International Review of
Accounting, Banking and Finance
Vol 12, No. 2, Summer, 2020, Pages 1-20

IRABF
©2020

Value at Risk based on Skewed Distributions: Evidence from Asian Equity Markets

Jo-Yu Wang[1], Cong-Duc Tran[*, 2], and Wen-Lin Wu[3]

1. *National Formosa University*
2. *Feng Chia University / Ton Duc Thang University*
3. *Feng Chia University*

Accepted February 2020

A B S T R A C T

It has been twenty years since the Basel Committee on Banking Supervision (BCBS) first announced the Capital Accord. Then, the concept of downsize risk or Value at Risk (VaR) was launched by Morgan (1997), which is a concept that has received significant attention from both investors and market risk management scholars. Furthermore, Polanski and Stoja (2010) apply the parametric density function of three skewed distributions to model VaR. Subsequently, we contribute to current literature by predicting one-day-ahead VaR to backtest the risk measurement performance of six Asian markets that receive less attention in academia.

By evaluating the risk modeling performance, the GHD-based model shows more reliable and efficient outcomes in terms of market volatility prediction compared to the NID- and STD-based models. Thus, we believe that this finding is useful for investors who want to minimize their risks before doing investment decisions. In addition, all derived risk forecast models are likely applied in Asian countries, especially in South Korea where has tight financial mechanism.

Keywords: Value at risk, expected shortfall, risk management, equity market, skewed distributions.

JEL Classification: C22, C25, C52, O30

[*]Corresponding author. Email address: mhmeddduc@gmail.com, Feng Chia University, No. 100, Wenhua Road, Xitun District, Taichung City, 407, Taiwan; or trancongduc@tdtu.edu.vn. Ton Duc Thang University, 19 Nguyen Huu Tho road, 7 district, Ho Chi Minh city, Viet Nam.

1. Introduction

Value at Risk (VaR), which summarizes the expected loss of a portfolio with a given probability, has attracted significant attention over the past thirty years. It has been used to predict extreme losses (Polanski and Stoja, 2010). In reality, many investors and financial institutions are preferable with profit-making rather than risk management. However, this may incur more risks for those involved in market trade. 2008 global financial crisis is a typical example that less risk management at least partially led to severe consequences. Hence, the demand for a more efficient risk-forecasting tool has been raised at numerous financial conferences around the world, and VaR is notable because of its characteristic of probability measurement of extreme losses.

Although VaR plays an important role in risk management, but there is no standard VaR modeling yet. In this study, we will compute VaR upon the empirical distribution for a given sample Financial returns are known not to follow a symmetric distribution as investors' reactions to good and bad financial news are different. It implies that extreme events are much more likely to occur in reality rather than be predicted by the symmetric thinner-tailed normal distribution (Turan et al., 2008). From that perspective, Skewed Student's t-distribution (STD) was firstly presented by Hansen (1994) and generalized hyperbolic distribution (GHD) by Barndorff-Nielsen (1977), offers flexibility in estimating VaR because property of fat-tailedness compared to the normal distribution. Those skewed distributions are underlined for describing financial factors and risk modelling. After then, Barndorff-Nielsen (1997) developed a special distribution that based on the origin of GHD namely normal-inverse Gaussian distribution (NID). The skewed distributions have widely employed due to its special characteristics on fitting data well as well as compute VaR (Eberlein et al., 1998; Theodossiou, 1998; Zhu and Galbraith, 2010). Furthermore, these distributions are noticed as the stylized facts solution and may be better than Student' t distribution to fit financial data (Pfaff, 2016).

Regarding to the critical role of risk management tool on securing the financial stability and improving the supervision of financial market, VaR has attracted a lot attention in both practical and academic field since its value captures closely to empirical loses (Andries and Nistor, 2016; Inui and Kijima, 2005). However, this is not true for most Asian countries, especially emerging economies such as Vietnam, Indonesia, or Malaysia whose financial system is likely unstable. Thus, extreme events, such as the financial crises in 2008, will have significant impacts on their financial systems. Consequently, risk evaluation methods in equity markets become crucial in this area. Hence, with the advantage of treating extreme uncertainty, VaR has become an ideal tool to improve risk management weakness in Asian countries.

In this study, we added two contributions to the current literature on risk management. Firstly, there are very few regarded papers was using VaR which measured upon empirical distribution and its implication in emerging areas such as Asia-Pacific. By testing the major equity indexes of Asian markets, we extend the work of Polanski and Stoja (2010) as well as Zeuli and Carvalhal (2018) since they only focus on employing VaR as risk estimation of financial assets in Western markets. Furthermore, the results from one-day VaR forecasting finally show the interesting evidences that the risk modelling is derived from GHD is very good at tracking the practical loses in most of countries. The results further reveal more empirical market risks by applying the best-fitting distribution to Asian investors. Secondly, by analyzing risk measurement is based on the aforementioned three skewed distributions of STD, GHD and NID, this research fills the gap between theory and practice of VaR. By answering the following question: How would the risk measure map the distributions output to the line of actual risk and its role in hedging? Hence, VaR forecasting from distribution fitting on financial data is revealed as an important step that should be routinely used as an empirical method in evaluating market risk. This study presents the advantages of forecasting VaR patterns using three skewed distributions on Asian equity returns, especially the generalized hyperbolic distribution.

Consequently, in order to asset the goodness of fitted risk measurement, we apply two steps analyze approach. Firstly, the VaR and Expected Shortfall (ES) are be measured along with three skewed distributions upon all six Asian countries from July 2000 to January 2017. The alternative econometric tests show the goodness of risk modelling derived from GHD in all evidences. Secondly, we analyzed the one-day VaR accuracy predicting method is known as an interval forecast with 3,500 in-sample observations with the daily out-of-sample prediction included three years in sum of 784 observations. The final risk backtesting results confirmed the outstanding of risk modelling derived from GHD in capturing the practical losses in equity market and its application in monitoring financial risk in the facts. Finally, we evaluate the validity of the risk forecasting model by following two important backtesting approaches, the unconditional coverage test proposed by Kupiec (1995) and conditional coverage test proposed by Christoffersen (1998b).

In sum, the risk modellings deriving from three-skewed distribution perform very well in most of cases, so that it shows the promising abilities in tracking the expected loses in a given horizon with both emerging and developed Asian countries. Although the model based upon GHD is outstanding compared the two model of STD and NID, but the practical results of three risk modelling should be put together to provide intuitive results for investors in monitoring market risk and secure their financial assets. Furthermore, although this paper underlines the outstanding of employing VaR as the risk management tool, it still has the limitation such as failed to capture the extremely loses. For instance, the time of China's currency crisis took placed in 2015. Several limitations were pointed in this study that could be improved in future research.

The rest of this paper is organized as follows: Section 2 provides a review of the literature. Section 3 outlines the research method of VaR and ES used in this study. Section 4 describes the data. Section 5 presents distribution estimation results and applications of skewed distributions in VaR forecasts. Finally, section 6 presents concluding remarks.

2. Literature review

Following the requirements of financial frameworks and their development, Polanski and Stoja (2010) acknowledged that VaR is a necessary tool for estimating the market risk of financial positions. Although the concept of VaR is not difficult to understand, its measurement is more complex due to non-standard estimating methods. VaR is noted as a concept in 1996, when financial experts became interested in forecasting the loss of an investment portfolio. Since the Basel Committee on Bank Supervision at the Bank for International Settlements requires financial institutions to meet capital requirements on the basis of VaR estimation, it allows them to use internal models for VaR calculations. The use of this method was first limited to the banking sector and was then extended to become a basic market risk management tool for financial institutions. VaR can be defined in a simple way that is the expected maximum loss of a portfolio in a certain holding period at a given probability.

It is interesting to note that some concepts in the literature are consistent with that of VaR. Markowitz (1952) is the first to propose the concept of modern portfolio theory, in which portfolio selection is used to gain the best return and to avert unnecessary loss. That is, it optimizes profit based on a determined level of risk, which is similar to Roy (1952). Both concepts have the same purpose as strengthening hedging and diversification effects by combining the covariance of risk factors. However, Markowitz (1952) uses the variance of data return and Roy (1952) estimates the portfolio using a metric of shortfall risk. Despite the limitation of dismissing extreme loss or return, majority of researchers in this period relied on theoretical implications rather than practical results due to the limited availability of processing strength. Since the Basle Bank Supervisors Committee allowed the critical value estimates from a bank's internal risk measurement model to become the basis for a bank's market risk regulatory capital requirement[1], a significantly body of research has contributed to the expansion of VaR measures. In the 1990s, Fallon (1996) and Kupiec (1995) introduced a technique for verifying the accuracy of VaR based on portfolio losses.

Since then, a vast amount of research has focused on constructing and evaluating VaR forecasts. Some researchers used parametric (Bollerslev, 1987; Engle, 2004, Engle and Manganelli, 2004; Bali and Theodossiou, 2008) and non-parametric approaches to measure market risks with different assumptions for the whole distribution of financial return (Yu and Jones, 1998; Chen and Tang, 2005; Cai and Wang, 2008). Other researches have been applied semi-parametric approaches that focus on tail distribution fitting rather than the whole distribution to evaluate VaR (McNeil and Frey, 2000; Fan and Gu, 2003; Francq and Zakoïan, 2018). McNeil (1999) and Gencay and Selcuk (2004) employed alternative methods by applying extreme value theory for risk management as well as practical aspects for estimating and assessing statistical models for tail-related risk measures. McDonald and Newey (1988) and Theodossiou (1998) developed and expanded a skewed version of the generalized T distribution. Those researchers argued that the skewed generalized T distribution is flexible and accommodates the skewness and excess kurtosis that is often present in financial data. Moreover, Bali and Theodossiou (2008) investigated the role of high-order moments in the estimation of conditional VaR. Christoffersen and Pelletier (2004) and Candelon et al. (2010) emphasized that backtesting is a key part of the internal model's approach to market risk management.

Among these VaR approaches, the parametric method is widely used by financial institutions due to its simplicity. This approach always assumes that the asset return follows a specific distribution such as normal distribution and most extreme events are concentrated on the left or right tail of the distribution (reflecting extreme loss and profit, respectively). This assumption helps to simplify the VaR estimation and could be a form of risk management. Milhøj (1985) emphasized that the distribution of asset returns is skewed, fat-tailed, and peaked around the mean. From this issue, we can ascertain that it is inefficient to forecast unexpected events using symmetric thinner-tailed normal distribution. Bollerslev (1987) also provided evidences to prove that the corresponding normal distribution is "thinner-tailed" than Student's *t* distribution, which is a powerful and flexible tool to analyze VaR. Following the idea that the normal distribution tail was proved thinner than Student's *t* distribution, Pownall and Koedijk (1999) investigated the downside risk in financial markets by applying the skewed Student's t-distribution-based method. Abad and Benito (2013) confirmed the Student's *t* distribution could show better performance than the normal distribution. This distribution provides a flexible tool for modeling the empirical distribution of financial data exhibiting skewness, leptokurtosis, and fat-tails (Turan et al., 2008).

Although the Student's t-distribution can estimate excess kurtosis, it does not show the skewness of return. To solve this issue, some scholars developed other distribution functions such as the new skewed Student's t-distribution proposed by Hansen (1994), the exponential generalized beta of the second kind of McDonald and Xu (1995), the generalized error distribution of Nelson (1991), and the skewed generalized Student's t-distribution of Theodossiou (2001). Some studies applied skewed distribution to estimate VaR (Bali and Theodossiou, 2008; Polanski and Stoja, 2010). Aas et al. (2005) presented a special case of the GHD to denote the generalized hyperbolic skewed Student's t-distribution. In addition, Artzner et al. (1999) proposed a coherent risk measure, mainly indicating that VaR fails to satisfy the subadditivity property. Since then, some relatively coherent risk measures have been proposed (Acerbi and Tasche, 2002; Dowd and Blake, 2006; Cont et al., 2010; Gao and Zhou, 2016).

[1] See An internal model-based approach to market risk capital requirements (Bank For International Settlements, 1995).

Some authors have debated the limitation of STD distribution in risk estimation due to the overestimation of the proportion of exceptions (Guermat and Harris, 2002; Angelidis et al., 2007). Despite in the fact that VaR as an ideal tool for risk management has gained significant attention from scholars, fewer studies use this concept in the Asian context. Several studies have investigated risk management based on VaR. For example, Mittnik and Paolella (2000) incorporated a GARCH model and non-normal distribution to model the return on the exchange rates of East Asian currencies against the U.S. dollar. Nieto (2016) summarized the alternative VaR forecast method and evaluated the results from application to the S&P500 index.

3. Methodology

3.1 VaR based on skewed densities

Previous researches outlined in section 2 emphasized the importance of symmetry and tail-fatness of returns since the characteristics of the distribution are the core of risk measurement[2]. Based on the VaR concept, three skewed distributions are applied to fit the distributions of six equity indexes of the major emerging markets in Asia. The best-fitting distribution will then be used to measure the market risk. Another important factor in using skewed distribution to fit the density of equity returns is that the skewed distributions reflect investors' unbalanced response to good and bad news.

· *Skewed Student's t-distribution*

The first skewed distribution is the skewed Student's t-distribution[3] (STD) introduced by Hansen (1994):

$$\boldsymbol{f}\ (\boldsymbol{x}|\boldsymbol{\eta},\boldsymbol{\lambda}) = \begin{cases} \boldsymbol{bc}\left[\mathbf{1}+\frac{1}{\eta-2}\left(\frac{a+bx}{1-\lambda}\right)^2\right]^{-(\eta+1)/2}, \boldsymbol{x} < -\frac{a}{b} \\ \boldsymbol{bc}\left[\mathbf{1}+\frac{1}{\eta-2}\left(\frac{a+bx}{1+\lambda}\right)^2\right]^{-(\eta+1)/2}, \boldsymbol{x} \geq -\frac{a}{b} \end{cases} \tag{1}$$

where the shape parameter (i.e., the degree of freedom) has its boundary: $2 < \eta < \infty$, and the skewness $(\lambda): -1 < \lambda < 1$. When λ is equal to zero (from equation 1), the skewed Student's t distribution is derived to Student's t-distribution. The constants a, b, and c are given by:

$$\boldsymbol{\alpha} = \boldsymbol{4\lambda c}\frac{\boldsymbol{\eta}-\mathbf{2}}{\boldsymbol{\eta}-\mathbf{1}}, \boldsymbol{b}^2 = \mathbf{1}+\mathbf{3}\boldsymbol{\lambda}^2-\boldsymbol{\alpha}^2, \boldsymbol{c} = \frac{\boldsymbol{\Gamma}\left(\frac{\boldsymbol{\eta}+\mathbf{1}}{\mathbf{2}}\right)}{\sqrt{\boldsymbol{\pi}(\boldsymbol{\eta}-\mathbf{2})}\boldsymbol{\Gamma}\left(\frac{\boldsymbol{\eta}}{\mathbf{2}}\right)}$$

· *Generalized hyperbolic distribution*

The second distribution is the GHD proposed by Barndorff-Nielsen (1977). GHD is appropriate for describing financial factors due to its semi-heavy tails or the fact that each distribution will have a different characteristic from normal distribution in the left tail (Chen et al., 2008). GHD can be presented as:

[2] Jondeau and Rockinger (2003), Patton (2004), Kun (2017), and Guidolin and Timmermann (2008) argued that both kurtosis and skewness are critical in asset allocation, asset pricing models, and risk management.

[3] This distribution allows for control of asymmetry and fatness and has been extended in the literature (Theodossiou, 1998; Aas et al., 2005; Zhu and Galbraith, 2010). However, their VaR forecasts perform less well than those of Hansen (1994).

$$\boldsymbol{f(x)} = \boldsymbol{\alpha(\lambda,\alpha,\beta,\delta)}\left[\boldsymbol{\delta^2} + (\boldsymbol{x}-\boldsymbol{\mu})^2\right)^{\left(\lambda-\frac{1}{2}\right)/2}\Bigg]\cdot \boldsymbol{K_{\lambda-1/2}}\left(\boldsymbol{\alpha}\sqrt{\boldsymbol{\delta^2}+(\boldsymbol{x}-\boldsymbol{\mu})^2}\right)\exp[\boldsymbol{\beta}(\boldsymbol{x}-\boldsymbol{\mu})] \quad (2)$$

where, $\alpha(\lambda,\alpha,\beta,\delta) = \frac{(\alpha^2-\beta^2)^{\lambda/2}}{\sqrt{2\pi}\alpha^{\lambda-1/2}\delta^{\lambda}K_{\lambda}\left(\delta\sqrt{\alpha^2-\beta^2}\right)}$, and $0 \leq |\beta| < \alpha$, μ and $\lambda \in \mathbf{R}$, and $\delta > 0$. The parameters μ and δ represent for the location and scale. The shape parameters, α and β, correspond to tail heaviness and asymmetry of the density, respectively. K_λ is a modified Bessel function of the third kind and $x \in \mathbf{R}$.

· *Normal-inverse Gaussian distribution*

The third is the normal-inverse Gaussian distribution (NID)[4], which is a specific case of GHD with $\lambda = -\frac{1}{2}$. It is defined as

$$f(x) = \frac{\delta\alpha \exp\left(\delta\sqrt{\alpha^2-\beta^2}\right)K_1\left(\alpha\sqrt{\delta^2+(x-\mu^2}\right)\exp(\beta(x-\mu))}{\pi\sqrt{\delta^2+(x-\mu)^2}} \quad (3)$$

where $\delta > 0$ and $0 < |\beta| \leq \alpha$. Similar to GHD, the parameters μ and δ represent location and scale, respectively. Both α and β specify the shape of the density, describing tail heaviness and asymmetry of the distribution, respectively. In the special case of $\beta = 0$, NID becomes a symmetric distribution.

According to Jorion (2007), VaR is the maximum potential losses with a given probability that investors would face. Therefore, VaR can be presented as

$$Pr(r_t \leq VaR) = \kappa \quad (4)$$

where κ is a given probability (confidence level) such as 1% or 5%. VaR can be also represented as the hurdle point of an inverse distribution, and this may be the best-fitting distribution. In this study, the VaR is therefore calculated based on the following equation.

$$VaR_X \cong \int_{-\infty}^{VaR} f(x)dx = \kappa \quad (5)$$

In Eq. (5), *f(x)* can be one of the three skewed distributions.

3.2 Backtesting of VaR forecast

Backtesting is critical and essential in the assessment of VaR modeling. The basic concept of backtesting is to compare estimated VaRs and actual returns. For a long position, it is considered a violation if $r_t > VaR_{t-1}$. A good VaR forecast needs to generate a violation rate equivalent to κ in Eq. (5). Furthermore, a violation at time t could not be predicted by another violation at time $t-1$. Thus, this study applies the unconditional coverage test proposed by Kupiec (1995) and Christoffersen's (1998a) independence test to examine the performance of VaR models with different distributions. The former is used to test if the violation equals to the confidence level in the calculation of VaR, based on the null hypothesis that the VaR model is adequate. Its likelihood ratio statistic can be presented as

$$LR_{uc} = 2\ln[(1-VR)^{T-N}VR^N] - 2\ln[(1-\kappa)^{T-N}\kappa^N] \quad (6)$$

In Eq. (6), *VR* is the violation rate of the VaR model with different densities, and κ is the given probability in Eq. (5), which is a desired *VR*. *T* and *N* are the numbers of observations and violations in the testing period, respectively. To obtain a good VaR forecast, *VR* is expected to be equivalent to κ.

[4] Barndorff-Nielsen (1977) also extended GHD and the special case known as the normal-inverse Gaussian distribution (NID).

Christoffersen's (1998a) independence test examines whether the likelihood of a VaR violation today depends on whether a VaR violation occurred on the previous day. It can be expressed as

$$LR_{ind} = -2\ln\left[\mathrm{L}\left(\widehat{\Pi}_2; \mathrm{I}_1, \mathrm{I}_2, \dots, \mathrm{I}_\mathrm{T}\right) \Big/ \mathrm{L}\left(\widehat{\Pi}_1; \mathrm{I}_1, \mathrm{I}_2, \dots, \mathrm{I}_\mathrm{T}\right)\right], \tag{7}$$

where I_j is j^{th} observation in the backtesting period and $\mathrm{I} = 1$ when it is a violation, otherwise $\mathrm{I} = 0$. In equation (7), $\mathrm{L}\left(\widehat{\Pi}_2; \mathrm{I}_1, \mathrm{I}_2, \dots, \mathrm{I}_\mathrm{n}\right)$ is the likelihood value under the null hypothesis, that is, $(1-\pi_2)^{(n_{00}+n_{10})}\pi_2{}^{(n_{01}+n_{11})}$, and n_{ij} is the number of observations with a value i followed by a value j [5]. The actual likelihood value is $(1-\pi_{01})^{n_{00}}\pi_{01}^{n_{01}}(1-\pi_{11})^{n_{10}}\pi_{11}^{n_{11}}$. The conditional coverage test (LR_{cc}) integrating LR_{uc} and LR_{ind} will be applied to test VaR models.

4. Data

In this paper, six equity indexes from Asian emerging markets are used to examine the skewness of index return distributions and VaR measures: the Taiwan Capitalization Weighted Stock Index (TAIEX), the Kuala Lumpur Composite Index (KLCI) of Malaysia, the Jakarta Composite Index (JCI) of Indonesia, the Korea Composite Stock Price Index (KOSPI) of South Korea, the Stock Exchange of Thailand (SET) Index, and the Vietnam Stock Index (VNI). The sample period spans from July 2000 to January 2017, and six equity indexes were carefully considered to be involved in this paper. Cheng (1993) pointed out the similar backgrounds of both Taiwan and South Korea from the early. Since then, they have kept the solid position as the growth economic motivation of Asian area. In another side, four other countries belong to ASEAN (Association of Southeast Asian Nations) and commonality of economy. Recently, Korea is one of the most investor and Taiwan has continuously increased their investment to these four ASEAN countries. Hence, there are a close connection of these six Asian countries that could be used to be practical evidences in this study.

Table 1 displays the data descriptions of the sample sets. The average return is relatively small and positive among all markets. These numbers show the differences among the countries, for example, high distance from the lowest value in the case of Taiwan (0.03%) and highest value in the case of Indonesia (0.168%). Hence, the expectations of investors in Indonesia and Vietnam are likely to be higher than those in other markets. However, stock returns of Korea, Taiwan, Vietnam, Malaysia, and Thailand have experienced less fluctuation compared to Indonesia (median value is approximately 0.05%). After the 1997 financial crisis, the Indonesian government restructured the banking section and private businesses were placed under government control. The Indonesian market is relatively vulnerable to the effects of extreme global events, especially from China and the U.S., who keep a high amount of Indonesian government bonds (Agusman et al., 2014). Moreover, the results of ADF and KPSS tests revealed that unit root did not display any significance, which means the data used in this study are stationary. In addition, the null hypothesis of the Jarque-Bera test could not be rejected in most cases. This indicates that the skewness and kurtosis of the data fit well with normal distribution.

---

[5] Christoffersen (1998) proposed a contingency table including four different outcomes between time *t* and *t-1*. n_{01} means the number of observations that are not a violation at time t-1, but it is a violation. More details can be found in Christoffersen (1998).

Table 1 Data Statistic Summary

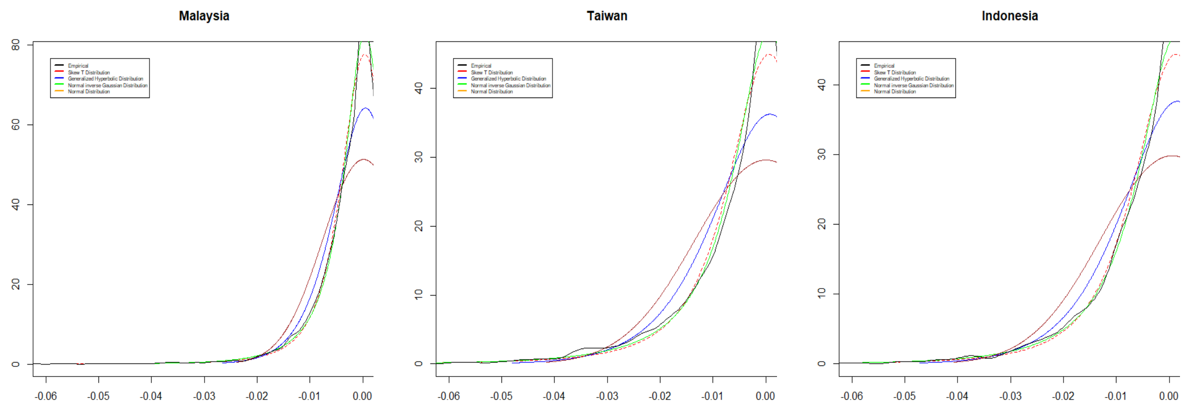
	Mean (10^{-2})	Median (10^{-2})	Skewness	Kurtosis	ADF test	KPSS test	JB test
Malaysia	0.0168	0.0014	-0.9156	11.7752	-15.514**	0.0879	0
Indonesia	0.0551	0.0494	-0.6936	7.3463	-14.612**	0.1258	0
Taiwan	0.0030	0.0000	-0.2752	3.7237	-14.967**	0.1071	0
Korea	0.0251	0.0128	-0.5156	6.7505	-16.619**	0.0695	0
Vietnam	0.0442	0.0000	-0.2549	3.3023	-13.013**	0.1988	0
Thailand	0.0389	0.0000	-0.7261	11.3136	-14.870**	0.0769	0

Note: * (**) means rejection of unit root hypothesis at the 5% (1%) significance level. KPSS test: The results reveal that the null hypothesis of trend stationarity cannot be rejected at critical values at the 10%, 5%, 2.5%, and 1% significance levels, respectively. JB test (Jarque-Bera): The results reveal that the null hypothesis "The distribution is normal" cannot be rejected with critical values of 0.347, 0.463, 0.574, and 0.739 at the 10%, 5%, 2.5%, and 1% significance levels, respectively.

5. Empirical results

5.1 Parameter estimation

In this section, we first estimate the goodness of fit of the three distributions to prepare for modeling VaR and backtesting in the next step. Figure 1. Fitted densities for each stock equity return shows the fitting results of the left rather than right tail of six Asian markets as there are more investors buying stocks (their risks are in the left tail of the distribution of stock returns) than those short-selling stocks. The black line corresponds to the empirical return, the red corresponds to the generalized skewed STD, the blue line to GHD, the green line to NID, and the orange line to normal distribution, which is included as a reference. In most cases, normal distribution has quite poor fit with the stock return, meaning Gaussian distribution fails to capture the excess kurtosis. All distributions, except Gaussian, fit the Malaysian stock returns quite well. The situation is the same for Indonesian and Taiwanese returns, that is, NID provides almost as good a fit as GHD. On the other hand, STD slightly underestimates the left tail. For Korea and Thailand, GHD underestimates the left tail and the empirical return increasingly moves to the right side. This situation is similar to NID and STD, however, overall, NID fits the left tail better than the others. Finally, for the case of Vietnam, both Gaussian and GHD distributions fail to fit the return. STD underestimates and NID slightly overestimates the left tail and NID fits the left tail quite well.



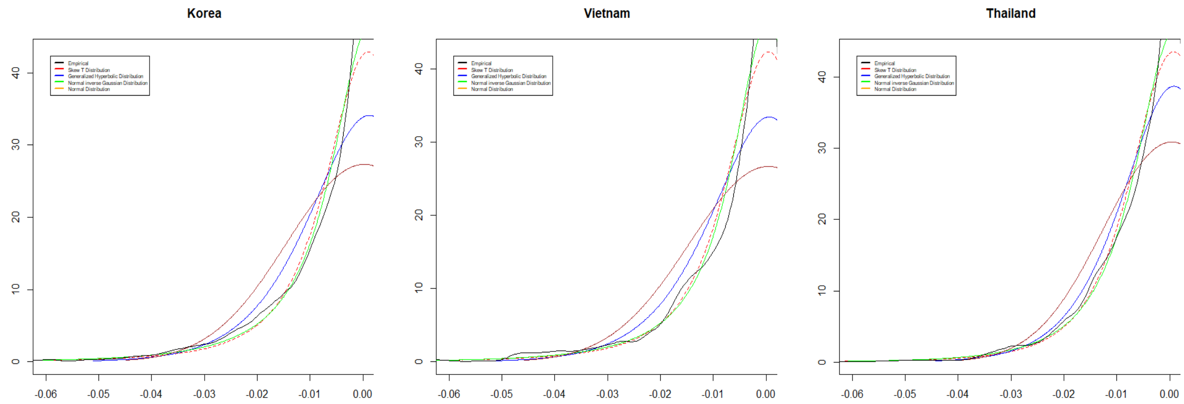


Figure 1 Fitted densities for each stock equity return

Table 2 shows the results of shape, location, dispersion, and skewness parameter estimation from fitting STD, GHD, and NID distributions of the six equity indexes. The shape and location parameters in each distribution describe the shift in the distribution to the right or left without changing the distribution or its standard deviation. Skewness controls the asymmetry and real-valued random variable around its mean. In most cases, skewness shows a negative number, meaning the left tail is fatter and longer than the right. The results presented in Figure 1. Fitted densities for each stock equity return reconfirm these outcomes. In the financial sector, the skewness and asymmetry characteristics have a close relationship. This relationship shows the different responses of market behavior to bad or good news that could have impacts on the fluctuation of market values. Results revealed that the skewness value was the highest among variables for Malaysia and was notably different in other negative cases. Vietnam is an interesting case when it shows the positive skewness value (its skewness is near to zero) which there are more low-priced than high-priced stocks. That means the Vietnamese market reacts very conservatively to good news and a downturn occurs in response to bad news.

Furthermore, Table 2 also shows the results of AICs (Akaike's an Information Criterion) and LLH (Log-likelihood) test to check whether a symmetric distribution has been fitted or not. Clearly, a GHD-based model is favored over the NID and STD distributions according to the AIC. However, the differences between the AIC and/or log-likelihood of the GHD and NID are rather small. A cross-comparison to the values of the STD model would yield a preference for the NID, if one had to choose between the restricted distributions. The reason for this is primarily that the unrestricted estimate of Shape 1 from GHD further to the parameter restriction for δ of the STD than that of the NID.

Table 2 Estimated parameters of the fitting distributions

	Shape 1	Shape 2	Shape 3	Location	Dispersion	Skewness	LLH	AIC
				Malaysia				
STD	-1.4125	2.8249	0	0.0004	0.0087	-0.0003	15266.13	-30524.27
GHD	2.8579	-	1.0648	0.0009	0.007	-0.0007	**16949.14**	**-33888.27**
NID	-0.5	-	0.0004	0.0077	-0.0002	-0.5	15280.15	-30552.30
				Indonesia				
STD	-1.4628	2.9256	0	0.0015	0.0146	-0.0011	12907.06	-25806.12
GHD	2.5334	-	1.2641	0.0028	0.012	-0.0024	**12919.35**	**-25828.69**
NID	-0.5	-	0.0015	0.0132	-0.0009	-0.5	12918.38	-25828.75
				Taiwan				
STD	-1.2878	2.5757	0	0.0008	0.017	-0.001	12787.49	-25566.99
GHD	2.6818	-	1.2001	0.0017	0.0125	-0.0016	**15051.59**	**-30093.17**
NID	-0.5	-	0.0008	0.0138	-0.0008	-0.5	12823.09	-25638.19
				Korea				
STD	-1.2639	2.5278	0	0.0012	0.0184	-0.0012	12559.44	-25110.87
GHD	2.6191	-	1.3295	0.0023	0.0132	-0.0021	**15306.95**	**-30603.90**
NID	-0.5	-	0.0011	0.0147	-0.0009	-0.5	12589.73	-25171.47
				Viet Nam				
STD	-1.1524	2.3048	0	0.0004	0.0233	0	12359.14	-24710.27
GHD	2.5494	-	0.7845	0.0007	0.0138	-0.0002	**16660.45**	**-33310.90**
NID	-0.5	-	0.0003	0.0157	0.0002	-0.5	12409.09	-24810.19
				Thailand				
STD	-1.6716	3.3433	0	0.0009	0.0134	-0.0005	12988.52	-25969.04
GHD	2.6072	-	1.2582	0.0013	0.0117	-0.001	**14684.13**	**-29358.26**
NID	-0.5	-	0.0008	0.0127	-0.0005	-0.5	12995.75	-25983.50

Note: LLH = Log-likelihood test; AIC = Akaike's an Information Criterion test.

5.2 VaR derived from STD, GHD, and NID

The results of VaR patterns with different probabilities of six markets are shown in Figure 2. VaR trajectory based on STD, GHD, and NID models. Generally, the VaR derived from NID could track the associated empirical loss levels quite closely in most cases. This model only overestimates the risk in the 98% and above confidence region. In ordering goodness of fit for the three distributions, the results can be summarized as the STD and NID models could track the data better than GHD, especially in Thailand. However, the results for Vietnam are complex since NID outperforms the other distributions. Both STD and NID track data rather well for the confidence region between 98% and 98.5%, but over-estimate for the region above these. This study focused on VaR at the 99% and 95% confidence levels. Thus, from these results, VaR trajectories based on the NID model fluctuate between 0.04 and 0.08, and real loss is mostly over-estimated at the 99% confidence level. However, the VaR trajectories at the 95% level were more complex. For example, NID can track data very well in Malaysian and Indonesian markets but it fails to do so in others. Furthermore, the VaR lines from 95% to 99% were spread out, became visible, and finally changed the goodness of fit of tracking data to NID.

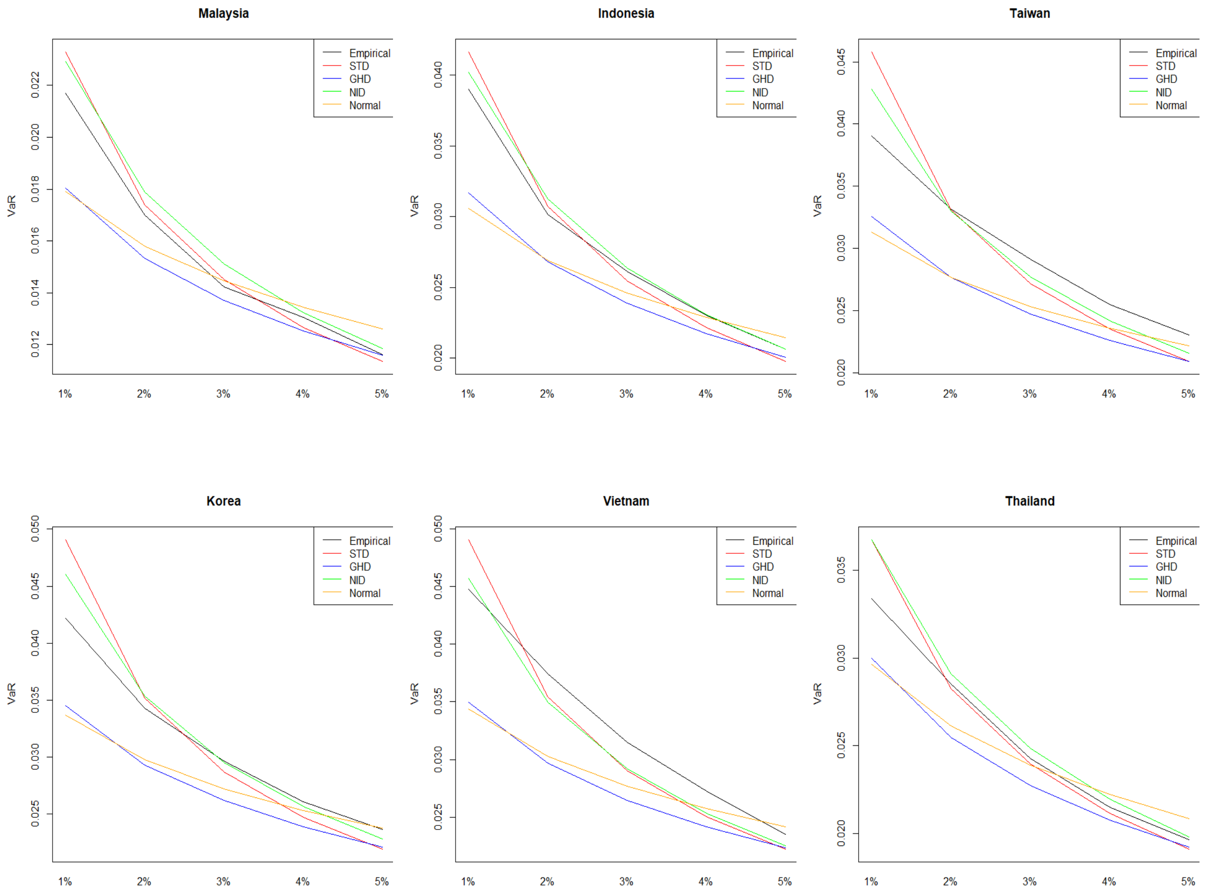


Figure 2 VaR trajectory based on STD, GHD, and NID models

5.3 Expected shortfall derived from STD, GHD, and NID

Expected shortfall (ES) trajectories are presented in Figure 3. The risk estimations derived from NID and STD consistently overestimates the expected loss in most cases (except Malaysia where the ES trajectory of NID is lower than the empirical line in the confidence region above 98%). In all models, the ES derived from GHD frequently underestimates the expected loss in all cases. Similar to the VaR, the trajectory of ES from NID-based shifts from underestimate to overestimate the expected loss among 6 cases. Furthermore, the overestimation is more severe for the STD-based models. For the next step, we apply backtesting or the so-called "Internal forecast" to benchmark the risk performance. Furthermore, the final outcome can also be used to identify the conservative nature across six markets.

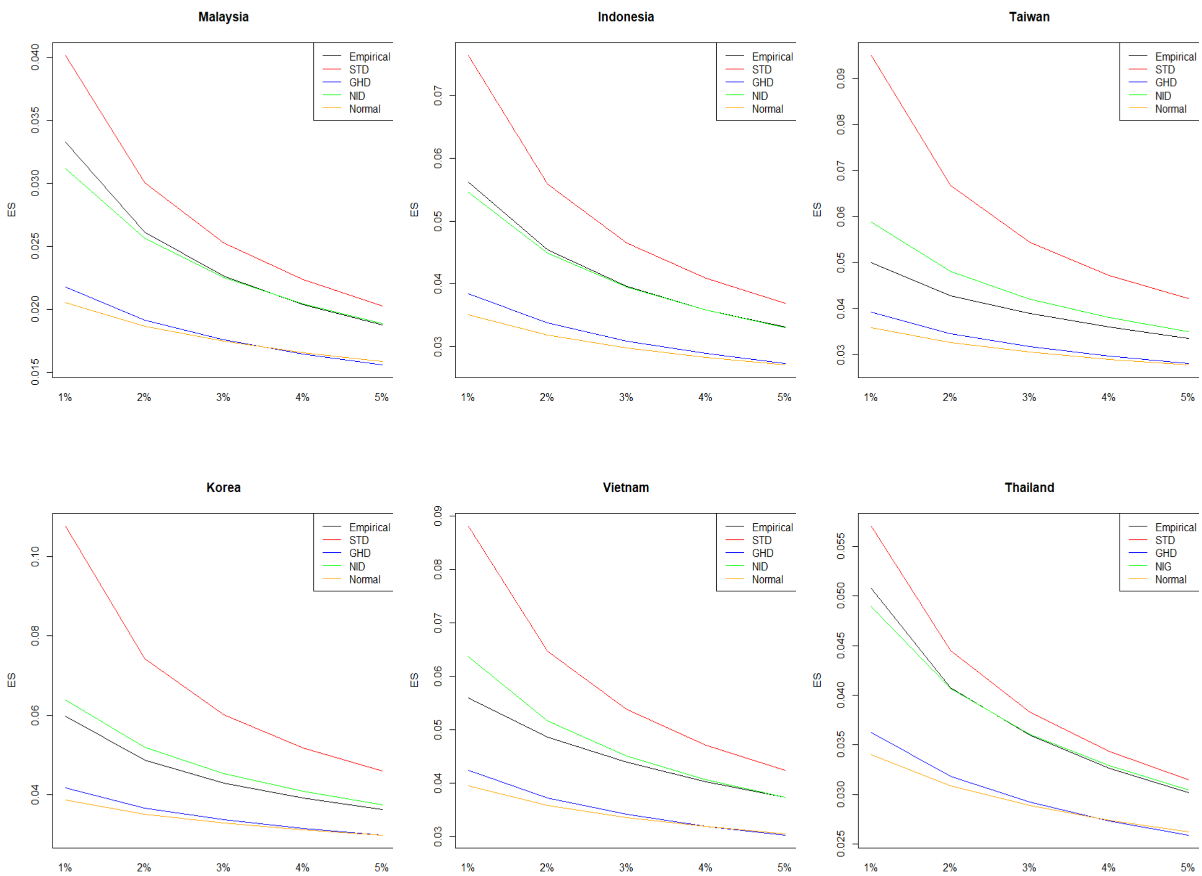


Figure 3 Expected shortfall trajectory based on STD, GHD, and NID models

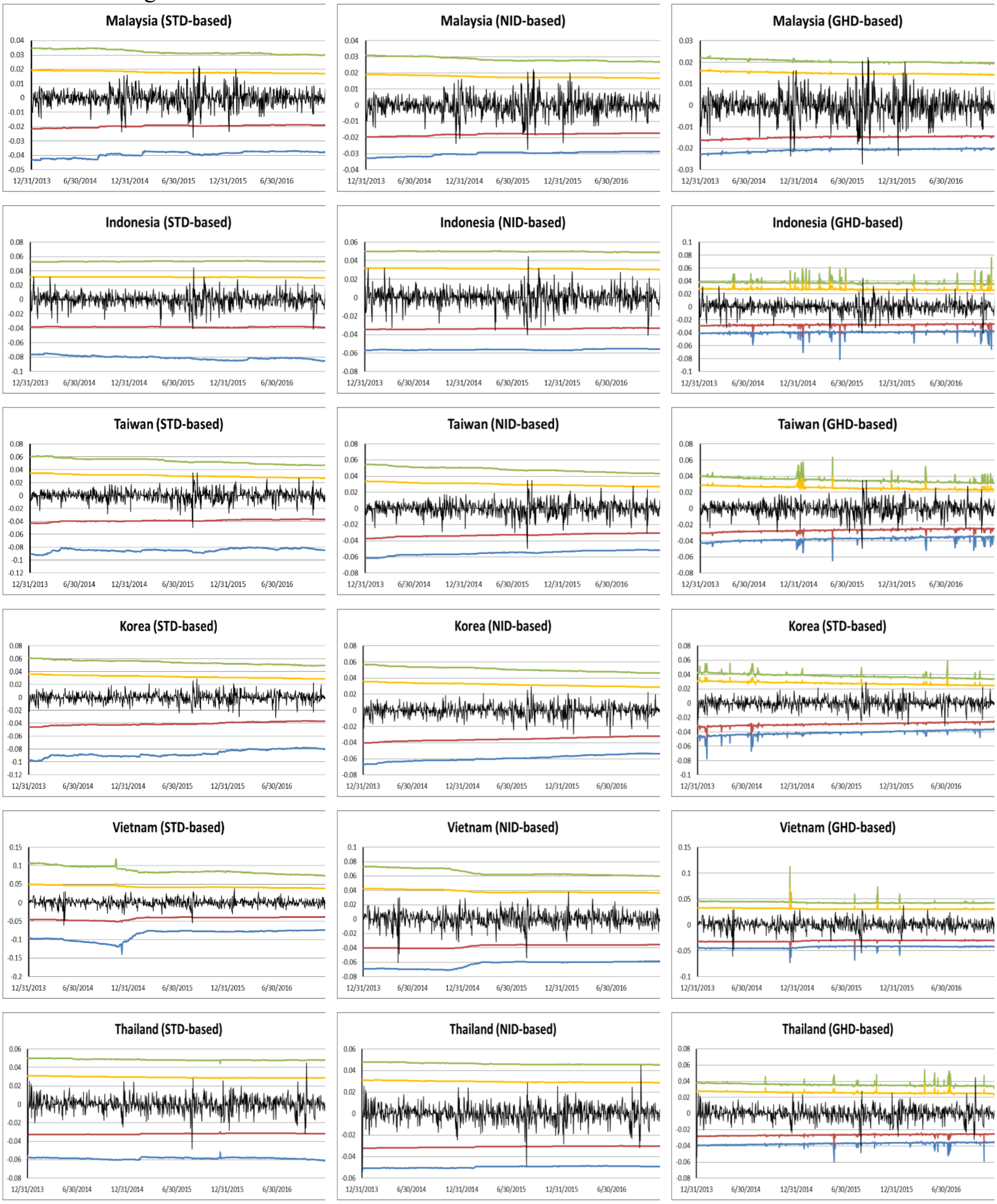
5.4 VaR backtesting

In this section, we analyze the one-day VaR accuracy predicting method which known as an interval forecast. The data for daily returns contained 4,284 observations. Among 3,500 in-sample data observations, the rolling out-of-sample forecasts started after day 3,501, which corresponds to the last day of 2013 (December 31, 2013) and lasted until the end of 2016 (December 31, 2016). Hence, the out-of-sample prediction included three years (784 observations) and needed to be updated daily.

Results of one-day VaR forecasts are presented in Note: Estimated one-day-ahead 1%, 5%, 95%, and 99% VaR for six markets are represented by green, orange, red, and blue lines, respectively. Empirical return is represented by the black line. The forecast sample period is from 28 July 2000 to 30 December 2016 (4,284 observations).

Figure 4. Three alternative distribution-based VaR forecasts follow orderly STD, NID, and GHD. The right tails of 1% and 5% VaR are represented by the green and orange lines, respectively, while the 95% and 99% VaR are represented by the red and blue lines, respectively. Due to the purpose of risk estimation, this section focuses on the 95% and 99% VaR forecasts. As shown, 99% VaR forecasts are too conservative for the actual returns of the three distribution-based approaches. The predicted value is generally not close to the empirical return. On the other hand, the plots of 95% VaR reflected the empirical losses very well. These are two interesting empirical findings. The 95% VaR NID-based forecasts reflect the market better than STD-based forecasts since the results of the NID-based forecasts gradually moved closer to empirical losses. However, the trajectories from the GHD-based forecasts

could track closer to actual losses. For instance, the 95% VaR GHD-based forecasts for Thailand frequently closes to -0.02 compared to STD and NID-based forecasts. Despite the fact that NID and STD-based forecasts show stable predicting outcomes (especially in Korea), the VaR predictions derived from GHD-based forecasts not only track the empirical data well but also interpret the market volatility, which would be an advantage for investors in terms of controlling investment decisions and making capital more efficient. In addition, all markets show a small VaR and the 95% VaR forecasts are in the lower range of their actual returns.



Note: Estimated one-day-ahead 1%, 5%, 95%, and 99% VaR for six markets are represented by green, orange, red, and blue lines, respectively. Empirical return is represented by the black line. The forecast sample period is from 28 July 2000 to 30 December 2016 (4,284 observations).

Figure 4 One-day-ahead VaR forecast

Following Polanski and Stoja (2010), a good VaR forecast needs to pass the unconditional and conditional tests of Kupiec (1995) and Christoffersen (1998b). Table 3 summarizes the performance statistics for predicting VaR based on the three distributions. This table reports the percentage of violation (number of returns that actually exceed the VaR forecast). The 99% VaR forecast derived from GHD performs favorably in most cases but did not pass the conditional accuracy test in Malaysia and Vietnam. On the other hand, the VaR forecast based on STD and NID did very well in both conditional and unconditional tests. Moreover, their exception rates are closer to the expected level. Backtesting results generally exhibited good performance in most cases with relatively low violation rates. The performance of NID and GHD may be comparable, although GHD's results show inadequacy in the unconditional accuracy test. Both GHD and NID/STD are very promising in terms of applying them in real-world situations since their performance can be used to compare each other.

Table 3 VaR estimation results

Models	**Malaysia**			**Indonesia**			**Taiwan**		
	$\%_x$	LR_{UC}	LR_{CC}	$\%_x$	LR_{UC}	LR_{CC}	$\%_x$	LR_{UC}	LR_{CC}
				α=1%					
STD	0	15.7589 (0.0000)	15.7589 (0.0000)	0	15.7589 (0.0000)	15.7589 (0.0000)	0	15.7589 (0.0000)	15.7589 (0.0000)
NID	0	15.7589 (0.0000)	15.7589 (0.0003)	0	15.7589 (0.0000)	15.7589 (0.0000)	0	15.7589 (0.0000)	15.7589 (0.0000)
GHD	0.3826	3.9463 (0.0469)	**3.9694 (0.1374)**	0.2551	6.2594 (0.0123)	6.2697 (0.0435)	0.1275	9.6216 (0.0019)	9.6241 (0.0081)
				α=5%					
STD	0.1020	53.7789 (0.0000)	53.8200 (0.0000)	0.0510	64.3257 (0.0000)	64.3359 (0.0000)		70.9892 (0.0000)	70.9917 (0.0000)
NID	0.1530	45.3353 (0.0000)	45.4280 (0.0000)	0.0765	58.7112 (0.0000)	58.7343 (0.0000)	0.0255	70.9892 (0.0000)	70.9917 (0.0000)
GHD	0.2806	29.4973 (0.0000)	31.6773 (0.0000)	0.1785	41.6537 (0.0000)	41.7800 (0.0000)	0.1530	45.3353 (0.0000)	49.9112 (0.0000)
Models	**Korea**			**Vietnam**			**Thailand**		
	$\%_x$	LR_{UC}	LR_{CC}	$\%_x$	LR_{UC}	LR_{CC}	$\%_x$	LR_{UC}	LR_{CC}
				α=1%					
STD	0	15.7589 (0.0000)	15.7589 (0.0000)	0	15.7589 (0.0000)	15.7589 (0.0000)	0	15.7589 (0.0000)	15.7589 (0.0000)
NID	0	15.7589 (0.0000)	15.7589 (0.0000)	0	15.7589 (0.0000)	15.7589 (0.0003)	0.1275	96.2162 (0.0019)	96.2418 (0.0081)
GHD	0	15.7589 (0.0000)	15.7589 (0.0000)	0.3826	3.9463 (0.0469)	**3.9694 (0.1374)**	0.2551	62.5946 (0.0123)	62.6970 (0.0435)
				α=5%					
STD	0	80.4278 (0.0000)	80.4278 (0.0000)	0.0765	58.7112 (0.0000)	58.7343 (0.0000)	0.0765	58.7112 (0.0000)	58.7343 (0.0000)
NID	0	80.4278 (0.0000)	80.4278 (0.0000)	0.0765	58.7112 (0.0000)	58.7343 (0.0000)	0.0765	58.7112 (0.0000)	58.7343 (0.0000)
GHD	0.0510	64.3257 (0.0000)	64.3359 (0.0000)	0.1530	45.3353 (0.0000)	45.4280 (0.0000)	0.1020	53.7789 (0.0000)	53.8200 (0.0000)

Note: The table presents the VR for each model. The LR_{UC} tests the null hypothesis of unconditional accuracy and LR_{CC} tests the null hypothesis of conditional accuracy for alternative confidence levels.

The cross-correlation from forecasting results reveal the particular similarities between the six markets. Panel A of Table 4. Correlation of actual return and VaR predicting across six markets reports cross-correlation between the daily actual return of six markets while other panels present alternative models with different confidence levels. While uniformly positive, the correlation coefficients for actual returns during this period were relatively low, below 0.5 in most of cases (except one case in which the correlation of Taiwan and Malaysia exceeded 0.5). Low correlation between these markets indicates that although markets share similarity in terms of geography and calendar systems, extreme events do not necessarily occur simultaneously. The other panels of Table 4. Correlation of actual return and VaR predicting across six markets present the correlation of VaR predictions determined from three models across six markets. As shown, the correlation coefficients for VaR forecasts are positive and extremely high in all cases. This means there is significant co-movement of these distribution-based VaR predicting trajectories across six cases (except Indonesia) despite showing different actual returns. Based on these outcomes, investors could optimize their portfolios by adopting a suitable risk management strategy.

This study found that daily 99% VaR forecasts derived from the three distributions over-estimate the market risk and are therefore not suitable for risk management. Conversely, the 95% VaR may reflect markets relatively well in all cases, especially in Korea and Thailand. These results indicate that a small number of exception rates are consistent with the significant conservativeness of VaR in six markets. It is interesting to note that the forecasting model may fit very well in Korea.

The second practice also contributes to the advantage of VaR forecasts based on GHD distribution. While the VaR forecasts derived from NID- and STD-based models show stability in tracking the empirical losses, the GHD model may reflect the volatility of market return. Even though it cannot satisfy the conditional accuracy test in the cases of Malaysia and Vietnam, its results could be compared with NID- and STD-based models for better performance of investment decisions. Furthermore, due to the correlation between risk forecasting results in six Asian markets, investors may consider increasing their portfolios in alternative markets to optimize their profits.

In addition, similar to Berkowitz and O'Brien (2002), the limitation of VaR forecasting is described by poor performance in periods subject to financial regime shifts. For example, the forecast model could not predict the extreme loss in the second half of 2015, which was similar to the downturn in equity markets in China and the U.S. The particular effect may be shown in the empirical returns of all cases and was hardly captured by the VaR forecasting models based on STD and NID. The 95% VaR GHD-based forecast predicted the downtrend, the predicted results could not predict the event close to the actual time of occurrence. Furthermore, this paper concentrates only on Asian markets as these have received less attention in terms of risk management. The final results and limitations are very interesting and are motivations for future studies.

Table 4 Correlation of actual return and VaR predicting across six markets

	Indonesia	Korea	Malaysia	Taiwan	Thailand	Vietnam
Panel A: Actual return Correlation coefficients						
Indonesia	1	0.4755	0.4650	0.4474	0.1825	0.3670
Korea	0.4755	1	0.4177	0.3779	0.1717	0.3542
Malaysia	0.4650	0.4177	1	0.5935	0.2071	0.3581
Taiwan	0.4474	0.3779	0.5935	1	0.1920	0.3554
Thailand	0.1825	0.1717	0.2071	0.1920	1	0.2111
Vietnam	0.3670	0.3542	0.3581	0.3554	0.2111	1
Panel B: 1% VaR predicting Correlation Coefficients (STD-based)						
Indonesia	1	-0.6797	-0.7216	-0.4455	0.1251	-0.6874
Korea	-0.6797	1	0.6773	0.7810	-0.1548	0.6028
Malaysia	-0.7216	0.6773	1	0.5359	0.0028	0.7223
Taiwan	-0.4455	0.7810	0.5359	1	0.0143	0.3376
Thailand	0.1251	-0.1548	0.0028	0.0143	1	0.2848
Vietnam	-0.6874	0.6028	0.7223	0.3376	0.2848	1
Panel C: 5% VaR predicting Correlation Coefficients (STD-based)						
Indonesia	1	-0.093	-0.1099	-0.1209	-0.2136	-0.1950
Korea	-0.0930	1	0.8250	0.9546	0.7796	0.7160
Malaysia	-0.1099	0.8250	1	0.8674	0.8411	0.7653
Taiwan	-0.1209	0.9546	0.8674	1	0.8077	0.6968
Thailand	-0.2136	0.7796	0.8411	0.8077	1	0.8877
Vietnam	-0.1950	0.7160	0.7653	0.6968	0.8877	1
Panel D: 1% VaR predicting Correlation Coefficients (NID-based)						
Indonesia	1	0.6696	0.5888	0.6288	0.5158	0.4945
Korea	0.6696	1	0.8904	0.9833	0.8607	0.8269
Malaysia	0.5888	0.8904	1	0.9245	0.8822	0.8822
Taiwan	0.6288	0.9833	0.9245	1	0.8747	0.8355
Thailand	0.5158	0.8607	0.8822	0.8747	1	0.9319
Vietnam	0.4945	0.8269	0.8822	0.8355	0.9319	1
Panel E: 5% VaR predicting Correlation Coefficients (NID-based)						
Indonesia	1	0.9080	0.8577	0.8910	0.8423	0.7346
Korea	0.9080	1	0.9033	0.9863	0.9373	0.8172
Malaysia	0.8577	0.9033	1	0.9421	0.9371	0.8506
Taiwan	0.8910	0.9863	0.9421	1	0.9536	0.8345
Thailand	0.8423	0.9373	0.9371	0.9536	1	0.9254
Vietnam	0.7346	0.8172	0.8506	0.8345	0.9254	1
Panel F: 1% VaR predicting Correlation Coefficients (GHD-based)						
Indonesia	1	0.2566	0.1851	0.2207	0.0994	0.1212
Korea	0.2566	1	0.7526	0.5541	0.3659	0.4587
Malaysia	0.1851	0.7526	1	0.6208	0.4320	0.5459
Taiwan	0.2207	0.5541	0.6208	1	0.3004	0.3825
Thailand	0.0994	0.3659	0.4320	0.3004	1	0.2810
Vietnam	0.1212	0.4587	0.5459	0.3825	0.2810	1
Panel G: 5% VaR predicting Correlation Coefficients (GHD-based)						
Indonesia	1	0.3693	0.3137	0.3086	0.2236	0.2462
Korea	0.3693	1	0.8059	0.7163	0.5376	0.5922
Malaysia	0.3137	0.8059	1	0.7633	0.5896	0.6606
Taiwan	0.3086	0.7163	0.7633	1	0.5120	0.5646
Thailand	0.2236	0.5376	0.5896	0.5120	1	0.4513
Vietnam	0.2462	0.5922	0.6606	0.5646	0.4513	1

6. Conclusion

The recent financial crises such as the global financial crisis in 2008, show the frangibility of world financial system. Either developing countries or developed countries whose have the tight regime got the significant consequences from these events. That situation has been the major reason for the shift of investment behavior from return to reduce the losses prior to any bad situations (Pfaff, 2013). From that scenario, financial market required the more efficient risk management tools in monitoring the potential lose in modern financial market. Among many approaches, the downside risk (particularly described by VaR) which was proposed by J. P. Morgan in 1996, is the promising risk management tool.

VaR has become the essential measure in risk management at commercial banks as an effective and efficient utilization of funds. Furthermore, controlling risks in financial institutions is also critical to optimize their profits. With the simply concept that could show the expected losses as a simple number, VaR may be the promising tools to help investors understand financial market operations and know how to protect their capital prior to uncertainty (Andries and Nistor, 2016; Inui and Kijima, 2005). However, despite the important role of VaR in financial field in modern era, its implication has been still limited.

Although the concept of VaR is not difficult to understand, its measurements have remained in complexity (Yu and Jones, 1998; Engle, 2004; Francq and Zakoïan, 2018). In this paper, we compute VaR upon three specialized skewed distributions: skewed Student's t-distribution (STD) was proposed by Hansen (1994); Generalized hyperbolic distribution (GHD) with its special case namely normal-inverse Gaussian distribution (NID) which were proposed by Barndorff-Nielsen (1977) and Barndorff-Nielsen (1997). With the special characteristics, those skewed distributions are noticed as flexible tools for modeling the empirical distribution of financial data exhibiting skewness, leptokurtosis, and fat-tails (Turan et al., 2008).

The final results show the goodness of using three skewed distributions to VaR/CVaR measurement. This study indicates that the GHD-based risk modellings are favored over the NID and STD distributions. However, due to the less differences of testing, the derived risk from GHD and NID may be used for cross-checking in several specified cases. We also found that the 99% VaR forecast is too conservative in reflecting market risk. It means predicted loses are too far from the empirical values; thus, the investors may lose their advantages in risk provision. On the contrary, 95% VaR derived from GHD and NID outperforms STD in most cases, but it cannot predict market at extremely events such as the noticeable breakpoint in 2015. Despite the fact that the GHD-based forecast model is inadequate in passing both conditional and unconditional tests, it is very necessary to apply it in real-world situations for market volatility's prediction. Furthermore, the forecasting model could be applied successfully in Korea which in term of stable volatility. Besides that, although it is an emerging economy, the current risk measurement also is very potential for using in Vietnam due to its performance in tracking both empirical loss and return.

In summary, our research offers the theoretical rationale how the risk modelling derives from skewed distributions could be applied in practice. Therefore, we confirm the promising of VaR and its necessary role in monitoring the financial risk. There are two main contributions are pointed from final results. Firstly, this paper not only explored VaR, which measured upon empirical distribution in Asian market, but also extents the work of Polanski and Stoja (2010), as well as Zeuli and Carvalhal (2018) since they only focus on Western markets. Furthermore, the results from one-day VaR forecasting finally show the interesting evidences that the risk modelling is derived from GHD is certainly helpful at tracking the practical losses in most of countries. Secondly, by analyzing risk measurement which is based on the aforementioned three skewed distributions of STD, GHD and NID, this research presents the advantages of forecasting VaR patterns in hedging. Hence, VaR forecasting from distribution fitting on financial data is revealed as an important step that should be routinely used as an empirical method in evaluating market risk. However, this study still has some limitations described as follows. First, although the risk forecasting presents the outstanding performance, it fails to capture the extreme event such as the breakpoint of financial markets in 2015. Hence, investors may not be satisfied and may want to identify a more accurate and efficient model for risk management. Future studies could extend our estimation by applying alternative methods and comparing the results with the origin models. Second, application this model in countries with similar backgrounds with Korean is able to find the regarded evidences to explain the goodness of risk forecasting in Korea. Finally, this paper only focuses on Asian market, the other regions could be added to explain the accuracy of risk modelling.

References

Aas, K., Haff, I. H., Dimakos, X. K. 2005. Risk Estimation Using the Multivariate Normal Inverse Gaussian Distribution. *The Journal of Risk*, 8, 39.

Abad, P., Benito, S. 2013. A Detailed Comparison of Value at Risk Estimates. *Mathematics and Computers in Simulation*, 94, 258-276.

Acerbi, C., Tasche, D. 2002. Expected Shortfall: A Natural Coherent Alternative to Value at Risk. *Economic Notes*, 31, 379-388.

Agusman, A., Cullen, G. S., Gasbarro, D., Monroe, G. S., Zumwalt, J. K. 2014. Government Intervention, Bank Ownership and Risk-Taking During the Indonesian Financial Crisis. *Pacific-Basin Finance Journal*, 30, 114-131.

Andrieş, A. M., Nistor, S. (2016). Systemic Risk, Corporate Governance and Regulation of Banks Across Emerging Countries. *Economics Letters*, 144, 59-63.

Angelidis, T., Benos, A., Degiannakis, S. 2007. A Robust Var Model under Different Time Periods and Weighting Schemes. *Review of Quantitative Finance and Accounting*, 28, 187-201.

Artzner, P., Delbaen, F., Eber, J. M., Heath, D. 1999. Coherent Measures of Risk. *Mathematical Finance*, 9, 203-228.

Bali, T. G., Theodossiou, P. 2008. Risk Measurement Performance of Alternative Distribution Functions. *Journal of Risk and Insurance*, 75, 411-437.

Barndorff-Nielsen, O. Exponentially Decreasing Distributions for The Logarithm of Particle Size. Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences, 1977. *The Royal Society*, 401-419.

Barndorff-Nielsen, O. E. 1997. Normal Inverse Gaussian Distributions and Stochastic Volatility Modelling. *Scandinavian Journal of Statistics*, 24, 1-13.

Berkowitz, J., O'Brien, J. 2002. How Accurate Are Value-At-Risk Models at Commercial Banks? *The Journal of Finance*, 57, 1093-1111.

Bollerslev, T. 1987. A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *The Review of Economics and Statistics*, 542-547.

Cai, Z., Wang, X. 2008. Nonparametric Estimation of Conditional Var and Expected Shortfall. *Journal of Econometrics*, 147, 120-130.

Candelon, B., Colletaz, G., Hurlin, C., Tokpavi, S. 2010. Backtesting Value-At-Risk: A GMM Duration-Based Test. *Journal of Financial Econometrics*, 9, 314-343.

Chen, S. X., Tang, C. Y. 2005. Nonparametric Inference of Value-At-Risk for Dependent Financial Returns. *Journal of Financial Econometrics*, 3, 227-255.

Chen, Y., Härdle, W., Jeong, S.-O. 2008. Nonparametric Risk Management with Generalized Hyperbolic Distributions. *Journal of The American Statistical Association*, 103, 910-923.

Cheng, T. J. (1993). Distinctions between the Taiwanese and Korean approaches to economic development. *The Journal of East Asian Affairs, 7*(1), 116-136.

Christoffersen, P. 1998a. Evaluating Interval Forecasts. *International Economic Review*, 39, 841-862.

Christoffersen, P., Pelletier, D. 2004. Backtesting Value-At-Risk: A Duration-Based Approach. *Journal of Financial Econometrics*, 2, 84-108.

Christoffersen, P. F. 1998b. Evaluating Interval Forecasts. *International Economic Review*, 841-862.

Cont, R., Deguest, R., Scandolo, G. 2010. Robustness and Sensitivity Analysis of Risk Measurement Procedures. *Quantitative Finance*, 10, 593-606.

Dowd, K., Blake, D. 2006. After Var: The Theory, Estimation, And Insurance Applications of Quantile-Based Risk Measures. *Journal of Risk and Insurance*, 73, 193-229.

Eberlein, E., Keller, U., Prause, K. 1998. New Insights into Smile, Mispricing, And Value at Risk: The Hyperbolic Model. *The Journal of Business*, 71, 371-405.

Engle, R. 2004. Risk and Volatility: Econometric Models and Financial Practice. *American Economic Review*, 94, 405-420.

Engle, R. F., Manganelli, S. 2004. Caviar: Conditional Autoregressive Value at Risk by Regression Quantiles. *Journal of Business & Economic Statistics*, 22, 367-381.

Inui, K., Kijima, M. (2005). On The Significance of Expected Shortfall as A Coherent Risk Measure. *Journal of Banking & Finance*, 29(4), 853-864.

Fallon, W. 1996. Calculating Value-At-Risk, Wharton School, University of Pennsylvania.

Fan, J., Gu, J. 2003. Semiparametric Estimation of Value at Risk. *The Econometrics Journal*, 6, 261-290.

Francq, C., Zakoïan, J.-M. 2018. Estimation Risk for The Var of Portfolios Driven by Semi-Parametric Multivariate Models. *Journal of Econometrics*.

Gao, C.-T., Zhou, X.-H. 2016. Forecasting Var and ES Using Dynamic Conditional Score Models and Skew Student Distribution. *Economic Modelling*, 53, 216-223.

Gencay, R., Selcuk, F. 2004. Extreme Value Theory and Value-At-Risk: Relative Performance in Emerging Markets. *International Journal of Forecasting*, 20, 287-303.

Guermat, C., Harris, R. D. 2002. Robust Conditional Variance Estimation and Value-At-Risk. *Journal of Risk*, 4, 25-42.

Guidolin, M., Timmermann, A. 2008. International Asset Allocation Under Regime Switching, Skew, And Kurtosis Preferences. *The Review of Financial Studies*, 21, 889-935.

Hansen, B. E. 1994. Autoregressive Conditional Density Estimation. *International Economic Review*, 705-730.

Jondeau, E., Rockinger, M. 2003. Conditional Volatility, Skewness, And Kurtosis: Existence, Persistence, and Comovements. *Journal of Economic Dynamics and Control*, 27, 1699-1737.

Jorion, P. 2007. Value at Risk: The New Benchmark for Managing Financial Risk, London, *Mcgraw-Hill Companies*.

Kun, P. K. 2017. Importance of Skewness in Investor Utility: Evidence from The Chinese Stock Markets. *Journal of Mathematical Finance*, 7, 881.

Kupiec, P. H. 1995. Techniques for Verifying the Accuracy of Risk Measurement Models. *The Journal of Derivatives*, 3, 73-84.

Markowitz, H. 1952. Portfolio Selection. *The Journal of Finance*, 7, 77-91.

McDonald, J. B., Newey, W. K. 1988. Partially Adaptive Estimation of Regression Models Via the Generalized T Distribution. *Econometric Theory*, 4, 428-457.

McDonald, J. B., Xu, Y. J. 1995. A Generalization of the Beta Distribution with Applications. *Journal of Econometrics*, 66, 133-152.

McNeil, A. J. 1999. Extreme Value Theory for Risk Managers. Departement Mathematik ETH Zentrum.

McNeil, A. J., Frey, R. 2000. Estimation of Tail-Related Risk Measures for Heteroscedastic Financial Time Series: An Extreme Value Approach. *Journal of Empirical Finance*, 7, 271-300.

Milhøj, A. 1985. The Moment Structure of ARCH Processes. *Scandinavian Journal of Statistics*, 281-292.

Mittnik, S., Paolella, M. S. 2000. Conditional Density and Value-At-Risk Prediction of Asian Currency Exchange Rates. *Journal of Forecasting*, 19, 313-333.

Morgan, J. 1997. Creditmetrics-Technical Document. JP Morgan, New York.

Nelson, D. B. 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica: Journal of The Econometric Society*, 347-370.

Patton, A. J. 2004. On The Out-Of-Sample Importance of Skewness and Asymmetric Dependence for Asset Allocation. *Journal of Financial Econometrics*, 2, 130-168.

Polanski, A., Stoja, E. 2010. Incorporating Higher Moments into Value-At-Risk Forecasting. *Journal of Forecasting*, 29, 523-535.

Pfaff, B. (2016). Financial Risk Modelling and Portfolio Optimization with R. John Wiley & Sons.

Pownall, R. A., Koedijk, K. G. 1999. Capturing Downside Risk in Financial Markets: The Case of the Asian Crisis. *Journal of International Money and Finance*, 18, 853-870.

Prause, K. 1999. The Generalized Hyperbolic Model: Estimation, Financial Derivatives, And Risk Measures. Phd Thesis, University of Freiburg.

Roy, A. 1952. Safety First and The Holding of Assets, Econo Metrica 20 (3): 431–449.

Theodossiou, P. 1998. Financial Data and The Skewed Generalized T Distribution. *Management Science*, 44, 1650-1661.

Theodossiou, P. 2001. Skewness and kurtosis in financial data and the pricing of options. Rutgers University.

Tian, W., Wang, T., Li, B. 2014. Risk Measures with Wang Transforms Under Flexible Skew-Generalized Settings. *International Journal of Intelligent Technologies and Applied Statistics*, 7, 185-205.

Turan, Hengyong, Yi 2008. The Role of Autoregressive Conditional Skewness and Kurtosis in The Estimation of Conditional Var. *Journal of Banking and Finance*, 32, 269-282.

Yu, K., Jones, M. 1998. Local Linear Quantile Regression. *Journal of The American Statistical Association*, 93, 228-237.

Zhu, D., Galbraith, J. W. 2010. A Generalized Asymmetric Student-T Distribution with Application to Financial Econometrics. *Journal of Econometrics*, 157, 297-305.

Zeuli, M., Carvalhal, A. (2018). Backtesting Basel III: Evaluating The Market Risk of Past Crises Through the Current Regulation. *Applied Economics*, 50(59), 6382-6396.

Nieto, M. R., Ruiz, E. (2016). Frontiers in Var Forecasting and Backtesting. *International Journal of Forecasting*, 32(2), 475-501.

Dickey, D. A., Fuller, W. A. (1979). Distribution of The Estimators for Autoregressive Time Series with A Unit Root. *Journal of The American Statistical Association*, 74(366a), 427-431.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., Shin, Y. (1992). Testing The Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root? *Journal of Econometrics*, 54(1-3), 159-178.

Luethi, D., Breymann, W. (2016). Ghyp: A Package on Generalized Hyperbolic Distribution and Its Special Cases [Computer Software Manual].