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The Devil is in the Tails - Modeling the Fat-Tails in Sub-Saharan Africa Equity Markets Using Extreme Value Theorem

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Abstract

This paper investigates the presence and implications of fat-tailed return distributions in Sub-Saharan African equity markets using Extreme Value Theory (EVT). While traditional asset pricing models often assume normality, frontier markets, characterised by low liquidity, regulatory asymmetries, and episodic volatility in returns, frequently exhibit return dynamics that deviate from Gaussian assumptions. We apply both block maxima and peaks-over-threshold approaches to daily equity index returns from selected Sub-Saharan exchanges, including Ghana, Nigeria, Kenya, and Botswana, over a 6-year period. Our findings reveal statistically significant tail heaviness and asymmetric risk exposures across markets, with implications for Value-at-Risk (VaR) estimation, portfolio optimisation, and systemic risk monitoring. The EVT-based models consistently outperform conventional parametric alternatives in capturing extreme downside risk. These results drive home the importance of tail-sensitive risk management frameworks in sub-Saharan stock markets and offer new insights into the structural fragility and resilience of frontier financial systems. The paper contributes to the literature by extending EVT applications to under-represented markets and by providing a robust empirical foundation for regulatory stress testing and financial innovation in the region.

Introduction

Equity markets are complex (Gomber, Sagade, Theissen, Weber, & Westheide, 2017). The characteristics of the data they produce have the seeds that determine the risk associated with such markets. The distribution of returns in sub-Saharan Africa (SSA) equity markets has long been characterized by fat-tails (Okorie, Nadarajah, Ohakwe, & Onyemachi, 2021). These fat-tails elevate the risk of equity investments and trading in the sub-region. Another feature in these markets is the thin and asynchronous trading, which has long been of concern to market players in SSA. Measuring the risks arising out of these characteristics is therefore important for the accurate pricing of financial instruments, building portfolios and for risk management in general.

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models have been the mainstay of volatility estimation to assess the risk involved in financial markets since the pioneering work of Engle (1982). Indeed, there are GARCH variants to capture stylized facts like asymmetry in distribution, fat-tails, leverage in markets, among others. However, the severity of the tails and extent of distribution asymmetries in the returns from the SSA markets differ substantially from those of the developed and emerging countries. These have led investors to perceive SSA markets as risk-prone, leading to higher risk premia in equity investments in the subregion (Lo, Marcelin, Bassène, & Lo, 2024; Korley & Giouvris, 2021). Nevertheless, SSA equity markets typically do not experience the wild swings that characterise the developed world markets. The return paths hardly switch unexpectedly. The biggest and lingering problem over many years has remained the extended periods of thin-trading and the tendency for asynchronous trades. This makes the volatility of the market returns appear benign but in effect risky because of the fat-tails induced by the asynchronous thin trades. Thin trades, according to Han et al. (2024), are markets with a limited number of traders, and the result is that investors are unable to offload their positions in a timely manner for an extended period of time. This evaporates liquidity from the markets, reducing market returns and showing losses, particularly in the left tails of asset return distributions. Characterizing the extreme outcomes of the distributions of returns, therefore, it is essential to correctly estimate the risk, particularly in the tails.

Pástor and Stambaugh (2003) identified illiquidity in financial assets as extremely risky, as investors demand premia against the difficulty of disposing of such assets. Van Van Oordt and Zhou (2016) explored the effect of tail risk in a range of markets and concluded that investors must look at these phenomena closely because of the spillover effects into the broader economy.

Andersen, Fusari and Todorov (2020) documented several instances of extreme tail events resulting in major market dislocations across the world's financial markets. Among others, the authors attributed the famous Black Monday event of 1987 to extreme outcomes that conventional models could not capture. In the review by Steffen (2023), extreme market movement and subsequent sudden reversals have been listed as factors leading to flash crashes, a phenomenon observed with the advent of electronic trading. In all these, conventional models of risk have failed as warning systems to market participants (Kyle & Obizhaeva, 2023). A jumping-off point of this paper, therefore, is to go beyond the GARCH models and look at the data from the SSA markets, their distribution and the behaviour of the tails in estimating the risk involved in equity trading. The fact is that tails matter; there is so much information in the tails of distributions that summarise much of the risk in the trading data. Unlike GARCH models, we use the extreme value theorem (EVT) to emphasize the centrality of tail behavior in risk estimation. It is in the tails of the distribution that are embedded odds of failure in the investment portfolios, asset mispricing and the inadequacy of risk management. We seek to characterise this information by estimating the Value at Risk (VaR) and Expected Tail (ES) parameters of the distributions. The novelty of this work is that we have gone beyond the central three standard deviations within the mean of the distribution into the tails, regions laden with so many unknowns in volatility estimation of financial returns.

The paper succeeds in assessing tail risks that investors and policymakers can rely on for accurate decision-making in the financial markets. According to Nadeem, Dumay and Massaro (2019), if we can measure it, then we can manage it. In so doing, the paper adds valuable depth to the quest for the most accurate means of assessing the risk of equity returns in the face of thin and asynchronous trading in the SSA region. Specifically, this paper, which employs EVT to assess VaR and ES contributes significantly to financial risk management by addressing the limitations of traditional risk measures with improved tail risk estimation, providing flexibility across markets, enhancing risk measures by employing a more robust methodology for assessing extreme losses, giving practical guidance to financial institutions in stress testing, regulatory compliance, and capital allocation.

The rest of the paper is organized as follows. The literature review looks at extant work in EVT, including incidents of tail risks in the financial markets in recent times. We explain the concept behind EVT and its use in estimating VaR and ES in the methodology section. The section on data and analysis builds the model for the four sampled countries and discusses the findings. The last section concludes the paper.

Literature Review

Equity markets are inherently risky. The data from these markets hold the information that describes much of the risk associated with the trading activities. One of the most studied characteristics is the nature of the distribution of returns. As a rule, market returns, be they from developed, emerging, or frontier markets, are non-Gaussian and follow known stylized facts (Cont, 2001). The distribution of SSA equity returns, however, remains an ongoing field of study due to the idiosyncratic nature of thin and asynchronous trades and general underdevelopment of market structures, known major causes of fat tails in the distribution of returns, which raises the risk to investment and trade in these markets (Aloui, Ben Aïssa, & Nguyen, 2011). From a statistical point of view, fat-tails point to a higher likelihood of extreme market movements than is contained in Gaussian distributions. The presence of fat tails in the SSA markets signals that those higher risks, for instance, sudden gains or falls in the prices, could be at hand and may bring about losses to investors. These characteristics can be understood and quantified through EVT. According to McNeil et al. (2000), EVT focuses on modeling tail behavior in the distribution. Unlike the assumptions underlying the Gaussian theory, EVT provides a pretty good understanding of extreme risks by incorporating behavior in the tails. The tail behaviour gets underestimated under traditional models, such as the normal distribution. Over the many years since Engle (1982), volatility in the mid-portions of the distribution of market returns is pretty much known in the finance industry (Eom, Kaizoji, & Scalas, 2019). What remains the focus of current intense research is the behaviour in the tails (Abanto-Valle, Langrock, Chen, & Cardoso, 2017; Lazar, Pan, & Wang, 2024; Kamronnaher, Bellucco, Huang, & Gallagher, 2024).

Tail events continue to roil financial markets of all kinds, irrespective of how developed these markets are. In recent memory, markets witnessed the high-frequency flash crash (Akansu, 2017), the stock market October 1987 crash (Leland & Rubinstein, 1998), the Chinese Stock Market Crash of 2015 (Xing & Ibragimov, 2023), among others. For an overview of financial market crashes, see Andraszewicz (2020) and Schulmerich et al. (2015). In all these cases, researchers and market participants point at tail events which classical heteroscedastic models fail to capture. This has Xing & Ibragimov (2023) advocating for the use of robust approaches to estimate the risk of financial returns.

Again, with globalization, stock markets are increasingly seeing the interconnectedness of the respective bourses in Africa. Gourene, Mendy and Diomande (2019) provide evidence of the integration of African exchanges using wavelet approaches, suggesting that an increasing trend of interconnectedness will leave countries exposed to market disruptions, as it happened in Nigeria within the network. Market reforms promoting openness across countries have left many exchanges vulnerable to crashes as a result of co-movements in trades and high correlation in assets (Hassan, Ibrahim, & Bala, 2024). There is ample evidence supporting this hypothesis. Obadiaru et. al (2020) investigated the effect of the Nigerian market collapse of January 2009 on selected regional and global markets and found contagion effects of one market on possibly others. This, the authors attributed to the dynamic and co-movement effects across stock markets, raising the possibility of cascading market turbulence leading to further crashes. This phenomenon has been confirmed in a paper by Owusu et al. (2024). Further, factors emanating outside the continent as a whole are leaving African stock markets prone to crashes. The Global Financial Crisis (GFC) and the recent COVID-19 pandemic are cases in point. Bello, Guo and Newaz (2022) have documented country-level financial crises resulting from the global financial crisis, the European debt crisis, Brexit, and COVID-19 episodes. Indeed, evidence abounds in the finance literature to suggest that African markets have become prone to market spillovers from the US, particularly (Mensi, Hammoudeh, Nguyen, & Kang, 2016; Neaime, 2012). As these cases point out, increasingly, market risk research is going to focus more on tail risk instead of the heteroscedasticity of the whole of the market returns. This is evidenced by works like Antwi, Gyamfi and Adam (2024), Ben Yaala and Henchiri (2024), Eita and Tchuinkam Djemo (2022), Wang et al. (2022), Okorie et al. (2021), Makatjane, Moroke and Munapo (2021), among others, in contemporary literature.

Asymmetric returns and thin trading in SSA equity markets

A singular characteristic of SSA equity markets is that they trade rather sporadically and asymmetrically. The nature of this trade poses a challenge that has captured the attention of investors and market regulators for some time now. Infrequent asymmetric trading in this context simply means that trades scattered in time are asymmetric; it means that market activities tend to bunch up in certain periods of time and thereby move into long sessions of inactivity. These thin markets appear to offer stability, but they mask risks associated with limited liquidity and low trading volume. The thin trading creates pricing inefficiencies and anomalies in the market, including fat-tails and jumps in volatility, as cited by Bekaert et al. (2007).

Studies indicate that thin trading worsens tail risks in equity markets as it amplifies the impact of extreme price movements. The lack of continuous trades means less price discovery and higher susceptibility to new information (Smith, Rangel, & Medvedev, 2020). On the other hand, high liquidity and continuously evolving trades exhibit smoother price adjustments, resulting in less severe fat tails. Thus, specific challenges have been set to the risk management of market participants in SSA, given that traditional tools like GARCH models, presupposing regular trading and symmetric distribution, may be very poor at estimating the underlying risks in these markets (Engle & Rangel, 2008).

The GARCH models have since remained the backbone of volatility modeling in finance, especially in capturing time-varying volatility and risk prediction in financial markets (Bollerslev, 1986). Variants of GARCH, including student-t GARCH, are used to handle distribution asymmetries, fat-tails, and leverage effects common in both developed and emerging markets (Hansen, 1994; Nelson, 1991). While these models provide a scaffold on which volatility can be modeled, their accuracy in SSA markets is questioned because of the peculiarities of the market data, including thin trading and market fragmentation (Ezeoha, Ebele, & Ndi Okereke, 2009). Other researchers, such as Olweny and Kimani (2011), postulated that the assumption of GARCH models may be too severe to capture the true risk profile of the SSA equity markets. EVT, on the other hand, accounts for the behavior of extreme events, making the models suitable for accurately estimating the overall volatility of the markets. Thus, EVT may provide a more applicable procedure or technique in assessing the tail risks of the SSA equity markets.

Application of extreme value theory (EVT) in risk estimation

EVT evolved from a sound methodology for dealing with extremely rare events. It gained notoriety in finance following the market crash of 1987 (Singh & Robert, 2013). The market crisis of 2007-2008 added some urgency to a review of the heteroscedastic models in use at the time. Rossignolo, Fethi and Shaban (2013) employed EVT in estimating the conditions precipitating the European Financial Crisis engulfing Portugal, Ireland, Greece and Spain. In the SSA context, where fat tails have been and are a perennial problem in the distribution of returns, not much work has been done in this regard. EVT, as a model, specializes in modeling the extremes of the distribution rather than its center, making it an ideal tool for estimating the risk of rare but potentially devastating market events (Embrechts, Kluppelberg, & Mikosch, 1997).

The two important estimates from EVT are VaR and ES, both widely used in risk management to forecast the probability of extreme losses over a specific period. VaR provides the threshold level beyond which the loss is less than a specific confidence level (Jorion, 2006). Expected shortfall, on the other hand, gives the average loss if the VaR threshold is breached, so it is a better measure that indicates tail risk (Acerbi & Tasche, 2002).

Indeed, in SSA markets, with their characteristic thin and asynchronous trading, EVT-based models potentially produce better risk estimates than traditional approaches such as GARCH (Lux & Sornette, 2002). In this respect, EVT can capture the fat tail risks of the SSA equity markets that are normally estimated by GARCH models through modeling the tail of the return distributions. Application of EVT has been seen to deliver improved risk predictions when markets are in a market, especially when liquidity is thin and financial asset correlations are nearly perfect in a number of recently studied emerging markets, including SSA (Leshoro, 2020).

The theoretical foundations of EVT, focusing on the asymptotic behavior of distributional tails, are particularly salient in modeling equity market returns in SSA. Kirchler and Huber (2007) concluded that markets often exhibit episodic volatility, low liquidity, and structural discontinuities that amplify the frequency and severity of extreme price movements. Empirical analysis of daily equity index returns from exchanges such as the NGX, NSE, GSE, and BSE reveals significant deviations from normality, with pronounced kurtosis and skewness in return distributions; applying EVT enables consistent estimation of tail risk across these markets.

Methodology

EVT allows for the modeling of the extreme returns in the tails using the Generalized Extreme Value (GEV) distribution or the Generalized Pareto Distribution (GPD). The GPD is generally used in finance, given its advantages, including its focus on tail behavior, threshold selection, computational efficiency, and better fit for heavy tails (McNeil & Frey, 2000). Given how fat the tails of market returns are on the generality of exchanges in SSA, we propose using EVT as the basis for estimating the market VaR and ES. The theory is developed as follows.

Consider a series of returns $\boldsymbol{r_i}$ with $\boldsymbol{i = 1, 2, \ldots T}$ being market returns coming from an unknown distribution $\boldsymbol{F}$ possible with extreme values above a threshold $\boldsymbol{\varpi}$. For these returns, we are interested in characterizing the values above this threshold, $\boldsymbol{\varpi}$, such that the distribution is given as:

$$\boldsymbol{F_{\varpi}(r) = P(L - \varpi \leq r | L > \varpi) = \frac{F(\varpi + r) - F(\varpi)}{1 - F(\varpi)}} \tag{1}$$

Invoking the so-called second theorem in EVT, credited to Balkema and de Haan (1974) and Pickands (1975) equation (1) can be approximated by the Generalized Pareto Distribution (GPD) with a shape parameter $\boldsymbol{\xi}$ and scale parameter $\boldsymbol{\sigma}$ as:

$$\mathbb{G}_{\xi,\sigma} = \begin{cases} \boldsymbol{1 - \left(1 + \frac{\xi x}{\sigma}\right)^{-\frac{1}{\xi}}} & \boldsymbol{if\ \xi \neq 0} \\ \boldsymbol{1 - e^{-\frac{x}{\sigma}}} & \boldsymbol{if\ \xi = 0} \end{cases} \tag{2}$$

Thus, we have

$$\mathbb{G}_{\xi,\sigma} = \boldsymbol{\frac{F(\varpi + r) - F(\varpi)}{1 - F(\varpi)}} \tag{3}$$

as the cumulative distribution function for the tails.

Value at Risk (VaR)

The VaR at a confidence level $\boldsymbol{q}$ is the quantile of the return distribution. This can be backed out of Equation (2) if we set it to the confidence level q as

$$\boldsymbol{q = 1 - \left(1 + \xi\left(\frac{VaR_q - \varpi}{\beta}\right)\right)^{-1/\xi}} \tag{4}$$

Backing out $\boldsymbol{VaR_q}$ from Equation (4), we have:

$$\boldsymbol{VaR_q = \varpi + \frac{\beta}{\xi}((1 - q)^{-\xi} - 1)} \tag{5}$$

Expected shortfall (ES)

Expected Shortfall (ES) is the expected value of returns given that they exceed the VaR. For the GPD, we can derive ES as follows:

For a given confidence interval of $\boldsymbol{q}$, the ES is defined mathematically as:

$$ES_q = E[r|r > VaR_q] \quad (6)$$

The conditional expectation in Equation (6) can be rewritten as:

$$ES_q = VaR_q + \frac{\beta + \xi VaR_q}{1-\xi} \quad (7)$$

Substituting Equation (5) into Equation (7) gives:

$$ES_q = \left[\varpi + \frac{\beta}{\xi}((1-q)^{-\xi} - 1)\right]\frac{\xi + \frac{1}{\xi}}{1-q} \quad (8)$$

As can be seen in Equations (6) and (8), the ES exceeds VaR by a factor of $\frac{\xi + \frac{1}{\xi}}{1-q}$ as expected from the fundamental definitions of the metrics.

Results

Sample data for the analyses were sourced from Bloomberg. It consists of varying lengths of the market indices of Ghana, Botswana, Kenya and Nigeria. These countries were chosen as broadly representing SSA based on the availability of data. The moments of the returns are shown in Table 1.

Table 1: Statistical summary of the returns

	Mean	Std	Skew	Kurtosis
Botswana	0.000831	0.019584	-0.27816	7.004439
Ghana	-0.0004	0.013741	-0.31478	69.52931
Kenya	0.000227	0.008905	-0.60456	5.645371
Nigeria	0.00017	0.033995	-1.1017	10.65132

The values of the third moments are negative, showing that the distributions of the returns are slightly negatively skewed. The fourth moments show heavy-tails with GSE of at 70, much pronounced than the rest of the exchanges. The price and return series were plotted as shown in Figures 1, 2, 3 and 4 for Botswana Stock Exchange (BSE), Ghana Stock Exchange (GSE), Nairobi Stock Exchange (NSE) and Nigeria Stock Exchange (NGX), respectively.

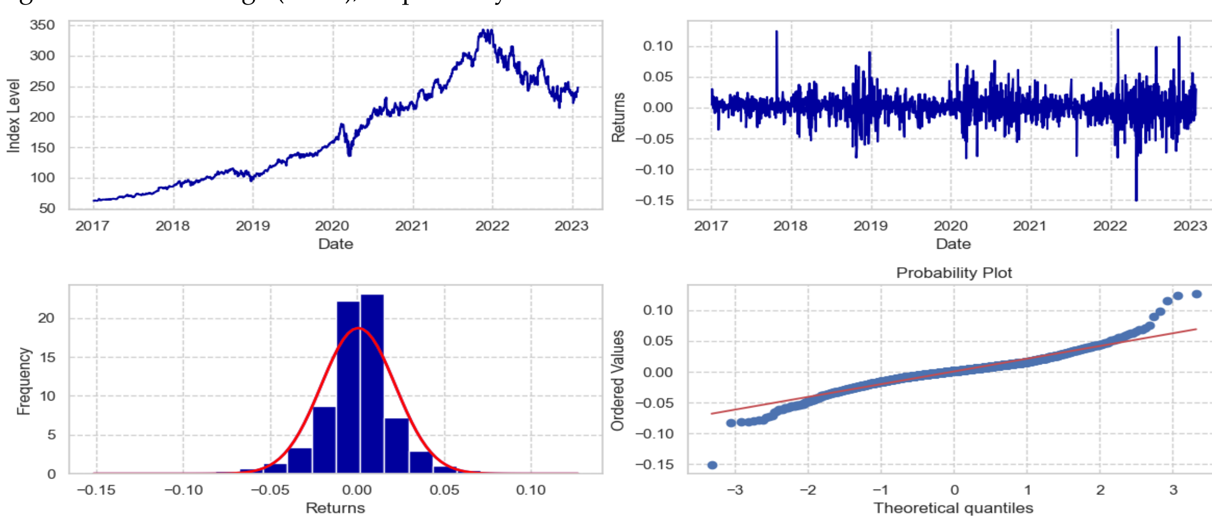

Figure 1: Graphical plots of the BSE index and returns

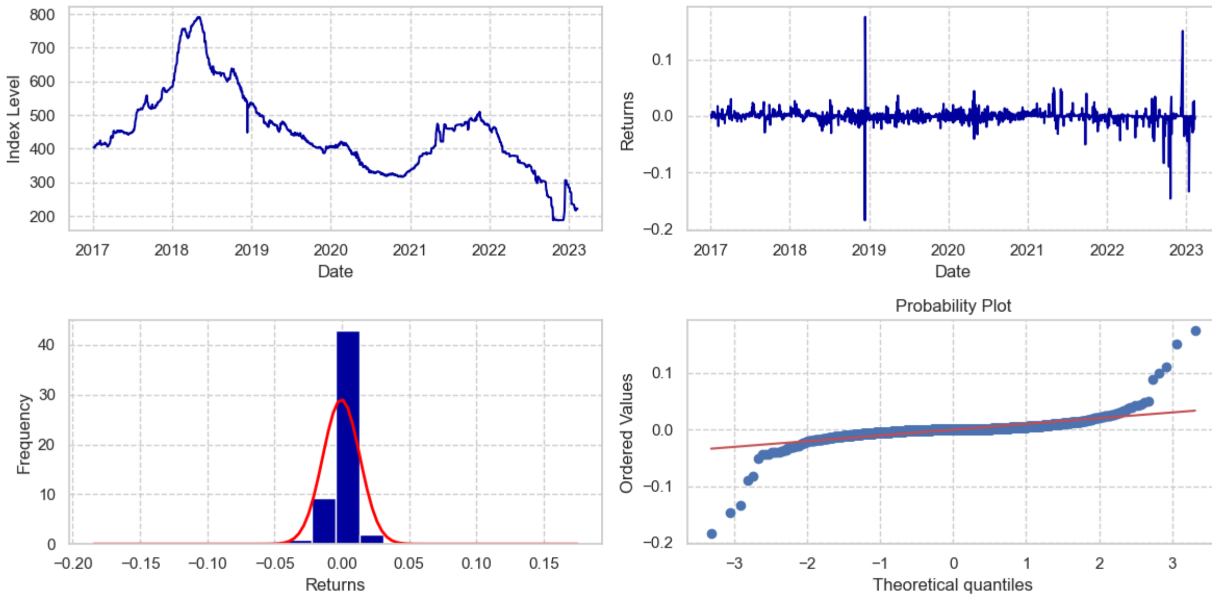

Figure 2: Index distribution of GSE

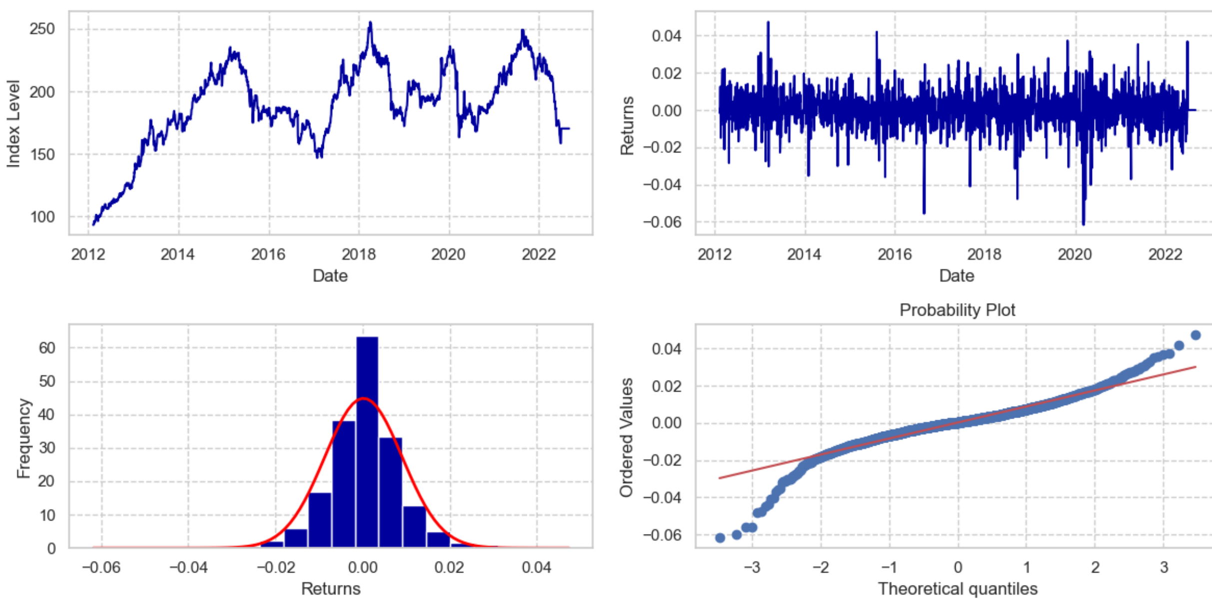

Figure 3: Index distribution of NSE

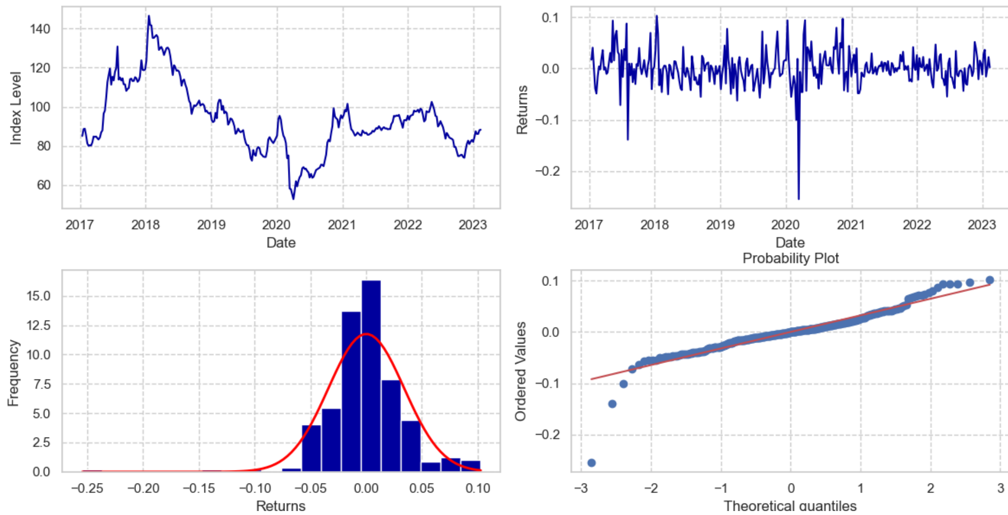

Figure 4: Index price and return distribution of NGX

In the figures, it is noted that all the returns exhibited marked departure from the Gaussian distribution with asymmetrical and fat tails. The tails of the GSE were particularly fat, as shown by the QQ plot and the kurtosis of 70. It is noted, however, that the returns of GSE showed extensive periods of benign volatility, occasionally interspersed with very high volatility, perhaps the result of asynchronous trading. The returns of BSE, NSE and NGX were volatile during the sample period, something that can be attributed to the diversity of industries constituting the index. The models shown in Equations (5) and (8) were run for the VaR and ES at $\boldsymbol{\alpha}$ levels of 0.01% for the EVT and normal distributions. The results are shown in Table 2.

Table 2: $\boldsymbol{VaR_{0.999}}$ and $\boldsymbol{ES_{0.999}}$ for EVT and Normal Distribution

	EVT Value at risk @ 0.999	**EVT Expected shortfall at 0.999**	**Normal Value at Risk @ 0.999**	**Normal Expected Shortfall @ 0.999**
Botswana	10.40%	12.30%	8.20%	11.70%
Ghana	14.00%	16.50%	5.00%	6.00%
Kenya	5.60%	5.90%	3.70%	4.30%
Nigeria	21.80%	25.40%	7.50%	8.30%

The graphical plots of the tails at the extreme 0.1% based on the recommendations of the BIS (2013) for the four exchanges is shown in Figures 2-5.

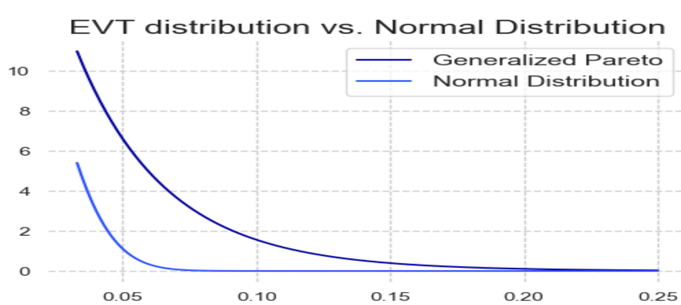

Fig 2: Tail plot for BSE returns: EVT versus Normal distribution at 0.1%

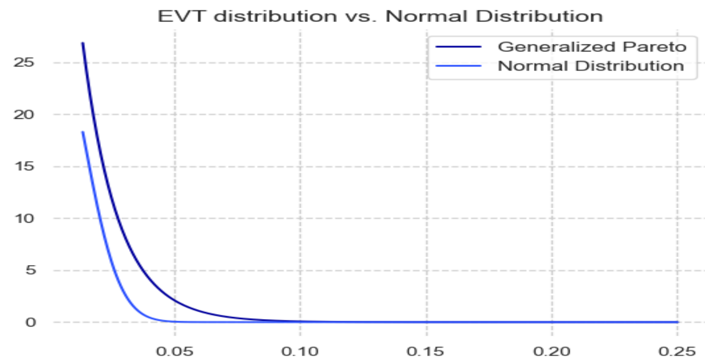

Figure 3: Tail plot for GSE returns: EVT versus Normal distribution at 0.1%

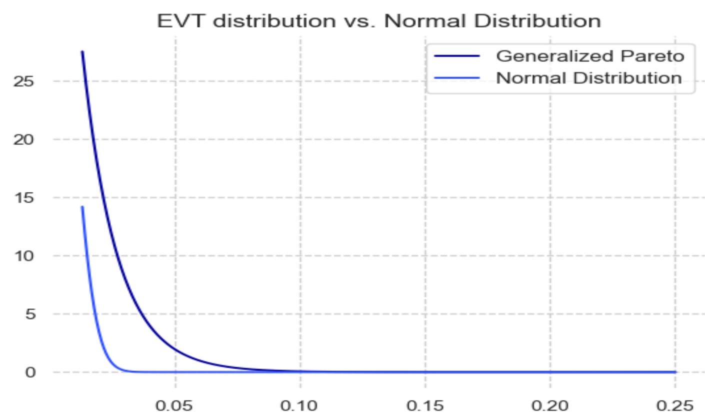

Fig 4: Tail plot for NSE returns: EVT versus Normal distribution at 0.1%

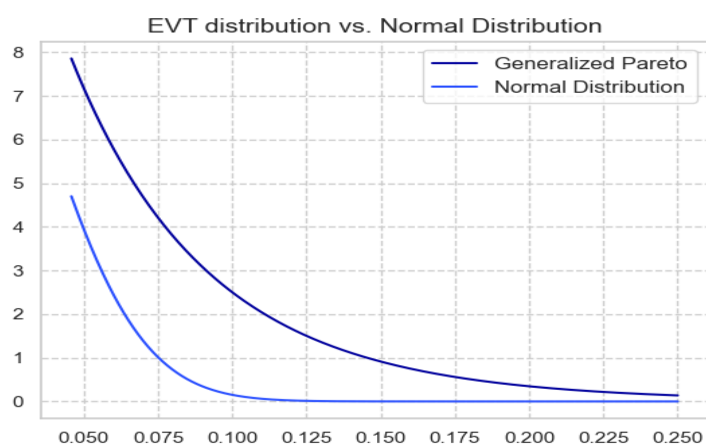

Figure 5: Tail plot for NSX returns: EVT versus Normal distribution at 0.1%

The empirical results demonstrate that the Generalized Pareto Distribution (GPD) provides superior fit for threshold exceedances, capturing both the scale and shape of extreme returns. Tail index estimates vary across the various exchanges, reflecting differences in market depth, regulatory regimes, and macroeconomic exposure. Notably, EVT-based Value-at-Risk (VaR) and Expected Shortfall (ES) measures outperform conventional parametric models, offering more accurate risk quantification during periods of market stress.

Discussions

The graphs (**Figures 2-5**) demonstrate the conservative nature of the EVT model in estimating the VaR and ES measures. The findings in **Table 2** are in line with the theory relating to VaR and ES. The $\boldsymbol{VaR_{0.099}}$ respectively for the EVT and $Normal$ are less than the corresponding values for $\boldsymbol{ES_{0.999}}$ for each distribution. This suggests that for extreme market outcomes, the EVT model might present conservative values for decision-making. The relatively large measures for Nigeria suggest wild swings in market returns and therefore, resulting fat tails and extreme outcomes. Nigeria relies on volatile crude oil exports. This feeds, potentially, through some latent mechanism and gets transmitted to the stock exchange.

Kenya's relatively quiet market is noteworthy. With sixty-two listed firms from relatively diverse industries, the NSE, it appears, benefits from diversification to keep market returns from extreme outcomes.

On the other hand, GSE, with its thirty-seven listed firms dominated by mining, brewing and telecommunication industries, has experienced moderately fewer extreme outcomes. The telecommunications and mining industries are going through booming times and that is reflected in the relative strength of these stocks in the GSE index. The brewery stocks are defensive by nature and hold relatively well during all stages of the business cycle of the economy (Richey, 2017).

Lastly, the BSE, with its thirty-six listed firms, is dominated by mining industries and financial services. These two industries are not enough for diversification in the portfolio of the BSE index. However, mining and telecommunication industry stocks have held up well during the sample period because of high diamond prices and increasingly, a mobile and affluent urbanized youth who use mobile services in communication.

Conclusion

These findings in this paper underscore the theoretical premise of EVT and demonstrate its practical utility in frontier market contexts. By isolating and modeling the statistical properties of extreme equity returns, EVT enhances the precision of financial risk management and supports the development of more resilient investment and regulatory frameworks in Sub-Saharan Africa. Indeed, correctly estimating the volatility of equity investments in the SSA region is an assurance to investors. In the long run, investors lower their assessment of risk premium in SSA based on the accurate estimation of the risks in the markets.

While the GARCH models have become widely used as a volatility model for both developed and emerging economies, the nature and characteristics of SSA markets, narrow their applications to risk estimation. EVT thus provides a more appropriate framework to model tail risks of SSA equity markets, as well as an efficient estimation of VaR and ES compared with traditional models like the student-t GARCH model. By developing the EVT-based models, a degree of investor confidence is embedded into these nascent markets for the purpose of improving risk management.

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Contribution of Authors

Carl Hope Korkpoe: Conceptualisation; Literature review; methodology; formal analysis; writing – original draft; writing – review.

George Amofa Sarpong: Literature review; methodology; formal analysis; writing – original draft; writing – review.

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