The Empirical Econometrics and Quantitative Economics Letters
ISSN 2286 – 7147
Volume 3, Number 1 (March 2014), pp. 33 - 44.

Forecasting Chinese Yuan currency risk with extreme value theory

Yichen Lan, Kanchana Chokethaworn, Chukiat Chaiboonsri

Faculty of Economics, Chiang Mai University
E-mail: lan_yichen@yeah.net

ABSTRACT

This paper is intended to measure the risk of CNY foreign exchange rate by introducing VaR based on the extreme value theory. In empirical study, it selects the negative daily log-returns of CNY foreign exchange rate including USD/CNY, EUR/CNY, JPY/CNY and HKD/CNY at the period of 1 September 2005–30 August 2013 as a sample data set, hoping to seek a perfect method to measure the tail risk in CNY foreign exchange rate market.

Keywords: Foreign exchange market; Value at risk; Expected Shortfall; Extreme value theory;

1. Introduction

Foreign exchange market is one of the most important financial markets in the world, trading in foreign exchange markets averaged \$5.3 trillion per day in April 2013, compared with \$4.0 trillion in April 2010 and \$3.3 trillion in April 2007. FX swaps were the most actively traded instruments in April 2013, at \$2.2 trillion per day, followed by spot trading at \$2.0 trillion. In April 2013, monthly bulletin on China FX spot traded on \$287.678 billion, the USD.CNY trading at \$260.921 billion, accounting for 90.70% of the total volume.

Traditional portfolio financial returns, especially exchange rate and interest rate returns, are not normally distributed. Over the past three decades, global financial crisis events occurred frequently, almost once every three to five years. Actually, tail risk has been an important topic in financial literature since academic researchers realized that market returns often violate normal assumptions.

The Basel II Accord requires that banks and other Authorized Deposit-taking Institutions (AIDs) communicate their daily VaR forecasts to monetary authorities usually the central bank at the beginning of each trading day. On the other hand, institutions and investors must pay attention to the risk that they incur as well as the expected return from their activities.

Standard VaR models face a series of problems: normally distributed returns hypothesis, not coherent, disregards of tail risk, i.e., focus on the centre of the distribution, the regular events, and have no tools for extreme events. Therefore, an alternative risk measurement, Expected Shortfall (ES), has been put in place as a supplement to VaR.

Under extreme market conditions, Extreme Value Theory (EVT) is a powerful complementary tool which relies on extreme observations to derive the distribution of the tails of loss distribution by modeling the extreme values in the financial market directly (no normal distribution assumptions). Therefore, VaR based on EVT can forecast the real risk of market more efficiently in predicting extreme-losses.EVT studies the tail of loss distribution by modeling the market extreme values directly. It contains two main approaches: Block Maxima(BM) and Peaks over Threshold (POT). But BM need a large amount of data which often cannot meet in practice. So this paper choose POT model to measure foreign exchange market risk.

2. Literature Review

Markowitz (1952) put forward the foundations of modern risk analysis in a paper concerning the principles of portfolio selection. Markowitz showed that a rational investor who behaves in a way that is consistent with Von Neuman–Morgenstern's expected utility maximization, should analyze alternative portfolios based on their mean and on the variance of their rates of return. Markowitz makes two additional assumptions: first of all, capital markets are perfect; the second, the rates of return is normally distributed.

The earliest definition of foreign exchange risk is from MiChael Adler and Bernard Dumas (1983).They think the exchange rate risk is real domestic currencies value of assets and liabilities or revenues on the sensitivity of the unexpected changes in exchange rates.

Ronald MacDonald (1988, 2007) is the first to present a comprehensive overview of both the theoretical and empirical strands of the exchange rate literature and is still in print today despite much of the material being dated. The author is attempting to produce a coherent overview of the main theoretical and empirical strands in the economics of exchange rate literature.

Danielsson et al. (1998) suggest that a good VaR model should correctly represent the likelihood of extreme events by providing smooth tail estimates which extend beyond the historical sample. Therefore, recent research on VaR is focusing on modeling event risks and many authors have suggested the use of statistical techniques developed for analyzing extreme realizations of random variables.

As Jorion (2000) claims, the EVT applies smooth curves through the extreme tails of the distribution (99.90%, 99.95%, etc.) and it provides not only a unique VaR estimate for the selected confidence level but its related confidence interval as well.

Michel Crouhy et al. (2001) think the exchange rate risk is mainly due to the imperfect correlations in the movement of currency prices and fluctuations in international interest rates. Foreign exchange risk is part of the major risks faced by large multinational corporations. Foreign exchange volatility can make a firm lose the return from expensive investments, and at the same time place at a competitive disadvantage compared with its foreign competitors.

ZHU et al. (2001) review the development of Extreme Value Theory and its applications in the areas of engineering, then focusing on the area of financial risk management.

Lan-Chih Ho et al. (2001) say VaR model provides estimates of the potential loss in a single statistic to which a bank is exposed over a given period of time with a given degree of confidence. They get conclusion that VaR measures generated via the extreme value theory are substantially different from those generated by traditional methods, such as the variance–covariance, both using Student’s t and normal distributions, and historical methods. This is especially the case in markets that are characterised by very fat tailed distributions, such as in Southeast Asia during the recent financial market crisis.

Yasuhiro Yamai et al. (2002) find that information given by VaR may mislead rational investors who maximize their expected utility. In particular, if rational investors apply only VaR as a riskmeasure, they are likely to construct a perverse position that would result in a larger loss in the states beyond the VaR level. Investors can relieve this problem by adopting expected shortfall. However, the effectiveness of expected shortfall, depends on the stability of the estimation and the choice of efficient back testing methods.

Stelios D. Bekiros et al. (2005) conducted a comparative evaluation of the predictive performance of various VaR models, with special emphasis on two methods of the Extreme Value. For routine confidence levels such as 90%, 95% and perhaps, even 99%, conventional methods may be sufficient. At higher confidence levels, however, the normal distribution underestimates potential losses. While the historical simulation method provides an improvement, it still suffers from lack of data in the tails that is therefore difficult to estimate VaR reliably.

Gavril, A. M. (2009) uses exchange rate returns for four currencies against the Euro and analyses the relative performance of several VaR models and Extreme Value Theory, respectively. The research shows that in extreme market conditions, extreme measures are required, and that no single measure can perform properly for both the centre and the tails of an exchange rate distribution.

ZongrunWang et al. (2010) adopt EVT-based VaR and ES to measure the exchange rate risk of CNY and find that ES cannot improve the tail risk problem of VaR in most of the cases. This result is in agreement with the one derived by Yasuhiro and Toshinao and confirms their opinions. By comparing the performance of HS and variance–covariance method, EVT-based VaR values can reflect the risks of EUR/CNY and JPY/CNY accurately and can pass the back testing well.

LI Xiangdong et al. (2011) compare the impact of the threshold value selection on the estimated consequence， and change the threshold quantile of different exchange rates ，then a corresponding change in the number of the extreme points will be shown. Results show that the left and right tails of the distribution of the logarithm gains of foreign exchanges are asymmetric，both having a fat tail to some degree，and a secondary moment． The distribution presents finite variance．

P. Araujo Santos et al.(2011) introduce a model based approach within the POT framework, that uses the durations between excesses as covariates, is proposed. Based on this approach, models for forecasting one-day-ahead Value-at-Risk were suggested and applied to actual data. Comparative studies provide proof that they can perform better than state-of-the art risk models and much better than the widely used RiskMetrics model, both in terms of out-of-sample accuracy and under the Basel II Accord.

Rokas Serepka (2012) makes performance analysis of foreign exchange rates time series. First, triangular arbitrage is detected and eliminated from the data series using linear algebra tools. Then Vector Autoregressive processes are calibrated and used to replicate dynamics in exchange rates as well as to forecast time series. Finally, optimal portfolio of currencies with minimal Expected Shortfall is formed using one time period ahead of forecasts.

Raúl de Jesúsa et al. (2012) confirm the high potential from EVT not only for describing the asymptotic behavior of the tails from the returns distribution of exchange rates, but also to quantify in a more precise way losses to which are exposed investors during periods of financial turbulences. The empirical evidence is a clear indication that the returns distribution from the peso/dollar exchange rates are characterized by heavy or fat tails resulting from excess kurtosis, derived from atypical or extreme movements which are not captured by the normal distribution.

3. Related Theories

3.1 Value at Risk

Suppose X is a random variable denoting the loss of a given asset or asset portfolio, we define VaR at the 100(1 – α) confidence level as

$$VaR_{\alpha}\left(X\right) = sup\{x \mid \mathrm{P}\left[X \geq x\right] > \alpha\}.$$

where $sup\{x \mid A\}$ is the upper limit of x given event A.

Artzner et al. (1997, 1999) have cited the following two shortcomings of VaR: it measures only percentiles of profit-loss distributions, and thus disregards any loss beyond the VaR level ("tail risk"); not coherent for lacking subadditivity.

Expected Shortfall (ES) is defined as the conditional expectation of loss given that the loss is beyond the VaR level. Suppose X is a random variable denoting the profit-loss of a given portfolio and VaRα(X) is the VaR at the 100(1 – α) percent confidence level. ESα(X) is defined as

$$ES_\alpha(X) = E\left[X \mid X \geq VaR_\alpha(X)\right].$$

3.2 Extreme Value Theory

There are for two alternative methods for generating extreme returns: the oldest BM and the more modern POT. As is mentioned above, we choose POT model to measure foreign exchange market risk.

Let x_1, x_2, . . . , x_n be the series of loss(the opposite of return). In this paper, the loss is negative logarithmic daily change of each exchange rate against CNY. Let F be the distribution function of it. Since what we are interested in are the losses that exceed a given threshold θ, we define the distribution function of excess losses $y_t = x_i - \theta$ given that x_i exceeds θ as

$$F_\theta(y) = P\left(x_t - \theta \leq y \mid x_t > \theta\right) = \frac{P\left(\theta < x_t \leq \theta + y\right)}{P\left(x_t > \theta\right)} = \frac{F(y+\theta) - F(\theta)}{1 - F(\theta)}.$$

We can derive the following equation from equation above

$$F(x) = \left[1 - F(\theta)\right] \cdot F_\theta(x - \theta) + F(\theta).$$

For a large class of underlying distribution functions F, for a sufficiently high threshold θ, the conditional excess distribution function F_θ is well approximated by

$$F_\theta(y) \approx G_{\xi,\sigma}(y), \ u \to \infty$$

where

$$G_{\xi,\sigma}(y) = \begin{cases} 1 - (1 + \xi \cdot \dfrac{y}{\sigma})^{-1/\xi}, & for \xi \neq 0 \\ 1 - \exp(-\dfrac{y}{\sigma}), & for \xi = 0 \end{cases}.$$

$G_{\xi,\sigma}$ is the Generalized Pareto Distribution (GPD) with ξ the shape parameter and σ the scale parameter, which measures the statistical dispersion of the series. The higher the scale parameter, the more spread out the distribution.

Thus, we can derive the tail estimation expression $F(x)$ as

$$\begin{aligned} F(x) &= \left[1 - F(\theta)\right] \cdot G_{\xi,\sigma}(x - \theta) + F(\theta) \\ &= 1 - p(1 + \xi \cdot \frac{x - \theta}{\sigma})^{-1/\xi}, \ x \geq \theta, \end{aligned}$$

where $P = 1 - F(\theta)$ is the tail probability, ξ the tail index and σ the scale parameter.

Let N_θ /n replace p, where n is the sample size, N_θ is the number of data points that exceed the threshold, then we can derive the estimation of tail as

$$F(x) = 1 - \frac{N_\theta}{n}(1 + \xi \cdot \frac{x-\theta}{\sigma})^{-1/\xi}, x \geq \theta.$$

Under the q confidence level, we can derive the expression of $VaRq$

$$VaR_q = F^{-1}(q) = \theta + \frac{\sigma}{\xi}\left\{\left[\frac{n}{N_\theta}(1-q)\right]^{-\xi} - 1\right\},$$

Then

$$ES = VaR_q + E(x - VaR_q \mid x > VaR_q),$$

where $E(x - VaR_q \mid x > VaR_q)$ is the conditional expectation of exceedances given the threshold equals to VaR_q. So

$$\begin{aligned} ES &= VaR_q + E(x - VaR_q \mid x > VaR_q) \\ &= VaR_q + \frac{\sigma + \xi\left(VaR_q - \theta\right)}{1-\xi} \\ &= \frac{VaRq + \sigma - \xi \cdot \theta}{1-\xi}. \end{aligned}$$

To estimate *VaR* and *ES*, we need to choose an appropriate threshold θ and estimate the parameters ξ, σ at first.

3.2.1 Threshold Selection

The choice of the optimal threshold θ is an important issue in the implementation of Extreme Value Theory since it is confronted with a bias–variance tradeoff.

DuMouchel (1983) predicts that the selection of a threshold around 10% of the data as the extreme data set is the right choice. Loretan and Philips(1994) also present the principal for threshold selection. They show that the threshold cannot be too low which means the number of data that exceed the threshold should be less than 10% of the sample size.

There are two main graphical tools that can be utilized to determine the appropriate threshold θ. Mean excess function (MEF) can help us choose the threshold u in the region where the curve is roughly linear, i.e. the data are well approximated by the GPD.Another useful graphical tool is the Hill estimator of the tail index. The idea behind the selection of the threshold for using this method is that choose the threshold in the area where the graph is fairly stable.

This paper also utilize thresh range plot (R project) to find an appropriate threshold. The idea behind threshrange plot is to find the lowest possible threshold whereby a higher threshold would give the same parameter estimates within uncertainty bounds.

3.2.2 Estimation of parameters ξ and σ

The parameters of the GPD model can be estimated through maximum-likelihood method (ML). Suppose that we define an excess over θ as yi = xi –θ, where i=1, 2 . . . , k, follow the GPD, the corresponding log-likelihood function with parameters ξ and σ is defined as

$$L(\xi,\sigma = \begin{cases} -k\ln\sigma-(1+\frac{1}{\xi})\sum_{i=1}^{k}\ln(1+\frac{\xi}{\sigma}\cdot y_i), & \xi\neq 0 \\ -k\ln\sigma-\frac{\xi}{\sigma}\sum_{i=1}^{k}y_i, & \xi=0 \end{cases}.$$

where we can get the estimation value of parameters ξ and σ, then derive VaR and ES.

4. Empirical study

4.1 Data Analysis

In an empirical study, it selects the daily negative log-returns ($-R_t$) of CNY exchange rate including USD/CNY, EUR/CNY, JPY/CNY and HKD/CNY at the period of 1 September 2005–30 August 2013 as a sample data sets.

In order to assess normality of data, we also use two graphical tools: histograms and QQ-Plots. Histogram is an effective graphical technique for showing both the skewness and kurtosis of data set. QQ-Plot is a tool to compare the empirical distribution with the normal. Histograms and QQ-Plot show high departure from normality of four CNY exchange rate loss return series and reject the normally distributions hypothesis.

4.2 Threshold Selection

The total number of each exchange rate return series observations is 2086, and the exceedances is USD/CNY 208, EUR/CNY 208, JPY/CNY 207, HKD/CNY 207, all less than 10% of the sample. Combine with MEF plot, Hill plot and thresh range plot, selections in the case are all less than 10% of the sample, consistent with the principle mentioned above, otherwise there may be excessive fitting.

TABLE 1. Threshold and number of excesses for each exchange rate of CNY

	USD/CNY	**EUR/CNY**	**JPY/CNY**	**HKD/CNY**
Threshold θ	0.0465	0.224	0.221	0.046
N_θ	208	208	207	207

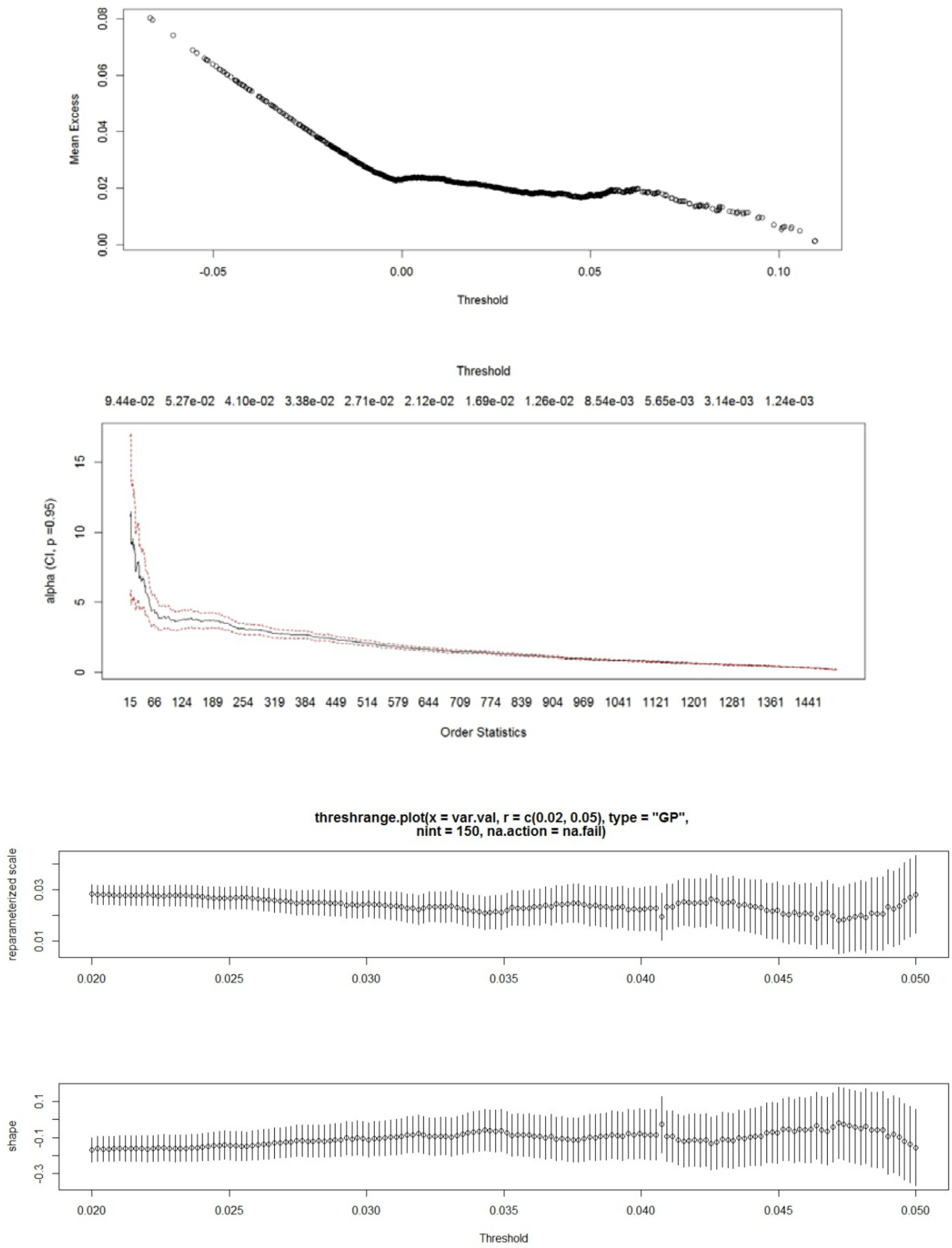

Figure 1. MEF plot, Hill plot and thresh range plot of USD/CNY

4.3 Diagnostic Plots for GPD Fit

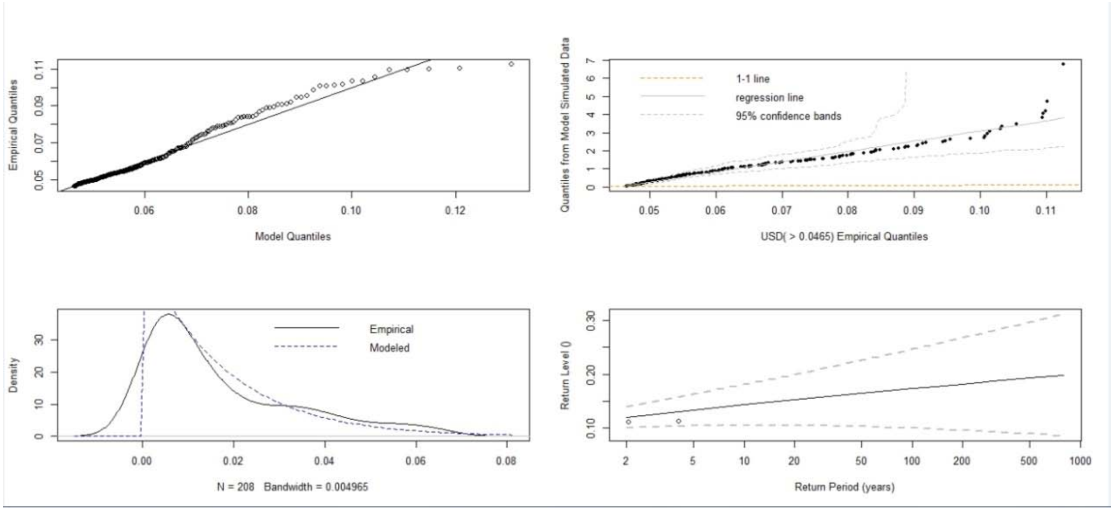

Figure 2: Diagnostic plots for GPD fit of USD/CNY

If the parametric model fits the data well, the QQ plot should have a linear form. The more linear the quartile plot, the more applicable the model in terms of goodness of fit. We compare the empirical distribution with the model. In the diagrams, the goodness-of –fit in the quartile plot is convincing which indicate that GPD fits the exchange rate returns of CNY perfectly, and the return level also illustrates the large certainties that fit well to the model.

4.4 Estimation of Parameters and Calculation of VaR (ES)

Table 2 displays the summary results of parameters estimation and return level from exchange rate loss return series of CNY based on Generalize Pareto Distributions method in the next twenty years (2013-2033). Since we study the daily negative log-returns, for four exchange rate loss return series, the loss risk will increase gradually during 2013-2033.

In 2017, the loss return level for USD/CNY is 0.134% (0.1144%, 0.1877%) at the confidence level of 95%; for EUR/CNY is 0.697% (0.6536%, 0.8965%); for JPY/CNY is 0.668% (0.6268%, 0.8565%); and for HKD/CNY is 0.126% (0.121%, 0.1455%). In 2033, the loss return level for USD/CNY is 0.153% (0.1414%, 0.2386%) at the confidence level of 95%; for EUR/CNY is 0.764% (0.6737%, 1.0768%); for JPY/CNY is 0.746% (0.6614%, 1.0493%); and for HKD/CNY is 0.136% (0.123%, 0.163%). In terms of return level, the risk of USD/CNY is similar to HKD/CNY, while the risk of EUR/CNY is the same as JPY/CNY.

The final results of calculation of VaR and ES are shown in table 3. Both in Value at Risk and Expected Shortfall, the risk of USD/CNY is similar to HKD/CNY, while the risk of EUR/CNY is close to JPY/CNY.

TABLE 2. The results of parameters estimation and return level (2013-2033)

	θ	**σ**	**ξ**	**5-year**	**10-year**	**20-year**
USD/ CNY	0.0465	0.01751267	-0.03952633	0.134	0.143	0.153
95%		(-4.2788, -3.821)	(-0.2089, 0.1306)	(0.1144, 0.1877)	(0.1503, 0.2102)	(0.1414, 0.2386)
EUR/ CNY	0.224	0.11548430	-0.13216010	0.697	0.732	0.764
95%		(-2.3677, -1.9666)	(-0.237, 0.0419)	(0.6536, 0.8965)	(0.6484, 0.985)	(0.6737, 1.0768)
JPY/ CNY	0.221	0.09589486	-0.08102268	0.668	0.708	0.746
95%		(-2.4481, -2.1075)	(-0.2116, 0.0267)	(0.6268, 0.8565)	(0.6123, 0.9514)	(0.6614, 1.0493)
HKD/ CNY	0.046	0.02234585	-0.17235494	0.126	0.131	0.136
95%		(-3.9964, -3.6171)	(-0.2693, -0.0179)	(0.121, 0.1455)	(0.1241, 0.161)	(0.123, 0.163)

TABLE 3. The results of VaR and ES calculation based on GPD model

	Risk	**USD/CNY**	**EUR/CNY**	**JPY/CNY**	**HKD/CNY**
0.95	**VaR**	0.0584249945	0.3001870312	0.2849389697	0.0604467360
	ES	0.0748183442	0.3932970201	0.3688542797	0.0773834870
0.99	**VaR**	0.0849977625	0.4530170834	0.4218195023	0.0883541442
	ES	0.1003807251	0.5282868084	0.4954756126	0.1011880595

With the probability of 95%, the loss risk of USD/CNY, EUR/CNY, JPY/CNY and HKD/CNY will be less than 0.0584249945, 0.3001870312, 0.2849389697 and 0.0604467360. It means that the extreme value in tomorrow's loss for USD/CNY will be 0.058425% at a significant level of 95%, for EUR/CNY 0.300187%, for JPY/CNY 0.284939%, and HKD/CNY 0.060447%. If we invest \$1 million in USD/CNY, we are 95% confident that our daily loss will do not exceed \$584.25 on one trade day. Then, assuming that the loss happens, the mean loss over a given day period, will be 0.0748183442, 0.3932970201, 0.3688542797, and 0.0773834870. It means that the average of USD/CNY loss will be 0.074818% under a level of 95% confidence, for EUR/CNY 0.393297%, for JPY/CNY 0.368854%, and for HKD/CNY 0.077383%. With the probability of 99%, the loss risk of USD/CNY, EUR/CNY, JPY/CNY and HKD/CNY will be less than 0.0849977625, 0.4530170834, 0.4218195023, and 0.0883541442. It means that the extreme value in tomorrow's loss for USD/CNY will be 0.084998% at a significant level of 99%, for EUR/CNY 0.453017%, for JPY/CNY 0.42182%, and HKD/CNY 0.088354%. If we invest \$1 million in USD/CNY, we are 95% confident that our daily loss will do not exceed \$849.98 on one trade day. Then, assuming that the loss happens, the mean loss over a given trade day, will be

0.1003807251, 0.5282868084, 0.4954756126, and 0.1011880595. It means that the average of USD/CNY loss will be 0.100381% under a level of 99% confidence, for EUR/CNY 0.528287%, for JPY/CNY 0.495476%, and for HKD/CNY 0.101188%.

In addition, under the confidence level of 95% and 99%, the ξ estimations of USD/CNY are the greatest among four loss return series, but VaR and ES of USD/CNY are smaller than others. At the same time, the ξ estimations of JPY/CNY are greater than that of EUR/CNY with the confidence level of 95% and 99%, but VaR and ES of JPY/CNY are smaller than that of EUR/CNY. The results indicate that VaR has tail risk in USD/CNY and JPY/CNY, and ES cannot remedy the risk in this case.

5. Conclusions

This study chooses VaR and ES based on POT method to investigate foreign exchange market risk in China. It selects four negative daily log-returns of the exchange rate as a data sample. In an empirical study, the result of parameters estimations show that the tail risk of USD/CNY is the greatest, followed by JPY/CNY, EUR/CNY, and HKD/CNY. Nevertheless, VaR and ES underestimate the tail risk when dealing with USD/CNY and JPY/CNY at low confidence level, and ES cannot improve the tail risk problem of VaR in this case, although ES has been introduced as a supplement to VaR.

The performance of POT is not always good since it is very sensitive to the selection of the appropriate high threshold and this choice can prove to be very difficult when the tails show significant departures from GPD distribution.

Further research will be divided into two parts: using standardized residuals instead of raw returns (which producing iid violations) as observations and removing the tendency to clustering of violations; comparing the performance of POT with traditional VaR methods in CNY foreign exchange market.

REFERENCES

Adler, M., Dumas, B. 1983. "International portfolio choice and corporation finance: A synthesis," The Journal of Finance 38(3), pp. 925-984.

Bekiros, S. D., Georgoutsos, D. A. 2005. "Estimation of Value-at-Risk by extreme value and conventional methods: a comparative evaluation of their predictive performance," Journal of International Financial Markets, Institutions and Money 15(3), pp. 209-228.

Carbaugh, R. J., Ghosh, K. 2010. "United-Continental Merger," Journal of Industrial Organization Education 5(1), pp. 1-12.

Cohen, L., Cornett, M., Marcus, A. J. and Tehranian, H. 2011. "Bank Earnings Management and Tail Risk during the Financial Crisis," Working paper, Boston College.

Crouhy, Michel, Dan Galai and Robert Mark. 2001. Risk Management. New York: McGraw-Hill, pp. 177-252.

Danielsson, J., Hartmann, P. and De Vries, C. G. 1998. "The cost of conservatism: Extreme returns, Value-at-Risk, and the Basle 'Multiplication Factor' Risk," January, www.RiskResearch.org.

Danielsson, J., De Vries, C. G. 2000. "Value-at-risk and extreme returns,"Annales d'Economie et de Statistique, pp. 239-270.

De Jesús, R., Ortiz, E. and Cabello, A. 2013. “Long run peso/dollar exchange rates and extreme value behavior: Value at Risk modeling,” The North American Journal of Economics and Finance 24, pp. 139-152.

Fernández, V. P. 2003. “Extreme value theory: value at risk and returns dependence around the world,” Centro de Economía Aplicada, Universidad de Chile, No. 161.

Gavril, A. M. 2009. “Exchange Rate Risk: Heads or Tails,” Bucharest University of Economics No. 35, Center for Advanced.

Ho, L. C., Cadle, J. and Theobald, M. 2001. “Estimation and hedging with a one-factor Heath-Jarrow-Morton model,”The Journal of Derivatives 8(4), pp. 49-61.

Ho, L. C., Burridge, P., Cadle, J. and Theobald, M. 2000. “Value-at-risk: Applying the extreme value approach to Asian markets in the recent financial turmoil,”Pacific-Basin Finance Journal 8(2), pp. 249-275.

Jorion, P. 2000. “Value at Risk,” The New Benchmark for Managing Financial Risk, 2nd Edition, New York.

Loretan, M., Phillips, P. C. 1994. “Testing the covariance stationarity of heavy tailed time series: An overview of the theory with applications to several financial datasets,” Journal of empirical finance 1(2), pp. 211-248.

Markowitz, H. 1952. “Portfolio selection,” The journal of finance 7(1), pp. 77-91.

McNeil, A.J. 1997. “Estimating the Tails of Loss Severity Distributions Using Extreme Value Theory,” ASTIN Bulletin 27, pp. 117-137.

McNeil, A.J. 1997. “The Peaks over Threshold Method for Estimating High Quantiles of Loss Distributions,” ETH preprint, www.math.ethz.ch/~mcneil.

McNeil, A.J.1998. “Calculating Quantile Risk Measures for Financial Return Series Using Extreme Value Theory,” ETH preprint, www.math.ethz.ch/~mcneil.

McNeil, A.J. 1999. “Extreme Value Theory for Risk Managers,” ETH preprint, www.math.ethz.ch/~mcneil.

MacDonald, R. 1999. “What do we really know about real exchange rates?” Springer Netherlands, pp. 19-65.

MacDonald, R. 2007, “Exchange rate economics: theories and evidence,” Psychology Press.

Santos, P. A., Alves, M. I. 2010. “Forecasting one-day-ahead Value-at-Risk with a Duration-based POT method,”Mathematics and Computers in Simulation.

Santos, P. A., Alves, M. I. 2011. “Forecasting Value-at-Risk with a Duration-based POT method,” Mathematics and Computers in Simulation.

Serpeka, R. 2012. “Analyzing and modelling exchange rate datausing VAR framework,”Doctoral dissertation, KTH.

Yamai, Y., Yoshiba, T. 2002. “On the validity of value-at-risk: comparative analyses with expected shortfall,” Monetary and Economic Studies 20(1), pp. 57-85.

Yamai, Y., Yoshiba, T. 2005. “Value-at-risk versus expected shortfall: A practical perspective,” Journal of Banking & Finance 29(4), pp. 997-1015.

Wang, Z., Wu, W., Chen, C. and Zhou, Y. 2010. “The exchange rate risk of Chinese yuan: Using VaR and ES based on extreme valuetheory,” Journal of Applied Statistics 37(2), pp. 265-282.

Zhu, Guoqing et al. 2001. “A review on the process of applications research of the extreme value theory,”. Journal of Systems Engineering 16(1), pp. 72-76.