RISK MANAGEMENT ON EQUITY MARKET: EVIDENCE FROM FOUR EUROPEAN COUNTRIES

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Abtract

Since J.P.Morgan proposed the RiskMetrics methodology to calculate the market risk and introduced the concept of Value at risk in 1996, then it has become the essential tool in the financial institutions. As known the distributions of financial assets return such as stock equity are more likely skewed and thick. In this paper, three special distributions such as generalised hyperbolic distribution (GHD), skew Student t distribution (STD), and normal inversed Gaussian distribution (NID) are applied to measure market risk of the four European countries.

By analysing the risk management in four European Union markets as United Kingdom, France, Greece and Spain, the final results show that Normal inversed Gaussian distribution outperforms three other models in most of cases (including Normal distribution). Then, the predicting results exhibited the instability of European economy from 2014 to the end of 2018. The risk measurement model did not capture the extreme loss in Greece well. The same situation also happened on Spain. Conversely, England and France were slightly conservative in risk management. Interesting that, the risk forecasting model could predict the "Brexit" event in UK instead of other countries.

Keywords: Value at risk, expected shortfall, risk management

JEL Classification: G10, G30, O30

Chapter 1: Introduction

Since Basel committee on Banking Supervision (BCBS) announced Capital and J.P.Morgan proposed the internal model measuring risk method in 1996, Value at Risk has become the essential tool and played an important role in risk management in general and financial sector in specific. However, the investor and manager had preferred the profit making rather than risk management until the Asian crisis from Thailand in 1997 and world financial crisis in 2008. After these events, more and more financial stakeholders shifted their attention from how to maximize profit to minimize extreme losses or risk management to reduce the influence from unexpected events.

Although this concept of risk management based on Value at Risk is simple, its measurements are complex. Moreover, these have not any standard methods for VaR estimation. It is a well-known reality that the financial market and its components are not symmetric due to the different response from investors when facing with bad or good news (Engle and Ng, 1993). This implies that extreme events are much more likely to occur in practise than would be predicted by the symmetric thinner-tailed normal distribution (Turan et al., 2008). Since skewed generalized t distribution (GT) was presented firstly by (McDonald & Newey 1988) and was extent by (Hansen, 1994; Theodossiou, 1998), that distribution supplied the flexible tool to estimate VaR due to its specific characteristics on fat-tailed, skewness and leptokutosis. Hence, scholars begun applying generalized skew t distribution and its adverse special cases to analyze VaR and their final outcomes showed that it could fit the data well (Zhu & Galbraith, 2010).

Europe is the most developed region of the world, where was the beginning of the modern finance and banking systems still used in most of financial institution today. It is interested that, despite the most developed region, its financial market was still suffered dramatically consequence from crisis happened in different areas, e.g. World financial crisis in 2008. The reason could be explained by European economy has exposure closely to United State. Furthermore, dissimilar reactions of each participant in Euro zone will lead the different outcome for every country.

Therefore, this research aims to two main purposes. Firstly, this paper will explore the impact of financial crisis in 2008, and especially the latter European debt crisis according to the equity data from four notable markets as England, France, Greece and Spain. The period will include the financial crisis in 2008 and Euro debt crisis, from 31st December, 2000 to 31st January, 2018. Secondly, this study will re-estimate the risk accuracy measurement through using semi-parametric method by focusing on tail distribution tail rather than the whole one. Then, the interval forecast method will be employed to predict accuracy of risk according to unconditional coverage proposed firstly by (Kupiec, 1995) and influential conditional coverage (CC) test presented by (Christoffersen, 1998). The rest of this study will be organized as follow: chapter 3 presents the literature review. Chapter 3 shows the methodology that used in this paper. Chapter 4 describes data and empirical outcome. Chapter 5 will conclude this research.

Chapter 2: Literature review

(Markowitz, 1952) firstly presented the portfolio optimization theory, one of method that accepted by most of financial institution as a risk measurement. The basic concept of this method tries to maximize the profit and minimize the risk for a given confident level. The theoretical portfolio concepts are unfortunately not directly applicable in practice. So far the population moments have been employed in the analysis, but these entities are unknown. Until 1996, the Basel accords explicitly recognize the role of Value at Risk (VaR) as a measure that financial institutions must implement and report in order to monitor their financial risk and determine the amount of capital that is subject to regulatory control. At the same time, they released the regulation to allow the banks using internal models to access the risk of their portfolios. Then, these are many scholars who used parametric for monitoring the market risk such as (Berkowitz et al., 2011), non-parametric (Cai & Wang, 2008). Those measurements aim to measure market risks with different assumption to the whole distribution of financial return. Moreover, (Fan and Gu, 2003) applied the semi-parametric approaches for VaR estimation due to its characteristic in improving the accuracy of risk. The semi-parametric will concentrate on tails of distribution instead of whole the distribution. In other hand, this method will capture the fatness and asymmetric of distribution, hence we will have the final outcomes those are more accurate than different methods.

Furthermore, (Engle and Ng, 1993) presented that investors will react different to good and bad news, the distribution of financial return are usually asymmetric. That’s reason why this study focuses on skewed distribution to estimate VaR. Therefore, there are researches that applied skewness distribution and confirm its goodness of fit to estimate VaR (Bali & Theodossiou, 2008). In additional, (Artzner et al., 1999) proposed a coherent risk measure, mainly indicating that VaR fails to satisfy the subadditivity property. They also demonstrate expected shortfall (ES) is a coherent risk measure. In this study, the VaR modeling will base on the parameters of generalized t distribution and its special cases named skew student t-distribution (ST), generalized hyperbolic skew student's t-distribution (GHD) and normal inverse gaussian distributions (NI) to calculate Value at Risk and interval forecasting model.

Finally, to evaluate performance of risk, VaR interval forecast method, or so-called "Backtesting", was first proposed in an often-cited endorsement of testing for independence of exceedances by (Christoffersen, 1998) and (Kupiec, 1995), will be applied.

Chapter 3: Methodology

In first step, we will use three models to fit data and compare each other including Skew student's t-distribution (ST), Generalised hyperbolic skew Student's t-distribution (GHD) and its special case is Normal inversed Gaussian distribution (NI). The most important purpose of this step is that from those results, we could see which model could fit data rather well than others. We will use the estimated distributions above to determine the risk by using:

$$VaR_{\alpha} = \inf\{l \in \mathbb{R} : (P(L > 1) \leq 1 - \alpha\} = \inf\{l \in \mathbb{R} : F_L(\mathrm{l}) \geq \alpha\}, \tag{1}$$

and expected shortfall (ES) at different confident levels:

$$ES_{\alpha} = \frac{1}{1-\alpha} \int_{\alpha}^{1} q_u(F_L) du, \tag{2}$$

Where $q_u(F_L)$ is the quantile function of the loss distribution (F_L) . The ES can therefore be expressed in terms of the VaR as

$$ES_{\alpha} = \frac{1}{1-\alpha} \int_{\alpha}^{1} VaR_u(\mathrm{L}) du, \tag{3}$$

Due to VaR only estimate a quartile of the distribution, ignores the important information regarding the tails of the distribution beyond this quantile. Conversely, ES could describe the tail risk better.

In second step, we will use the interval forecast method according "Backtesting" methods for evaluate risk performance. Given a set of VaR estimates, the indicator variable is constructed as:

$$E_t = 1 \text{ if exceedance occurs and 0 if no exceedance occurs}, \tag{4}$$

In particular, the assumption above could be defined by the section below. When finished estimate parameters from all above models. Then, this paper use the strategy called backtesting point VaR forecast to estimate VaR accuracy. Initially, Kupiec proposed the backtesting process called as unconditional coverage of Hansen which testing the null hypothesis:

$$H_0 = E\left[I_t^\alpha\right] = \alpha, \tag{5}$$

That equation estimates the performance of VaR forecast that based on VaR failtures. I_t^α is denoted by $1(R_t < -VaR_t^\alpha)$ and t is the horizon time as t = T+1,...T+H, 1(.) is the indicator function. However, due to the unconditional converage eliminates the conditional converage, so the violations can cluster over time. On the other hand, Christoffersen introduced the the alternative test as conditional converage (CC) test which different null hypothesis as

$$H_0 : E\left[I_t^\alpha \middle| I_{t-1}^\alpha\right], \tag{6}$$

Generally, this method explained VaR predicting that will be valid if the violation process which is explained by the real return excesses to VaR predicting. I_t^α follows two assumptions as unconditional coverage and independent (IND) hypotheses. In another hand, the violations should not be accrued one percent of the time, but they should also be independent and identically distributed (i.i.d). The likelihood framework behind will be a simple feature to express those assumptions as:

$$LR_{cc} = LR_{UC} + LR_{ind}, \tag{7}$$

The equation (7) could be explained from the conditional coverage test LR_{cc}, it will be decomposed into the unconditional coverage test LR_{uc}, that is, violation rate of a plus a test that violations are independent LR_{ind} .

Chapter 4: Empirical results

The data used are daily stock market indexes for four European countries, the national names will be used instead of theirs stock exchange following as United Kingdom (UK), France, Greece and Spain (FTSE100, XLON, XATH, BMEX respectively). The sample period runs from January 2000 to January 2018 due to two reasons. First, the period of sample content the data of European equity market after financial crisis in 1997. By using this sample, we will have the overall viewpoint of risk management in this region through VaR and Expected shortfall trajectory. Second, the financial crisis of 2008 and European debt crisis since the end of 2009 will be included as noticeable events which are expected to show the significant effect to risk performance on final results. This period also contained alternative notable events both in Europe and Asian such as "Brexit" or China stuns financial markets by devaluating "Yuan"[1].

Table 1 displays the descriptive statistics for each stock return. For all evidences, their average return is relatively small and negative value (excepting UK). However, these show the different from each country e.g., high distance from lowest value as United Kingdom ($0.19\,e^{-4}$). Moreover, the results of ADF and KPSS's test showed that there were no unit-root significances, which means the data used in this paper is stationary. In addition, the null hypothesis of JB's test could not be rejected at most cases. This indicates that the skewness and kurtosis of the data fit with normal distribution well.

Tab. 1: Data Statistic Summary

	Mean	**Median**	**Skewness**	**Kurtosis**	**ADF test**	**KPSS test**	**Jarque Bera**
UK	$0.19\,e^{-4}$	0.0	-0.16	6.59	-17.421*	0.1762	0
France	$-0.17\,e^{-4}$	0.0	-0.04	5.15	-16.636*	0.1779	0
Greece	$-3.99\,e^{-4}$	0.0	-0.34	7.04	-15.683*	0.1310	0
Spain	$-0.23\,e^{-4}$	$2.74\,e^{-4}$	-0.08	6.09	-16.442*	0.0785	0

Souce: Author's calculation

(*Dickey-Fuller test or unitt roots: $\Delta X_t = \alpha_0 + p_0 X_{t-1} + \sum_{i=1}^{k} p_i \Delta X_{t-1} + e_t$ Lags is choosen by 1 in this test. * and** interprets rejection of unit root hypothesis at 5% and 1% significant levels, respectively.

*KPSS test: The results denotes that the null hypothesis of trend stationarity can not reject at critical values at 10%; 5%, 2.5% and 1% significant levels, respectively.

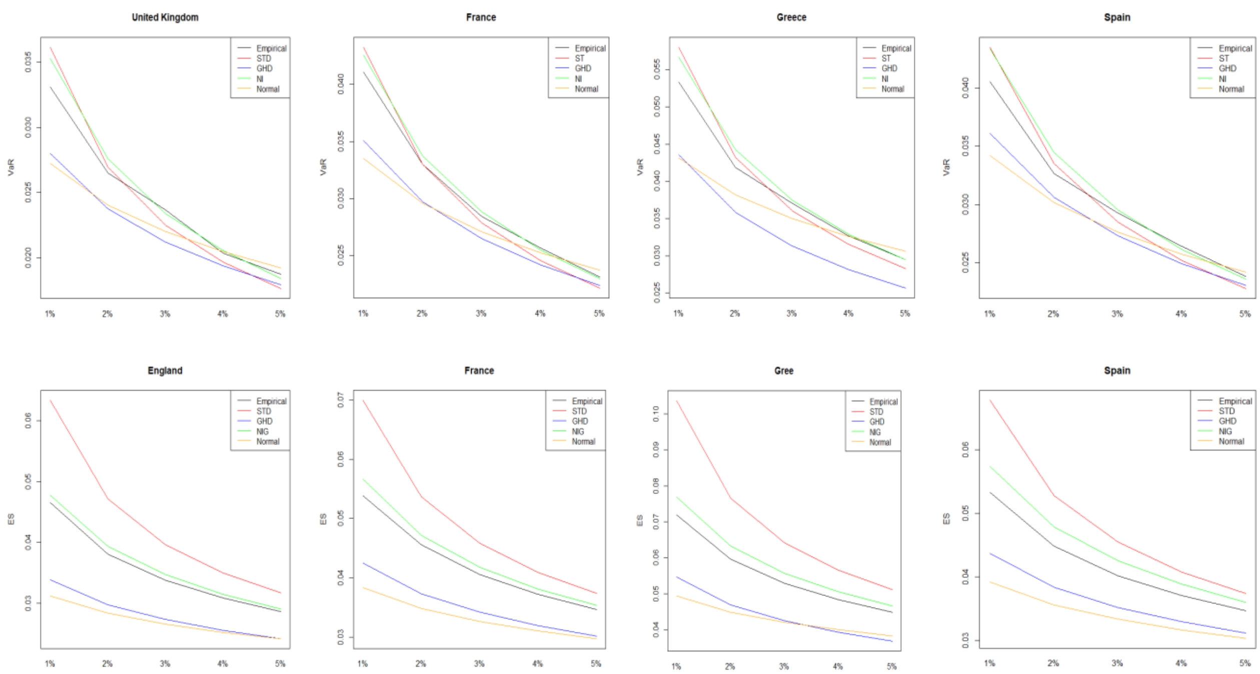
*Jarque Bera test: The results denotes null hypothesis "The distribution is normal" cannot reject with critical values as 0.347; 0.463; 0.574; 0.739 at 10%; 5%; 2.5% and 1%, respectively).

Figure 1 shows the VaR and Expected shortfall trajectory form using the parameters of four models. This outcome aims to exhibits the goodness of fitting from each model to each data series. The upper figures show the VaR trajectory and lower figures show Expected shortfall for

[1] By devaluating Yuan in August 2015, Chinese government wanted to support their goods on exporting sector. It also let the negative influences on international market, especially with U.S. stocks such as copper and oil. According to research of Antonio Graceffo was published on brooklynmonk.wordpress.com in September 13, 2015.

each country. With the cases of VaR, the outcomes are not quite simple to express. However, the VaR derived from NI could generally track the associated empirical loss levels quite closely in most of cases with the confidence level at 95%, although those results are difficult to express. The lower outcomes of expected shortfall look better than the upper. In most of cases, the expected shortfall trajectory from NI distribution fit the empirical data rather well than the others, although it is slightly overestimate the data at 99% confidence level. With the expected shortfall that based on GHD and Normal distribution, those results show too conservative. Hence, the investors put their stock holding position in too low with theirs capability. Summary all, Normal inversed Gaussian distribution parameters will be used for one-day risk accuracy predicting method in next step.

Fig. 1: VaR and Expected shortfall trajectory

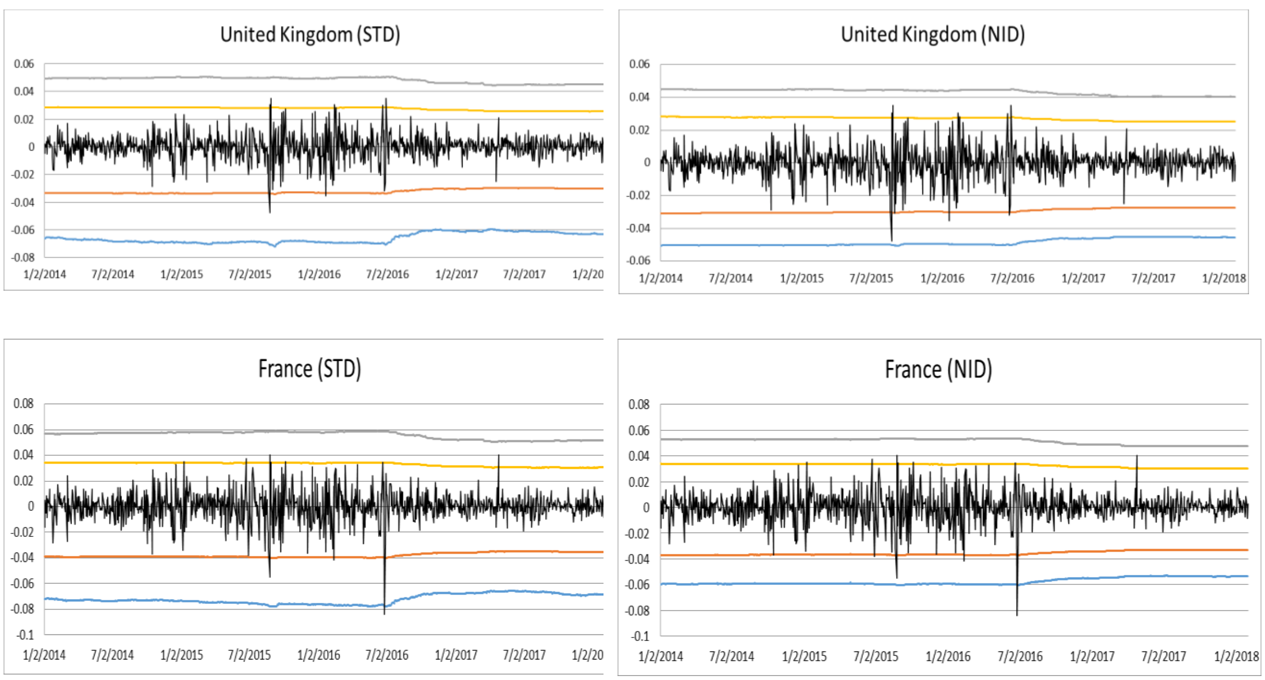


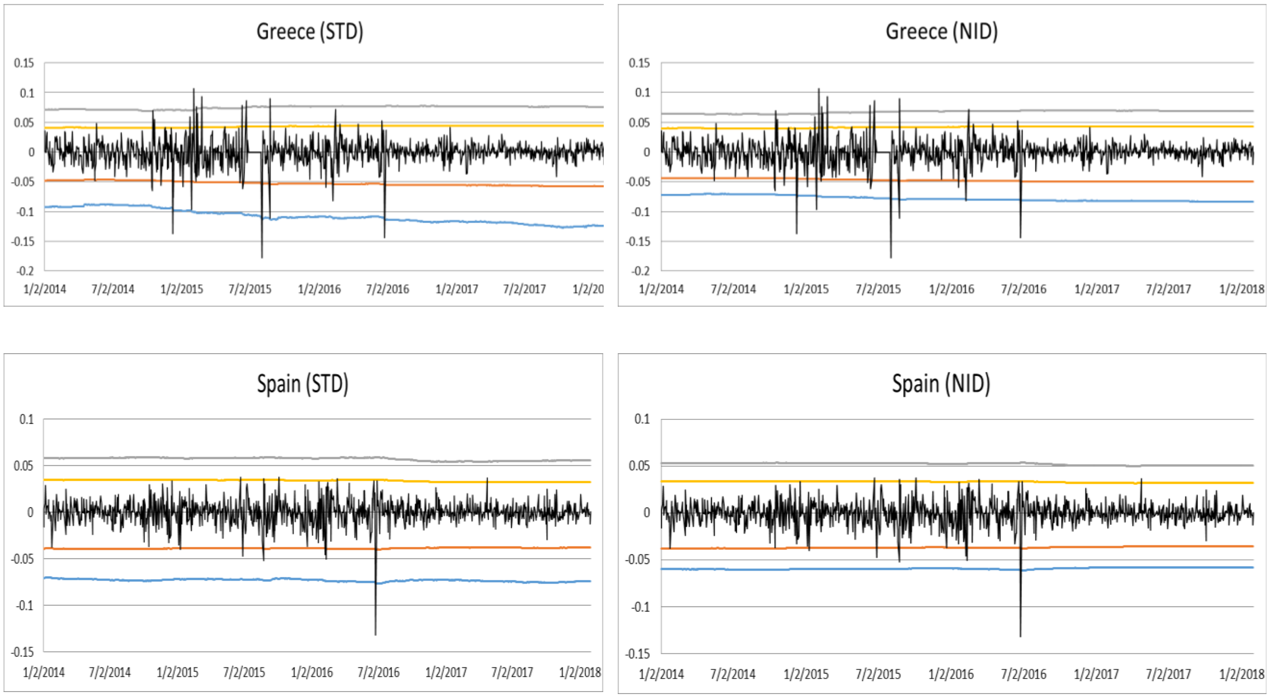
Souce: Author’s calculation

Results of one-day VaR and expected shortfall forecasts are presented in Figure 2 by the solid line that compares to actual return. The left side describes the VaR forecasts determined from ST and the right is from NI. The right tails of VaR (0.01 and 0.05 percent VaR) is plotted as two upper lines as well beside the 99 and 95 percent VaR. Due to the 99 percentile VaR forecasts is too conservative with actual return and we concentrate on losses than profit. According to interval forecasting results, these show several interested findings. Firstly, most of evidences had the similar trend in period from February 2015 to February 2016. Obviously, the risk forecasting model could not predict well the accuracy of return from all countries in this period. United Kingdom seems to be very efficient in controlling the risk and performs rather well than other cases due to its violation was only two in whole time with ST-based model and four in NI-based model. Conversely, Greece is the worst case as the risk predicting model could not to track the empirical return well. The numbers of violation generally spread from December 2014 and it stopped on February 2016, with an extreme devaluation that broken the forecasting performance line at 99^{th} and 95^{th} percentile. Furthermore, from those outcomes, we also found that the 1-day ahead forecasting NI-based was better than ST-based, although slightly huger on number of violation.

Fig. 2: Equity return daily VaR models.

Time series of daily return as reported by 5 markets for January 2014 to 1st January 2018 (Black lines) plotted with forecasts from 4 interval VaR models. The models are used to forecast the 1-day ahead 99^{th} ,95^{th}, 0.01^{th} and 0.05^{th} percentile of real return with the red, blue, green and orange lines, respectively.





Source: Author's calculation

The results from table 2 confirmed the outcome above by exhibiting the number of violations that the forecasting model fails to predict empirical return. This table contributes to the conservative characteristics of all European countries that be used in this study. Although, the forecasting model seems to be fail to track Greece market, its violation number is still in allowed limitation, according to suppose of (Kupiec, 1995). Generally, all European markets are substantial conservative, investors could lose their advantage due to laying their capital in too low risk position. However, that context might be acceptable from 2014 to 2016 when Europe just recovered their economic after the financial crisis in 2008. Furthermore, the unexpected event as crisis of Greece and the Brexit (this is the prospective withdrawal of the United Kingdom from European Union) were happened continuously, those are the reasons created the conservative and panic psychology not only at single investor, but also for whole the markets.

Tab. 2: Interval forecasting of equity markets VaR models

	United Kingdom	**France**	**Greece**	**Spain**
	95 percent STD-based VaR			
Number of violations	2	3	14	6

Violation rate	0.19%	0.28%	1.31%	0.56%
0.05 percent STD-based VaR				
Number of violations	0	0	3	0
Violation rate	-	-	0.28%	-
95 percent NIG-based VaR				
Number of violations	**4**	**5**	18	7
Violation rate	0.38%	0.47%	1.69%	0.66%
0.05 percent NIG-based VaR				
Number of violations	0	0	7	0
Violation rate	-	-	0.66%	-

Source: Author’s calculation

Chapter 5: Conclusion

Profit is the most important goal in business. However, the uncertainly characteristic of market makes the investor have to think about how to control the risk due to the loss sometime could collapse their business if profit is less than the risk. To date, these are more and more people who begin caring about risk management and VaR become the essential tool to estimate the risk. We also emphasize that despite the VaR concept is very simple but its measure is highly complex. As Basel committee on Banking Supervision (BCBS) announced Capital Accord incorporating market risks, risk management became a critical issue in banking sector. Since J.P.Morgan proposed the RiskMetrics methodology to calculate the market risk and introduced the concept of Value at risk in 1996, then it has become the essential tool in the financial institutions. Although previous research focused on VaR modelling of matured markets, however less attention had been paid on Europe after the world financial crisis 2008. As known the distributions of financial assets return such as stock equity are more likely skewed and thick. In this paper, three special distributions such as generalized hyperbolic skew student's t-Distribution

(GHD), skew Student's t-distribution (ST), and normal inversed Gaussian distribution (NI) are applied to measure market risk of the European countries.

In this study, we have argued for a special case of the generalised hyperbolic distribution that we denote is NI and then comparing it to ST, GHD and Gaussian distribution. ST and NI could be very useful to apply for finance field, especial in banking and stock market. By analysing the risk management in four European Union markets as United Kingdom, France, Greece and Spain, the final results show that NI distribution outperforms three other models in most of cases (including Normal distribution). Then, the predicting results exhibited the instability of European economy from 2014 to the end of 2018. The risk measurement model did not capture the extreme loss in Greece well. The same situation also happened on Spain. Conversely, England, France and Germany were slightly conservative in risk management. That demonstrated the different from risk management prior to uncertainty even in European Union. Finally, the model could not predict the consequence of United Kingdom leaving European Union to the financial market in 2016. However, that event was objectivity and it drove hard to most of other risk measurement tools.

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Preferences

Morgan, J. P. (1996). Riskmetrics technical document.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The journal of finance*, *48*(5), 1749-1778.

Bali, T. G., Mo, H., & Tang, Y. (2008). The role of autoregressive conditional skewness and kurtosis in the estimation of conditional VaR. *Journal of Banking & Finance*, *32*(2), 269-282.

McDonald, J. B., & Newey, W. K. (1988). Partially adaptive estimation of regression models via the generalized t distribution. *Econometric theory*, *4*(3), 428-457.

Hansen, B. E. (1994). Autoregressive conditional density estimation. *International Economic Review*, 705-730.

Theodossiou, P. (1998). Financial data and the skewed generalized t distribution. *Management Science*, *44*(12-part-1), 1650-1661.

Zhu, D., & Galbraith, J. W. (2010). A generalized asymmetric Student-t distribution with application to financial econometrics. *Journal of Econometrics*, *157*(2), 297-305.

Kupiec, P. (1995). Techniques for verifying the accuracy of risk measurement models.

Christoffersen, P. F. (1998). Evaluating interval forecasts. *International economic review*, 841-862.

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

Berkowitz, J., Christoffersen, P., & Pelletier, D. (2011). Evaluating value-at-risk models with desk-level data. *Management Science*, *57*(12), 2213-2227.

Cai, Z., & Wang, X. (2008). Nonparametric estimation of conditional VaR and expected shortfall. *Journal of Econometrics*, *147*(1), 120-130.

Fan, J., & Gu, J. (2003). Semiparametric estimation of Value at Risk. *The Econometrics Journal*, *6*(2), 261-290.

Polanski, A., & Stoja, E. (2010). Incorporating higher moments into value-at-risk forecasting. *Journal of Forecasting*, *29*(6), 523-535.

Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent measures of risk. *Mathematical finance*, *9*(3), 203-228.

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