are

Table 3: Violation ratio of EVT approach

	Block Maxima		GPD (Static)		GPD (Dynamic)	
	0.95	0.99	0.95	0.99	0.95	0.99
Bangladesh	0.0408	0	0.9735	0.9618	6.2256	31.0114
China	0.0408	0.0292	1.0732	1.079	7.6874	38.4369
Hong Kong	0.0466	0.0292	1.0087	1.0496	9.7609	48.8047
India	0.0577	0.0577	1.056	1.0675	9.5961	48.0958
Indonesia	0.0408	0.0292	0.974	0.9915	9.548	47.7399
Iran	0.0542	0.1356	1.0521	1.0304	4.0727	25.7863
Iraq	0.0049	0	1.0398	1.069	3.0904	14.5044
Israel	0.0292	0.0292	1.068	1.0213	9.5769	47.7969
Japan	0.035	0.0292	1.0443	1.021	9.8483	49.2707
Kazakhstan	0.0816	0.0874	1.0434	1.0784	8.0618	40.6587
Korea	0.0817	0.0292	1.0499	1.079	9.2972	45.9609
Kuwait	0.0494	0.074	1.0612	1.0612	6.5449	32.7246
Malaysia	0.0466	0	1.0726	1.0493	9.3967	46.9251
Oman	0.0048	0	2.0553	1.3815	2.0553	10.2763
Pakistan	0.0526	0.0263	1.0673	1.0515	7.103	35.5152
Philippines	0.0583	0	1.0612	1.0787	9.8309	49.0671
Qatar	0.1743	0.339	0.9249	1.0412	6.6392	33.0993
Saudi Arabia	0.1218	0.0794	0.9846	1.0588	6.0296	30.1482
Singapore	0.0466	0.0583	1.0379	1.0787	9.3644	46.8222
Sri Lanka	0.0583	0	1.0496	1.0787	9.0087	45.0146
Taiwan	0.0408	0.0291	0.9793	1.0784	9.8164	48.7904
Thailand	0.0525	0.0583	1.0204	1.0496	9.2362	46.0641
Turkey	0.0583	0.0292	1.0379	1.0787	9.7784	48.8338
UAE	0.0635	0.0794	1.122	0.9526	5.1389	25.6946
Vietnam	0.0466	0	1.0729	1.0787	6.1399	30.8163

less than chi square values at 1 degree of freedom. So kupiec back testing results shows that GPD Static is the best method for forecasting in extreme tails distribution in Asian currencies.

Table 5 reports the results of Christoffersen test of independence at 95% and 99% level of significance. Results of Christoffersen test at 95% level of significance shows that null hypothesis of independence is accepted for 20% currencies when VaR is estimated by using GPD static. Results indicate that there is no clustering in 20% Asian currencies but 80% currencies have clustering in their markets like Chinese Yuan Renminbi, Kazakhstani Tenge, Sri Lankan Rupee, Pakistani Rupee, Indonesian Rupiah, Hong Kong Dollar, Korean Won, Indian Rupee, Turkish Lira, Vietnami Dong, Saudi Riyal, Israeli Shekel, Iraqi Dinar, Qatari Riyal, Thai Baht, Singapore Dollar, UAE Dirham, Taiwani Dollar, Malaysian Ringgit and Philippines Peso because their likelihood ratio lies between 3.952 - 21.25 which is greater than chi square at 1 degree of freedom.

At 99% confidence interval Christoffersen's test provides that the null hypothesis has been accepted for 48% currencies when VaR is estimated by using GPD static. However, there is 0% correct forecasting by block maxima and GPD dynamic so their null hypothesis acceptance or rejection does not matter. Remaining 52% currency markets i-e Kazakhstani Tenge, Indonesian Rupiah, Pakistan Rupee, Qatari Riyal, Sri Lankan Rupee, Saudi Riyal, Korean Won, Thai Baht, Hong Kong Dollar, Indian Rupee, Taiwani Dollar, Turkish Lira and Chinese Yuan Renminbi have the likelihood ratio between 7.28 - 50.79 which

Table 4: Kupiec back testing of EVT approach

	Block Maxima		GPD (Static)		GPD (Dynamic)	
	0.95	0.99	0.95	0.99	0.95	0.99
Bangladesh	292.49	59.875	0.1281	0.0512	2386	5598.5
China	292.29	59.836	0.9454	0.2109	3544.8	7613.1
Hong Kong	286.03	59.855	0.0138	0.0837	5456.8	10700.4
India	277.52	54.22	0.5617	0.1561	5349.5	10589.9
Indonesia	292.29	59.836	0.1226	0.0025	5245.3	10366.8
Iran	299.05	44.055	0.5177	0.034	1073.1	4603.8
Iraq	409.49	73.28	0.3397	0.1936	623.96	2161.1
Israel	305.72	59.797	0.8165	0.0156	5270.5	10378.3
Japan	298.83	59.816	0.3499	0.0152	5540.7	10839.7
Kazakhstan	252.43	48.287	0.336	0.2077	3869.6	8253.4
Korea	252.24	59.836	0.4419	0.2109	5002	9821.5
Kuwait	334.51	59.771	0.7839	0.1503	3100.9	7144.3
Malaysia	286.13	59.875	0.9301	0.0828	5101	10121.9
Oman	410.51	73.476	187.82	5.4207	187.82	1247.3
Pakistan	310.33	67.166	0.8881	0.1003	3396.5	7542.9
Philippines	274.04	59.855	0.664	0.2093	5526.5	10782.3
Qatar	222.54	24.491	1.2548	0.0697	3247.6	7402
Saudi Arabia	242.49	54.683	0.0471	0.1293	2469.9	5918.5
Singapore	286.03	53.538	0.2563	0.2093	5068.3	10087.3
Sri Lanka	274.04	59.855	0.4367	0.2093	4729	9537.8
Taiwan	292.49	59.875	0.0778	0.2077	5513.6	10699.1
Thailand	279.92	53.538	0.0747	0.0837	4944.9	9855.8
Turkey	274.04	59.855	0.2563	0.2093	5474.2	10709.5
UAE	296.32	54.702	2.8523	0.087	1798.9	4692.8
Vietnam	286.03	59.855	0.9377	0.2093	2322.5	5546.1

is more than the tabulated value so the null hypothesis is rejected indicating violations are not independent.

Expected shortfall's debate beyond VaR refers to the expected losses incurred when VaR is being violated. It is average of all losses which are greater or equal than VaR. The expected shortfall measures more uncertainty than VaR. It is used to obtain the expectation of tails. It is said to be the sub additive risk measure. Table 6 shows the results of expected shortfall under all methods like block maxima, GPD static and GPD dynamic of EVT Approach with 95% and 99% significance level.

According to GEV Block Maxima Approach at 95% confidence interval, maximum loss incurred in a day reported by Irani Rial with 30.60% followed by Iraqi Dinar with 27.98% and Kazakhstani Tenge with 25.06% loss. Other 19 Asian currencies report losses between 1.12% -22.41%. However, minimum loss is reported by UAE Dirham with 0.15% ES in a day followed by Hong Kong Dollar with 0.22% and Saudi Riyal with 0.64% expected shortfall. GPD Static method estimation of expected shortfall is reported in 3rd column, maximum loss is suffered by Irani Rial with 3.95% followed by Turkish Lira with 2.45% and Kazakhstani Tenge with 1.72%. The maximum loss expected in a day is for UAE Dirham with 0.04% followed by Omani Rial with 0.06% and Hong Kong Dollar with 0.08%. Remaining currencies generally bear losses between 0.09%-1.69% in a day .

In GPD Dynamic estimation, worst expected loss is forecasted for Hong

Table 5: Christoffersen test of independence

	Block Maxima		GPD (Static)		GPD (Dynamic)	
	0.95	0.99	0.95	0.99	0.95	0.99
Bangladesh	6.2529	12.737	1.7983	0.9584	17.625	17.373
China	6.817	12.735	21.254	7.2784	0.5472	0.5472
Hong Kong	5.7598	12.737	23.493	7.5834	0.3575	0.3575
India	5.3442	12.756	19.721	7.3355	3.2945	2.5595
Indonesia	6.2518	12.735	23.558	23.558	0.4943	0.8253
Iran	5.0758	5.0758	1.4229	0.678	21.014	6.9858
Iraq	13.1	13.101	12.225	0.4143	19.504	28.282
Israel	7.4797	12.734	13.06	0.7961	6.0708	6.0292
Japan	6.817	12.735	2.2678	3.7616	6.0377	5.3794
Kazakhstan	10.905	9.2888	91.42	50.793	3.6033	3.395
Korea	19.219	12.735	22.932	11.969	0.6493	1.2254
Kuwait	5.2592	9.6208	1.8528	6.5225	15.052	15.052
Malaysia	5.7604	12.737	6.1631	0.6555	8.0572	8.0123
Oman	13.105	13.106	0.92	0.04019	0.92	0.92
Pakistan	14.218	12.943	26.835	22.393	20.486	19.842
Philippines	4.9348	12.736	3.9525	0.6548	0.0943	0.0588
Qatar	8.5886	4.0513	11.78	21.561	104.33	105.22
Saudi Arabia	2.2772	9.481	14.833	16.638	65.317	65.317
Singapore	5.7598	10.645	7.4363	3.3867	0.7099	0.7099
Sri Lanka	5.3238	12.737	52.525	17.289	3.031	2.8191
Taiwan	6.2529	12.736	6.5244	7.2815	1.2387	1.4307
Thailand	5.3244	10.645	8.1276	7.5834	10.763	11.084
Turkey	23.84	12.736	19.028	7.28	0.1593	0.2157
UAE	4.7698	0.8504	6.626	0.8504	50.875	50.875
Vietnam	5.7598	12.736	15.417	3.3867	0.5663	0.754

Kong Dollar with 0.41% expected shortfall in a day followed by Irani Rial 0.04% and Pakistani Rupee with 0.03%. Least losses are estimated by UAE Dirham, Saudi Riyal, Qatari Riyal, Omani Rial, Kuwaiti Dinar, Taiwani Dollar, Philippines Peso, Bangladeshi Taka, Sri Lankan Rupee, Malaysian Ringgit, Indonesian Rupiah, Thai Baht, Indian Rupee, Iraqi Dinar, Israel Shekel with almost 0% expected shortfall. However, Chinese Yuan Renminbi, Singapore Dollar, Korean Won, Japanese Yen with 0.01% and last 3 currencies of Asian Market Turkish Lira, Vietnami Dong and Kazakhstani Tenge with 0.02% expected shortfall is also not at extreme stage. Finally expected shortfall is estimated at 99% confidence level, Block Maxima method's results illustrate that maximum loss reported in a day by Irani Rial is 241.40% followed by Iraqi Dinar with 204.89%, Omani Rial with 111.86%, and Kazakhstani Tenge with 104.01% expected shortfall. However, Hong Kong Dollar with 0.39%, UAE Dirham with 0.44% and Taiwani Dollar 1.93% are the countries which suffered least losses in a day during this period. Other countries suffered losses between 2.12% - 53.12%.

GPD Static shows that maximum loss incurred by Kazakhstan Tenge with 4.60% followed by Turkish Lira with 4.38% and Korean Won with 3.23% expected shortfall. However, minimum loss is suffered by UAE Dirham with 0.08%, Hong Kong Dollar with 0.14% and Omani Rial with 0.15%. Rest of the currencies reported loss between 0.17% - 2.79%.

GPD Dynamic indicates that the highest loss is faced by Hong Kong Dollar

Table 6: Expected shortfall of EVT approach

	Block Maxima		GPD (Static)		GPD (Dynamic)	
	0.95	0.99	0.95	0.99	0.95	0.99
Bangladesh	-0.04569	-0.107142	-0.0094461	-0.0196844	-0.00002867	-0.00002858
China	-0.0111984	-0.0211911	-0.0036129	-0.0064703	-0.00008283	-0.00008283
Hong Kong	-0.0021842	-0.0038738	-0.0007729	-0.0013563	-0.00408592	-0.02042461
India	-0.0243128	-0.0375433	-0.0111814	-0.01825	-0.00004604	-0.00004594
Indonesia	-0.0359728	-0.0677596	-0.0107429	-0.0215457	-0.00004256	-0.00004236
Iran	-0.3061895	-2.413998	-0.0395436	-0.0017255	-0.00038811	-0.00038022
Iraq	-0.2797656	-2.048945	-0.0130074	-0.0278519	-0.00004685	-0.00004743
Israel	-0.0285549	-0.046368	-0.0115106	-0.0184367	-0.00004753	-0.00004763
Japan	-0.0328213	-0.0501683	-0.0144897	-0.0228665	-0.00013561	-0.00013538
Kazakhstan	-0.2506489	-1.0401118	-0.0172093	-0.0460126	-0.00020984	-0.00020896
Korea	-0.0437408	-0.0784073	-0.0169147	-0.0323379	-0.00011647	-0.00011685
Kuwait	-0.0115534	-0.0221403	-0.0038949	-0.0079507	-0.00000816	-0.00000815
Malaysia	-0.0149979	-0.0202791	-0.0094176	-0.0141356	-0.00004028	-0.00004036
Oman	-0.2240939	-1.1186399	-0.0005646	-0.0015006	-0.000004	-0.000004
Pakistan	-0.054314	-0.1504869	-0.0088338	-0.0196637	-0.00026989	-0.00026981
Philippines	-0.0158553	-0.0228509	-0.0084269	-0.0123824	-0.00002616	-0.00002621
Qatar	-0.0500317	-0.2302882	-0.000863	-0.0146346	-0.00000203	-0.00000205
Saudi Arabia	-0.0064106	-0.023203	-0.0009384	-0.0023098	-0.00000024	-0.00000024
Singapore	-0.0148641	-0.0213451	-0.0079123	-0.012059	-0.00008398	-0.00008402
Sri Lanka	-0.0420859	-0.1156395	-0.0064661	-0.0134869	-0.00003215	-0.00003211
Taiwan	-0.0135157	-0.0192639	-0.0067348	-0.0103491	-0.00002283	-0.00002286
Thailand	-0.03281	-0.0644121	-0.0095308	-0.0203721	-0.00004381	-0.00004395
Turkey	-0.0621916	-0.1055026	-0.0244607	-0.0437657	-0.00015464	-0.00015336
UAE	-0.001544	-0.0044298	-0.0003622	-0.0007563	-0.00000002	-0.00000002
Vietnam	-0.1303075	-0.5311744	-0.0051439	-0.0138723	-0.00020273	-0.00020243

with 2.04% followed by Irani Rial with 0.04% and Pakistani Rupee with 0.03%. Low loss reporting currencies are UAE Dirham, Saudi Riyal, Qatari Riyal, Omani Rial, Kuwaiti Dinar, Taiwani Dollar, Philippines Peso, Bangladeshi Taka, Sri Lankan Rupee, Malaysian Ringgit, Indonesian Rupiah, Thai Baht, Indian Rupee, Iraqi Dinar and Israeli Shekel that are almost 0. Table 7 explains the method for EVT approach at 95% and 99% confidence interval for 25 Asian countries.

The analysis of EVT based approach shows that GPD static perform better than block maxima and GPD dynamic at both 95% and 99% confidence interval. In 96% cases VR ratio estimation is correct. While other two models block maxima and GPD dynamic fail to estimate the correct losses. Results of Kupiec test also support the strength of GPD static estimation. At 95% level of significance, the observed and expected violations are same in 96% cases. At

Table 7: Method selection criteria for Asian currency market

Approaches	Method	VR		Kupiec		Christoffersen	
		95%	99%	95%	99%	95%	99%
EVT	Block Maxima	0%	0%	0%	0%	4%	12%
	GPD (Static)	96%	96%	96%	100%	20%	48%
	GPD (Dynamic)	0%	0%	0%	0%	52%	60%

99% confidence level, 100% observed and expected violations are same but other two methods again fail to predict the losses at both 95% and 99% confidence intervals. Christoffersen test at 95% confidence level identify exception clustering in many cases and only 20% of the above qualify independence test and at 99% confidence interval only 48% cases qualify independence test. The selection of 1 method from EVT approach in the above table provides that GPD static for both 95% and 99% confidence intervals is best, except for Omani currency. However, other two methods block maxima and GPD dynamic fail to correctly forecast the losses.

5 Conclusion

The finding of this study shows the results of EVT approach at 95% and 99% that GPD static method performs better for both intervals because this model provides a better estimation of extreme loss forecasting in the left tail of the distribution. Most risky currencies are Turkish Lira and Irani Rial and less risky currencies are UAE Dirham, Omani Rial and Saudi Riyal.

However, the estimation of VaR for the Gulf currencies (Omani Rial, UAE Dirham, Irani Rial and Iraqi Dinar) is an issue due to very low volatility in currency price. The results of these currencies are unable to capture market dynamics. There is no free float in these currency markets. Most of transactions are done in only one commodity which is oil. Currency price is kept constant with US dollar through managed float. When governments prefer managed float or artificially stabilize their currencies then VaR model does not work on forecasting the financial risk because VaR model gives better results on free floating currency markets.

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