Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 221 (2023) 912–919

Procedia Computer Science

www.elsevier.com/locate/procedia

10th International Conference on Information Technology and Quantitative Management

Does ESG risk management ensure better risk management? Evidence from India

Swati Sharma*

Jindal Global Business School, O. P. Jindal Global University, Sonipat, India

Abstract

Sustainability practices by business are being priced and reflected in its market return. Hence the index constituting those companies based on its Environmental, Social and Governance parameter are of interest for researcher to analyze such index performance. The present study investigates the performance of such two indexes i.e., NIFTY 100 Enhanced ESG & NIFTY 100 Sector Leaders Index which are based on better ESG risk managing stocks. For this purpose, the study analyzes the return behavior of index and calculates Value at Risk to predict the return for post covid time. The results indicate that even with a turbulent market, ESG index performance is found to be comparatively stable. VaR prediction confirms the robustness of tested VaR models for prediction. Lastly, this study concludes that including sustainable activities into business practices not only attracts more profit but also makes financial market and economy stable.

Keywords: Carbon Performance; ESG Risk, EVT, GARCH, Green Practices; Sustainability; Value at Risk.

1. Introduction

Scarcity of resources has led business entities to employ resources efficiently and smartly. Such careful use of resources makes corporate social responsibility and sustainability practices more relevant to the present day. Achieving sustainable development goals is the primary motive for the firms which want to survive in the long term. Waddock and Graves 1997 [1] discuss the implication of the relationship between social and financial performance of a company. Their findings confirm the need to use sacred resources strategically and efficiently. The achievement in terms of SDGs or according to ESG parameter are also being included into market return and hence a separate index

* Corresponding author. Tel.: +91 9795684488
E-mail address: swati@jgu.edu.in

10.1016/j.procs.2023.08.068

based on ESG activities are developed in many economies. Indian stock exchange NSE (National Stock Exchange) has such three indices named NIFTY 100 ESG Index, NIFTY 100 Enhanced ESG Index and NIFTY 100 ESG Sector Leader Index. These indices consist of companies based on their ESG parameter. Subsequently, such indices performance attracts attention of researchers [2-10].

This Environmental, Social and Governance parameters for business is not only in practice in developed economies but emerging market like India has also working in this direction. According to report of World Economic Forum 2022 [11] India has pledged that it will reach net zero emissions by 2070 and has also announced that 50% of energy will be renewable energy by 2030. Achieving such a target is only possible when an inclusive ESG activities drive is employed by companies. Business is used to be run on profit basis and if ESG activities turns out to be profitable, SDGs implementation will be effective and efficient. Hence, this study attempts to analyze the Indian ESG based index i.e., NIFTY 100 Enhanced ESG index and Nifty100 ESG Sector Leaders Index. These two Indexes reflect the performance of companies within NIFTY100 index, based on its Environmental, Social and Governance (ESG) score. NIFTY 100 Enhanced ESG index results in portfolio with similar sector exposure vis-à-vis Nifty 100 (parent index) with better ESG performing stocks whereas Nifty100 ESG Sector Leaders Index includes only selected companies based on their ESG risk management within each sector of the Nifty100. Both indexes exclude companies that are involved in any major Environmental, Social or Governance controversy Hence, these two indices are based on better performing ESG risk stocks. However, these two indexes' performances are not thoroughly explored in literature. The performance analysis of such indexes will enable to comment on the inter-relationship of risk management and ESG risk management. Hence, the present study investigates both ESG based indexes performance by modelling risk with different Value at Risk (VaR) method. VaR calculation is employed to profile risk for investors. This study integrates results for index performance and VaR calculations to comment on overall evaluation of index.

The remaining study is presented in four sections. The section on introduction is followed by the section on research methodology. The research methodology section is followed by the section on data analysis and findings. Lastly, the scope and implication of the study is discussed before concluding remark on the present paper.

2. Research Methodology

The study employs daily closing prices from January 2021 to December 2022 for analysis. This time frame is chosen to study the most recent impact on index performance after pandemic. 2021-22 is marked with declining phase of covid and return phase to normal market situation.

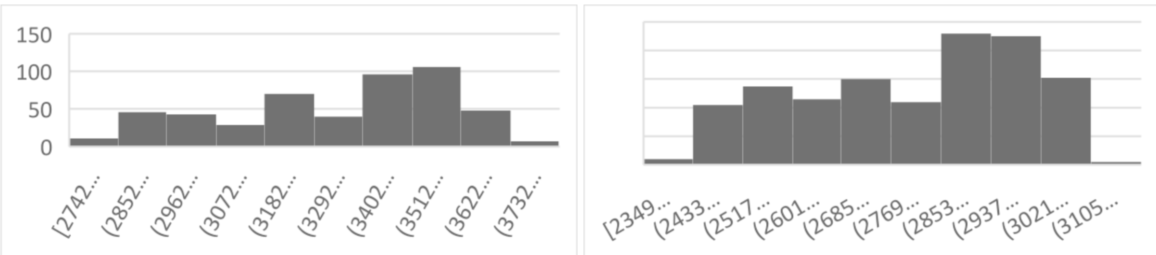

Figure 1 Histogram of Price series of (a) NIFTY100 Enhanced ESG index (b) NIFTY100 ESG Sector Leader index

Table 1. Descriptive Statistics

	NIFTY100 Enhanced ESG	NIFTY100 ESG Sector Leader		NIFTY100 Enhanced ESG	NIFTY100 ESG Sector Leader
Mean	3343.6505	2805.5861	Kurtosis	-0.9798	-1.1214
Standard Error	11.4402	8.5276	Skewness	-0.4511	-0.3463
Median	3417.455	2847.3	Range	1025.72	761
Mode	3510.33	3001.9	Minimum	2742.39	2349.75
Standard Deviation	254.7863	189.9194	Maximum	3768.11	3110.75

Sample Variance	64916.0504	36069.3864	Sum	1658450.65	1391570.7

Figure 1 and table 1 show the distribution properties of both price series. It can be observed from the price histogram of both indexes that it is not a normally distributed time series as a bell shaped curved can't be fit rather it has fat tail. Table 1 shows descriptive statistics of both indexes price series. It is evident that Mean, Median and mode are found to be inequal and non-zero, and kurtosis and moment found to be negative for both return series data. Hence, the results presented in table 1 also confirm that the closing price of both indexes are not normally distributed. These two price-series are further converted into return series by taking log difference of two consecutive days. For remaining of the study, we use return series instead of price series for data analysis. These two return-series are further checked for normality, stationarity, and serial correlation. Based on time series properties of two indexes, the study fit Value at Risk (VaR) models to compare and analyze indexes' performance.

3. Data Analysis & Findings

Results of data analysis for employed research methodology are explained in this section. The statistical tests for normality, serial correlation, stationarity, ARCH effect, value at risk calculation and back-testing employed in the present study is described as follows:

3.1. Stationarity of data

The analysis starts with checking the stationarity of data to ensure the reliability of results. The study employs ADF Test (Augmented Dickey Fuller test) which is a popular statistical test to check if a data is stationary or not. Table 2 summarizes the results of the stationarity test at 95% confidence level. Evidently the results confirm the stationarity of data for return series.

Table 2. ADF Test

NIFTY100 Enhanced ESG index		**NIFTY100 ESG Sector Leader**	
P Value	0.01	P Value	0.01
Null Hypothesis	Non stationary	Null Hypothesis	Non stationary
Decision	Reject	Decision	Reject

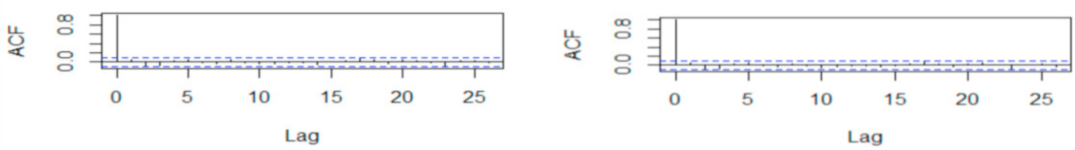

Figure 2 (a) ACF Plot of NIFTY100 Enhanced ESG index return (b) ACF Plot of NIFTY100 ESG Sector Leader index return

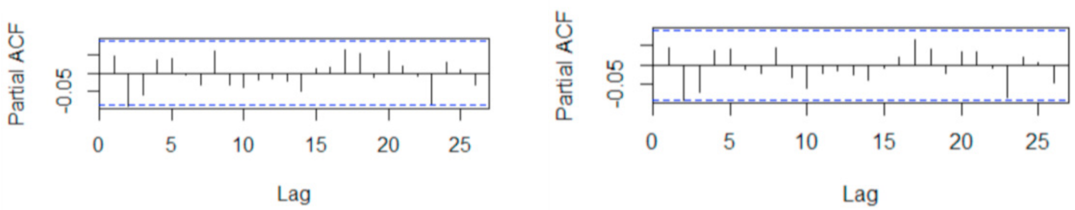

Figure 3 (a) PACF Plot of NIFTY100 Enhanced ESG index return (b) PACF Plot of NIFTY100 ESG Sector Leader index return

The study also uses Autocorrelation and Partial-autocorrelation plot to detect stationarity in both return series data. Figure 2 shows auto-correlation plot for both indexes. It can be observed that return series is stationary at higher lag. Hence, at lag one return series can be stationary. Figure 3 shows partial-autocorrelation plot for both return series. PACF of return series does not have unit root. Hence, ACF and PACF plot indicates that both return time series are stationary.

3.2. Serial correlation

The study employs the Ljung Box test to detect serial autocorrelation in return time series at 95% confidence level for different lags. This test analyses the time series to know whether or not errors are independently and identically distributed (i.e. white noise) or does serial autocorrelations exist in the errors or whether residuals of time series are non-zero. Table 3 summarizes the results of serial correlation test. It is found that return time-series is serially correlated.

Table 3. LJung Box Test

NIFTY100 Enhanced ESG index		**NIFTY100 ESG Sector Leader**	
P Value	0.2958	P Value	0.3212
Null Hypothesis	No serial correlation	Null Hypothesis	No serial correlation
Decision	Do not reject	Decision	Do not reject

3.3. Normality of data

Jarque-Bera test is used to check normality of data. It checks whether the kurtosis is higher than 3 and mean, median and mode is 0 for data or not which ultimately a test for checking whether time series is normally distributed or not. Table 4 summarizes the results of this test that confirms that at 0.05 significance level return time-series are found to be not normally distributed. Therefore, any statistical test which assumes data to be normally distributed can't be employed for both time series.

Table 4. Jarque-Bera Test

NIFTY100 Enhanced ESG index		NIFTY100 ESG Sector Leader	
P Value	2.2e-16	P Value	5.107E-15
Null Hypothesis	Normal distribution	Null Hypothesis	Normal distribution
Decision	Reject	Decision	Reject

3.4. Value at Risk

Value at risk (VaR) calculates the maximum losses with given probability which can occur over a certain time period. Hence, VaR can be seen as the value loss that should not be exceeded for that certain time period given the confidence level. VaR also consider the magnitude of loss if actual losses exceed the expected loss. Therefore, VaR can be seen as a parameter which helps investors to take investment decision and also signifies the health of given stock or index. The present study employs parametric VaR and EVT VaR model as explained below:

3.4.1. Parametric VaR

Both return series of indexes are not normally distributed. Hence, mean and variance equation of series can't be modelled based on normality assumptions. Literature suggests that GARCH model adequately captures the properties of not normally distributed time series, hence GARCH model can be employed to calculate VaR for these series as well [12]. Before employing GARCH model, both return series are checked for volatility clustering and ARCH effect. Figure 4 shows volatility clustering for both indexes' return series and table 5 shows whether ARCH effect is present in time series or not. As per ARCH-LM test, the null hypothesis of no ARCH effect is rejected for both return series. Hence, both series can be modelled with GARCH model as volatility clustering and ARCH effect is present for indexes' return series.

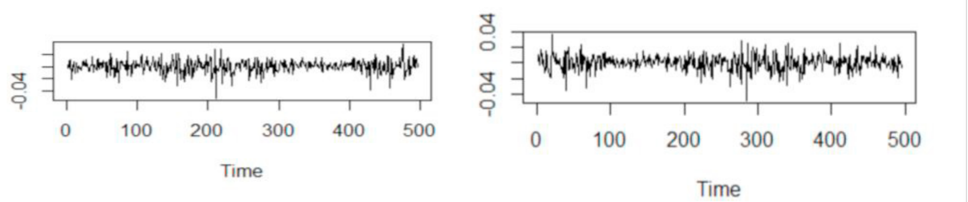

Figure 4 Volatility clustering of (a) NIFTY100 Enhanced ESG index return (b) NIFTY100 ESG Sector Leader index return

Table 5. ARCH-LM Test

NIFTY100 Enhanced ESG index		NIFTY100 ESG Sector Leader	
P Value	0.002499	P Value	0.0006744
Null Hypothesis	no ARCH effects	Null Hypothesis	no ARCH effects
Decision	Reject	Decision	Reject

The next step is to fit appropriate GRACH model. The statistical test reveals that standard GARCH model can't be fit as the effect of good and bad news are not symmetrical to both return series. Hence, we employ ARMA-EGARCH Model to fit mean and variance equation for computing parametric Value at Risk which capture asymmetrical effect of good and bad new on time series. The study assume that the non-normality of data can be accommodated with conditional mean returns, by employing following ARMA (1,1) model

$$r_t = a_0 + a_1 r_{t-1} + e_t + m_1 e_{t-1} \tag{1}$$

Where, a_1 is parameters, r_{t-1} are lagged returns. For variance calculation, the conditional variance h_t follows EGARCH (1,1) model as explained by Nelson 1991 [9] is employed:

$$log\ h_t = \omega + \frac{\alpha_1 \varepsilon_{t-1} + \gamma_1 |\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \beta_1\ log\ h_{t-1} \tag{2}$$

Equation 2 EGARCH model is tested with Student-*t* distribution instead of normal distribution. Table 6 summarizes the result of estimated parameter from equation 1 and 2. Except ω, all parameters are found statistically significant at 95% confidence level for NIFTY100 Enhance ESG index, whereas, except α_0, all parameters are found statistically significant at 95% confidence level for NIFTY100 ESG Sector Leader index.

Table 6. Parameter estimates for the ARMA-EGARCH (1,1)

	Mean Equation			Variance Equation			
	a_0	a_1	m_1	ω	α_1	β_1	γ_1
NIFTY100 Enhanced ESG	0.001639*	-0.215954*	0.322224*	0.002812	0.169248*	0.998700*	0.179369*
NIFTY100 ESG Sector Leader	0.000384	0.125983*	0.262027*	-0.635325*	-0.219927*	0.932277*	0.090891*

3.4.2. Extreme Value Theory-Value at Risk (EVT-VaR)

The descriptive statistics of price series show negative kurtosis and moments for both price series which confirms negatively skewed data. This negative skewness also confirms fat tail of distribution. Traditional VaR model on such time series tend to underestimate the real risk. Hence, risk modelling with extreme events seems to be perfect for such time series risk modelling. One of such risk models is Extreme Value Theory (EVT). The EVT relates to the asymptotic behavior of extreme observations of a random Variable. It provides the fundamentals for the statistical modelling of rare events and is used to compute tail-related risk measures. There are two different ways of identifying extremes in real data over a certain time horizon. One is Block Maxima method and the other is Peak over Threshold (PoT) method. This study employs PoT method for EVT modelling as block maxima method is not suited for financial time series because of volatility clustering (Figure 4). The PoT method identifies extreme observations that exceed a high threshold u and specifically models these 'exceedances' separately from non-extreme observations. A rule of thumb is that u should be approximately equal to the 95th percentile of the empirical distribution. The present study also fixes value of $\boldsymbol{u}$ in this way only. Given a high threshold u, the probability distribution of excess value of x over threshold u is defined by

$$F_u(y) = Pr(X - u \le y | X > u) = \frac{F(y+u) - F(u)}{1 - F(u)} \tag{3}$$

Setting $x = y + u$ for $x>u$, we have the following representation

$$F(x) = [1 - F(u)]F_u(y) + F(u) \tag{4}$$

A theorem by Balkema and De Haan, 1974 [13] and Pickands III, 1975 [14] shows that for a sufficiently high threshold u, the distribution function of the excess may be approximated by the generalized pareto distribution (gpd) because as the threshold gets large, the excess distribution $f_u(y)$ converges to the gpd. The gpd in general is defined as

$$G_{\xi\psi}(y) = 1 - \left(1 + \frac{\xi y}{\psi}\right)^{-1/\xi}, \text{ if } \xi \neq 0 \tag{5}$$

$$= 1 - exp^{-y/\xi} \quad , \text{if } \xi = 0 \tag{6}$$

Where $\xi = 1/\alpha$ is the shape parameter, α is the tail index, and ψ is the scale parameter. For $x > u$, where ξ and ψ can be estimated by the method of maximum likelihood. For a given probability $q > f(u)$, the tail quantile can be obtained by inverting the tail estimation formula above to get [15].

$$VaR_q = x_q = u + \frac{\psi}{\xi}\left[\left(\frac{1-q}{k/n}\right)^{-\xi} - 1\right] \tag{7}$$

Since VaR is an extreme quantile, it is equivalent to x-quantile. Table 7 shows parameter estimated of GPD fit for EVT and value of EVT-VaR for two quantiles i.e., 99% and 95% for both indexes.

Table 7. Parameter estimates for GPD fit of EVT-VaR

	NIFTY100 Enhanced ESG		**NIFTY100 ESG Sector Leader**	
	99%	95%	99%	95%
u	147.0000	147.0000	168.8098	168.8098
β	57.1322	57.1322	32.5316	32.5316
ξ	0.1423	0.1423	0.4362	0.4362
n	500.0000	500.0000	495.0000	495.0000
n_u	25.0000	25.0000	24.0000	24.0000
VaR	250.3321	147.0000	242.7178	167.8154
Likelihood	-129.6917	-129.6917	-124.7715	-124.7715

Interestingly, EVT-VaR computation for both indexes follow each other closely, e.g., EVT-VaR@99% for NIFTY100 Enhanced ESG is 250.3321 whereas for NIFTY100 ESG Sector Leader, it is 242.7178. the reason of such close proximity can be attributed to the fact that 60% stock of both indexes' composition are same.

3.5. Back-testing; Likelihood Ratio Test

The robustness of any VaR model can only be confirmed with back-testing result of applied model. Therefore, to check the robustness of AR-EGARCH model, the present study employs the unconditional coverage test proposed by Kupiec, 1995 [16]. For every *t+1* day return forecasting, variable I_{t+1},is used to indicate the exceedance of calculated VaR value by comparing the $V\hat{a}R_q^{t+1}$with the r_{t+1} by following equation:

$$I_{t+1} = \begin{cases} 1, if\ r_{t+1} < V\hat{a}R_q^{t+1} \\ 0,\ otherwise \end{cases} \quad (8)$$

The unconditional coverage test examines whether the realized value at risk equals to calculated value at risk. This comparison of realized and calculated VaR tests if the variable I_{t+1}follows an *iid* Bernoulli process with parameters p; where p stands for VaR's theoretical coverage rate α. The unconditional coverage likelihood ratio test follows a χ^2distribution with one degree of freedom and is calculated with following equation:

$$LR_{uc} = 2\log\left[\frac{(1-p)^{T_0}\, p^{T_1}}{(1-T_1/T)^{T_0}(T_1/T)^{T_1}}\right] \sim \chi^2\,(1) \quad (9)$$

where T_0 and T_1 are the number of zeros and ones, respectively in the violation sequence.

Table 8. Back-testing of ARMA-EGARCH-VaR (1,1) & EVT-VaR for NIFTY100 Enhanced ESG index

	Parametric VaR @ 99%		Parametric @95%		EVT-VaR @99%		EVT-VaR @95%	
Quantile	99%	95%	99%	95%	99%	95%	99%	95%
Kupiec Chi-squared	1.5999	16.0195	86.8966	5.5768	0.7599	18.4809	206.2560	42.4021
p-value	21%	0%	0%	2%	38%	0%	0%	0%

Table 9. Back-testing of ARMA-EGARCH-VaR (1,1) & EVT-VaR for NIFTY100 ESG Sector Leader index

	Parametric VaR @ 99%		Parametric @95%		EVT-VaR @99%		EVT-VaR @95%	
Quantile	99%	95%	99%	95%	99%	95%	99%	95%
Kupiec Chi-squared	0.2107	21.2331	86.8966	5.5768	0.7599	18.4809	41.7062	0.0026
p-value	65%	0%	0%	2%	38%	0%	0%	96%

Tables 8 show statistics of unconditional coverage test for two quantiles i.e., 95% and 99%. For NIFTY100 Enhanced ESG index, the result suggests that at 99%, ARMA-EGARCH (1,1) VaR@99% & EVT @99% is significant. Table 9 summarizes the back testing result NIFTY100 ESG Sector Leader index. The result suggests that at 99%, ARMA-EGARCH (1,1) VaR@99% & EVT@99%, both models are significant. Whereas at 95%, only EVT@95% is found to be significant.

4. Scope & Implications of the study

This study has employed ARMA-EGARCH model to be fitted for Value at Risk. As time series are found to be not normally distributed, one can employ other methods including different GARCH specification, EWMA etc. for value at risk. We suggest modelling two stage conditional EVT VaR to return forecast. The present study used unconditional coverage test for back-testing VaR model. The unconditional coverage test is not free from some limitation as this test does not properly characterize the behaviour of the model in the presence of clustering. Therefore, it calculates correct number of violations, but those violation may occur in clusters. Hence, we suggest to employs another likelihood ratio rest i.e., the test of independence and the test of conditional coverage suggested by Christoffersen 1998 [17]. A comparative study of other indices and other sustainability indices from India and other countries can also be investigated for further research.

5. Conclusion

The findings of the study conclude that both specialized ESG indexes have performed better. Back-testing result suggests at higher level of confidence i.e., 99%, tested VaR models are robust. Such results also indicate the efficiency of market to absorb the shock efficiently. This study also indicates that there is low risk and positive performance for index consists of stocks based on its ESG activities. Hence, it can be concluded that the stocks which have a higher score of managing ESG risks are performing better overall. This study also proposes that there is a positive correlation between ESG risk management and overall risk management. The findings of the present study also advocate the need to include sustainable finance as common business practice for enhanced performance of index and stocks. NIFTY 100 Enhanced ESG index and NIFTY100 Sector Leader index performance analysis confirms that financial incentive to include ESG investing practices by companies exists. Though a comparative studies and further exploration of data will provide more insight on such index performance. Lastly, this study emphasizes on having a clear public policy for ESG investing in India because energy efficiency and clean energy investment is not a future but the present business activity.

References

[1] Waddock, S. A., & Graves, S. B. (1997) "The corporate social performance-financial performance link." *Strategic management journal* 303-319.

[2] Vadithala, Usha Kiran, and Gattaiah Tadoori. (2021). "Market Efficiency of ESG and Traditional Indices-Pre and Post COVID Analysis of NSE Indices." *Available at SSRN 3807952*.

[3] Meher, Bharat Kumar, Iqbal Thonse Hawaldar, Latasha Mohapatra, Cristi Marcel Spulbar, and Felicia Ramona Birau. (2020). "The effects of environment, society and governance scores on investment returns and stock market volatility." *International Journal of Energy Economics and Policy* **10(4)** 234-239.

[4] Jasuja, Deepmala, Jaya Mamta Prosad, and Neeraj Nautiyal. (2021) "A Comparative performance analysis of sustainability themed indices in India: markov regime switching approach." *FIIB Business Review*, 23197145211052805.

[5] Balasubramanian, A. M. D. P. (2019)."A study on relationship between corporate financial performance and environmental social & governance score (ESG score)." *FIFI-2019*.

[6] Konar, S. and Mark, A. C. (2001) "Does the Market Value Environmental Performance?" *The Review of Economics and Statistics* **83(2):** 281–89.

[7] Statman, M. (2000) "Socially responsible mutual funds." *Financial Analysts Journal* 30-39.

[8] Ortas, E., Moneva, J. M., Burritt, R., and Tingey-Holyoak, J. (2014) "Does sustainability investment provide adaptive resilience to ethical investors? Evidence from Spain." *Journal of Business Ethics* **124(2)**: 297-309.

[9] Lopez, V. M., Garcia, A., & Rodriguez, L. (2007) "Sustainable Development and Corporate Performance: A Study Based on the Dow Jones Sustainability Index." *Journal of Business Ethics* **75**: 285-300.

[10] Albertini E. (2013) "Does Environmental Management Improve Financial Performance? A Meta-Analytical Review." *Organization & Environment.* **26(4)**:431-457.

[11] World Economic Forum, The Global Risk Report 2022 (2022) https://www3.weforum.org/docs/WEF_The_Global_Risks_Report_2022.pdf.

[12] Nelson, D. B. (1991) "Conditional Heteroskedasticity in Asset Returns: A New Approach." *Econometrica*, ***59*(2)**: 347–370.

[13] Balkema, August A., and Laurens De Haan. (1974) "Residual Lifetime at Great Age." *The Annals of Probability* 792–804.

[14] Pickands III, James. (1975) "Statistical Inference Using Extreme Order Statistics." *Annals of Statistics*. 119–131.

[15] Embrechts, P., Claudia, K. and Thomas, M. (1997). *Modelling Extremal Events*. Berlin, Heidelberg: Springer Berlin Heidelberg.

[16] Kupiec, Paul H. (1995) "Techniques for verifying the accuracy of risk measurement models". *Division of Research and Statistics, Division of Monetary Affairs, Federal Reserve Board*, **95(24).**

[17] Christoffersen, P. F. (1998) "Evaluating Interval Forecasts." *International Economic Review* ***39*(4)**: 841–862.