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An Insight on the Effects of Tail Risks on Expected Returns on African Stockn Markets

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ABSTRACT

This article investigates the tail risk-return trade-off in African stock markets using panel data from 741 companies in 12 countries spanning the period from 2000 to 2022. The Generalized Least Square (GLS) and Fixed Effects (FE) methods are used to analyze the direct effect of tail risk on expected returns. We further apply Fama and Macbeth's sequential estimation technique to determine whether the risk is priced. Unlike kurtosis, most tail risk factors positively and significantly explain expected returns on African stock markets. Additionally, we find that, among the variables considered, monthly loss and skewness are the ones with significant risk prices. These results are robust to alternative model specifications and the consideration of region and country specificities.

1. Introduction

Financial research has recently focused more on the possibility of unexpected shifts in stock prices (extreme distribution events) and their effect on asset pricing (Safdar and Odusami, 2022; Chaudhry et al., 2022). Conventional asset pricing models, including Sharpe's (1964), Lintner's (1965), and Mossin's (1966) capital asset pricing models (CAPM), Merton's (1973) intertemporal CAPM, and Breeden's (1979) consumption-based CAPM, assume that investors have symmetric preferences for downside losses and upside gains. An asset or portfolio's risk in the event of an adverse economic situation is referred to as downside loss whereas upside gains refer to a favorable outcome. Financial economists have, however, acknowledged that investors are more worried about potential losses than potential gains (Roy, 1952; Markowitz 1959). Thus, investors need a premium as compensation for holding assets in an environment where they are more concerned with downside risk than upside gains and this has resulted in the advent of novel concepts in asset pricing and risk management, such as value at risk and expected shortfall.

Rational behavior theories have been developed to promote asymmetric emphasis while including downside risk-related factors in asset pricing models. Such models include Bawa and Lindenberg (1977) lower-partial moment framework, the loss aversion of Kahneman and Tversky (1979) in their prospect theory, Gul's (1991) disappointment aversion model, which has been generalized by Routledge and Zin (2010) and revisited by Farago and Tégongap (2018). Accordingly, we examine the relationship between tail risk and expected returns on the African stock markets. Tail risks include downside risks and higher-order moments (Iqbal and Azher, 2014; Ivanovski et al., 2015, Mhiri and Prigent 2010) since they help to capture the extreme levels of distribution. To achieve this, we first examine the impact of these risk measures on expected returns. Secondly, we verify if these risks are priced on African stock markets.

The existing literature on tail risks which is mostly focused on developed stock markets leads to mixed conclusions (Long et al., 2019). Some studies find that tail risks positively impact stock returns, following traditional finance principles regarding the risk-return tradeoff (Bali et al., 2014). Kelly and Jiang (2014), Iqbal and Azher (2014), Iqbal et al (2013), Bolleslev et al., (2014), and, Chen et al., (2018) show that there is a positive relation between tail risks and expected returns. However, another strand of the literature finds a negative relationship between tail risks and expected stock returns (Sun et al., 2022; Long et al., 2018; Atilgan et al., 2019, 2020; Yang and Ma, 2021; and Gao et al., 2019). Based on the mixed findings on the relationship between tail risk and expected returns, we provide a comprehensive answer to the intriguing issue of the impact of tail risks on expected returns on African stock markets.

According to Nsowu et al., (2013), the return distributions on African financial markets have heavier tails than those of developed stock markets. Moreover, African stock markets are characterized by thick tails. African stock markets are also characterized by uncertain socio-political and economic conditions which lead to low liquidity, high volatility, infrequent trading, and low market depth (Afego, 2015). Additionally, these financial markets do not fare well on the number of listed stocks, the number of traded securities, efficiency, speed, value, and the number of transactions (Avoutou, 2018). Volatility in the African markets is much more pronounced due to external and internal shocks (Ibragimov et al., 2013) with rare occurrences. The African stock markets are often associated with high returns (Iqbal and Azher, 2014). All of this emphasizes how essential it is to highlight the relevance of tail risks in African financial markets, which differ significantly from those of other financial markets.

The main contribution of this paper is to revisit the relationship between tail risk and expected return in the African context. This investigation is important because studies that focus on African markets are scant despite the growing importance of these markets on the world stage. Since most transactions are made on just a few sizable equities with substantial total market capitalizations, Adjasi and Yartey (2007) argued that the rapid growth of African stock markets did not correspond to their maturity. African stock markets also offer strong returns despite their modest size and lack of liquidity. Next, this study examines whether tail-risk is priced, an issue that has completely been neglected in the literature. Using a panel data of 741 companies in 12 different countries in Africa, we construct a series of related down risk factors (value at risk, expected shortfall, and monthly loss), higher order moments (skewness and the kurtosis), and addition variables (illiquidity and second order moment) and investigate their potential impact of expected return on both the global and country levels. Results show that there exists a significant relationship between most risk factors and expected returns. On the one hand, skewness, monthly loss, expected shortfall, and value at risk have a positive and significant relation with expected returns. On the other hand, kurtosis and expected shortfall have a negative impact on expected returns. Furthermore, using the Fama and Macbeth framework, we find a significant risk premium of tail risk on the African stock markets. Our findings are robust to alternative model specifications, even when country and region specificities are considered.

The findings of this study are of great interest to domestic and international investors seeking to diversify their portfolios by foraying into African stock markets. The findings are also of interest to market regulators who need to understand the sources of volatility in order to design appropriate stabilization policies.

The remainder of the article unfolds as follows. Section 2 reviews the literature on the relationship between tail risks and expected returns. Section 3 highlights the methodology while section 4 displays the empirical results and discussion. Finally, section 5 concludes the article.

2. Tail Risk and Expected Returns: A literature review

In this section, we highlight this study's theoretical baseline and a summary of the empirical literature concerning the relationship between tail risks and expected stock returns.

2.1 The theoretical framework of the study

This study is based on asset pricing theories with a focus on the Arbitrage Pricing Theory (APT). These theories on risk could be traced from the works of Knight (1921), who viewed risk as one of the most important factors to be considered in the valuation of financial assets. The foundation of the risk-return tradeoff was laid down by Markowitz (1952), who asserted that investors expect to be compensated for taking risks. Investors in the financial market seek to optimize their investment decisions by building efficient and diversified portfolios. Taking off from Markowitz in the early sixties, the capital asset pricing theory was developed. The capital asset pricing model (CAPM), developed independently by Sharpe (1964), Litner (1965), and Mossin (1966), is the most widely recognized in asset pricing literature. It extends the concept of market equilibrium to determine the market price of risky assets. The model emphasizes the existence of a linear relationship between market beta (systematic risk)[1] and expected returns. One implication of the model is that those who want a high return hold a portfolio heavily weighted with risky assets and those who desire a low return hold a portfolio heavily weighted with a riskless asset.

The CAPM is criticized given that the market is the only factor for asset pricing and the only risk which is priced. As a response to this criticism, Ross (1973) formulated the Arbitrage Pricing Theory (APT) which attempts to identify several risk factors which could determine asset prices. This study uses the APT by modeling the returns on the African stock markets as a linear function of various factors. The APT has a similar intuition as the CAPM but it is much more sophisticated. It assumes that the expected return is a linear function of various factors.

Another important theory worth mentioning is the extreme value theory (EVT). This theory has been applied in several other disciplines such as insurance and engineering. For more than three decades now, finance practitioners and academics have based the distribution of asset returns on the Gaussian distribution but in reality, most financial data tend to exhibit extreme returns thus, drifting away from the normality assumption. The extreme quantiles of the return distribution are of great significance in finance. McNeil and Frey (2000), Gilli and Kellezi (2006), and Onour (2010) amongst many others have examined the tails of financial data series. EVT plays an important role in estimating the probability of extraordinary events or losses for adequate risk management in various financial institutions. It enables modeling the behavior of extreme outcomes found in the tails of the distribution. EVT provides some modern tools (Peaks-over-Threshold, Generalized Pareto Distribution) which can be used to calculate the extreme quantiles of a distribution or in other words, to model the heavy tailed data found in the distribution. According to Yu et al., (2020), EVT is one of the best methods for examining financial markets' tail behavior.

Stocks' tail risk occurs when there is an adverse scenario in the market. Following the disappointment aversion theory which is a theory on rational behavior developed by Gul (1991), these adverse scenarios (tailed risk) witnessed in stock markets have an important weight in the utility functions of investors. The disappointment aversion theory suggests priced tail risk on the stock market. In line with Farago and Tedongap (2018), investors on financial markets required compensation for exposure to disappointment-related risk factors. Routledge and Zin (2003) extend Gul's idea of disappointment aversion by focusing on more extreme outcomes (Generalized disappointment aversion). That is, an outcome is disappointing only when it is sufficiently far from normal conditions. Including the disappointment aversion theory in this paper makes it one of the first studies that use this theory in the study of tail risks and expected stock returns.

2.2 Summary empirical literature review linking tail risks and expected returns

The relationship between a stock's tail risks and projected returns has been extensively studied in the literature. The existing literature shows that relationships can be either positive, negative, or insignificant based on the market and time frame. More recently, Lee and Yang (2022) examined the pricing of tail risks for 43000 stocks from 46 countries between 1995 and 2013. The results reveal that tail risks are priced on the market independently of the local and global market returns. Freire (2021) measured

[1] Under perfect market conditions and in the absence of transaction costs, the most appropriate measure of undiversifiable risk in the financial market is represented by systematic risk (beta).

and investigated the origins of tail risk variations in Brazil from 2001 to 2020. The country has undergone a series of events such as corruption scandals, the corona virus pandemic, economic recession, and many more that have caused tail risk to be at its peak. Freire (2021) concludes that tail risk can strongly predict stock market returns and economic activities. Several studies have examined the relationship between tail risks and expected returns in emerging markets. For example, Okorie et al. (2021) used EVT to analyze the tail behavior of the 12 most established African stock markets using three advanced stock markets as benchmarks. The results show that many of the African stock markets are prone to higher risk and can yield higher expected returns compared to some major developed stock markets. Using daily data and the conditional EVT proposed by McNail and Fray (2000), Totic and Bozovic (2015) examined the left-tail behavior of returns on stocks in Bulgaria (SOFIX), Croatia (CROBEX), Hungary (BUX), Romania (BET), Slovenia (SBITOP) and Serbia (BELEX) between October 2004 and September 2013 and found that VaR and ES are good predictions. A general conclusion derived from the above findings is that there exists a positive relationship between tail risks and expected stock returns. The relationship between tail risks and expected stock returns is significant according to Gui and Zhu (2021). In the US context, Bali and Cakici (2004) examined the impact of tail risk measures on expected returns using a univariate and multivariate analysis based on Fama and Macbeth (1973) to demonstrate that size, liquidity, and Value at Risk (VaR) explain cross-sectional variation in expected returns on the NYSE, Amex and Nasdaq stock exchange for the period from 1963 to 2001. They found that VaR is a significant and positive determinant of the cross-section of expected returns. Thus, the greater the stock's potential fall in value, the greater the expected return. Iqbal and Azher (2014) studied the effect of VaR (a measure of downside risk) on expected stock returns in Pakistan. The data consisted of monthly information from 231 stocks traded on the Karachi Stock Exchange (KSE) from October 1992 to June 2008. The results showed that VaR, compared to other factors, explains the expected cross-sectional and time series variations of return better. According to Mhiri and Prigent (2010), a portfolio is optimized when the higher moments are taken into consideration. The higher moments of return distribution are the skewness and kurtosis which impact investors' decisions and cannot be neglected. Incorporating skewness and kurtosis into an investor's portfolio will lead to the optimization of the portfolio. Ivanovski et al. (2015) revealed the existence of high volatility and asymmetric distribution in the Macedonian Stock Exchange (MSE). Using daily stock returns and the EWMA (Exponentially Weighted Moving Average) and GARCH (Generalised Autoregressive Conditional Heteroscedasticity) models, the authors showed that the leptokurtic distribution of stocks in the MSE has a positive impact on returns.

While the studies cited above show that the relationship between tail risks and expected returns is positive, others report a negative relationship between the two variables. For example, Sun et al (2022) study the cross-sectional relationship between the changes in left-tail risks and expected returns in the Chinese stock market and find a negative relation. This negative relationship is explained by investors’ under-reaction and the disposition effect explained by Shefrin and Statman (1985). Yang and Ma (2021) investigated the relationship between VaR and expected returns under different mispricing statuses (underpricing or overpricing). They found that there is a negative relationship between VaR and expected returns when stocks are overpriced, contrary to the findings in the case of underpriced stocks. Thus, higher VaR leads to higher mispricing. Long et al., (2019) looked into the impact of three measures of tail risk on the expected returns on 39 international markets (21 developed and 18 emergings) between 1980 and 2015 and also found a negative relationship between tail risks and expected returns after controlling for variables such as beta, size, and book-to-market (known as the "tail risk puzzle")[2]. Following Huang et al. (2012), Long et al., (2018) studied idiosyncratic tail risks and expected returns in the Chinese stock markets using EVT and found a negative relationship. They employed univariate analysis, bivariate portfolio analysis as well as Fama and MacBeth regression (1973) analysis to study the relationship between idiosyncratic tail risks and expected returns. The findings showed that idiosyncratic tail risks and expected returns are significantly and negatively correlated after controlling for size, book-to-market ratio, beta, momentum, reversal, liquidity, downside beta, co-skewness, co-kurtosis, idiosyncratic kurtosis, and volatility for both portfolio analysis and cross-sectional regressions. The negative relationship is explained by the dominance of individual investors and short sales in the markets. Li and Rose (2009) studied tail risks in emerging stock markets by comparing the investable and non-investable segments in terms of expected shortfall, volatility-filtered returns, and tail dependency on the world market. They demonstrated that lower tail risk is associated with investable portfolios and that emerging markets are more sensitive to world market losses than gains. Atilgan et al (2020) focused their analyses on the stocks traded in 23 countries and regions. The results revealed a negative relation between VaR and future returns.

The empirical evidence above shows that most of the studies carried out on developing markets (Okorie et al., 2021; Ivanovski et al., 2015; Iqbal and Azher, 2014; Totic and Bozovic, 2016) demonstrate a positive and significant relationship between tail risks and expected returns whereas those carried out on developed countries reveal a negative relationship (Sun et al., 2022; Atilgan et al., 2020).

3. Methodology

3.1 Data and sampling

Our data is retrieved from Thomson Reuters (DataStream) now known as Refinitiv Eikon [3]and from the U.S. Federal Reserve System[4] used to compute excess returns. The data consist of monthly stock data from August, 2010 to August, 2022. Monthly data

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[2] They employ three proxies of tail risk including that of Kelly and Jiang (2014), tail risk following Van Oordt and Zhou (2016) and Huang et al. (2012) and Long et al. (2008).

[3] https://eikon.refinitiv.com/

[4] 4 fred.stlouisefed.org

is used to test the relationship between tail risks and expected stock returns because it offers more accurate estimations compared to daily data with compounding microstructure problems (Zhang et al., 2021). Moreover, in the African context daily data shows important weaknesses concerning lack of information. For our analysis, we clean the data as follows; we include only stock markets (countries) with at least 9 listed companies; We identify and include only stocks with at least 10 years of monthly observations; the monthly historical prices are used to compute for return and excess return which are the dependent variables, Value at risk, expected shortfall, kurtosis, skewness which are our independent variables as well as illiquidity and second moment which are the control variables. The calculation is done for all the stocks. The initial sample includes 15 African stock markets with a total of 1882 firms listed in the markets. For a stock/firm to be included in the final sample, it must have information available over the entire period of study, that is, there must not be any missing values. This screening resulted in the final sample being comprised of 741 firms. The next step consists of transforming our data from a wide structure to a longitudinal data structure that is the panel data format; last, we give the stocks and the dates an identity for final analysis. Table 1 shows our final sample of 741 companies and their country/region of origin.

Table 1: Number of stocks per country and per region

Country/Regions	Eastern	Northern	Southern	Western	Total
Botswana	/	/	15	/	**15**
Ivory Coast	/	/	/	33	**33**
Egypt	/	91	/	/	**91**
Ghana	/	/	/	49	**49**
South Africa	/	/	132	/	**132**
Kenya	51	/	/	/	**51**
Mauritius	/	/	58	/	**58**
Morocco	/	60	/	/	**60**
Namibia	/	/	21	/	**21**
Nigeria	/	/	/	130	**130**
Tunisia	/	51	/	/	**51**
Zimbabwe	/	/	50	/	**50**
Total	**51**	**202**	**276**	**212**	**741**

*Sources: Authors Notes: This table shows details about the repartition of companies among country's stock market and by region*From Table 1, we observe that Nigeria and South Africa are the countries with the highest number of stocks in the final sample, whereas Botswana and the Ivory Coast only have 15 and 33 stocks in the final sample, respectively. Regionally, considering the number of companies in the final sample, the Southern and Western Africa regions are in the lead. The least-represented region is East Africa. Only the Kenyan financial market, with 52 enterprises, is present in the studied sample.

3.2 Econometric model

To capture the relationship between extreme risks and expected returns, we rely on Ross's (1973) general asset pricing model from a panel point of view, and establish the following global theoretical model:

$$RET_{it} = \beta_0 + \sum_{i=1}^{7}\sum_{t=1}^{151} \beta_i . X_{it} \qquad (1)$$

Where, RET_{it} is the dependent variable, the expected returns of a stock.

β_0, is the is the constant term;

X_{it}, represents the dépendent variables which are the extreme risk factors of variable i at time t;

β_i, is the systematic risk associated with these last variables for a given stock.

The complete empirical form of this model is as follows:

$$RET_{it} = \beta_0 + \beta_1 . DSR_{it} + \beta_2 . ES_{it} + \beta_3 . VaR_{it} + \beta_4 . Kurt_{it} + \beta_5 . Skew_{it} + \beta_6 . ILLQ_{it} + \beta_7 . SECM_{it} + \varepsilon_{it} \qquad (2)$$

Where DSR is the monthly loss, VaR refers to the Value at Risk, ES is the Expected shortfall, Skew denotes the skewness, Kurt is the kurtosis, ILLQ and SECM are illiquidity, and second-order moment factors respectively. ε, represents the error term. Model (2) is in its global form, which only indicates the set of variables considered in this study. In reality, even though it is sometimes estimated in this form, various variables are usually accounted for either simultaneously or separately. The control variables are the only permanent ones and the calculation of these variables is provided in the next subsection.

3.3 Variables

3.3.1 Explained variables

To examine the impact of tail risk on asset prices, the dependent variables of this study are expected returns and excess returns (return surplus). Expected returns are computed using stock prices. Following the existing literature, monthly stock returns are calculated as follows:

$$RET_{it)} = ln(\frac{P_{it}}{P_{it-1}})$$

Where P_t stands for the monthly stock price index at time t and P_{t-1} is its previous period (month) value. After obtaining the monthly stock returns, we compute the excess returns as the difference between the stock return and the U.S. Treasury bill rate (considered as the risk-free rate, R_f). The monthly stock excess return is denoted as follows:

$$ERET_{it} = RET_{it} - R_{f\ it}$$

3.3.2 Explanatory variables

Based on existing literature (Atilgan et al., 2019, 2020; Bali et al., 2009; Zhang et al., 2021), several risk metrics can be used to measure extreme event risks. There are Value at risk (VaR), Skewness, kurtosis, Expected Shortfall (ES), and monthly loss (downside risk).

Value at risk is a financial measure of the maximum risk of an investment over a specified time period. It indicates the potential losses for an investment for a given period. The confidence level and the target horizon are the required decision variables for VaR estimation. Following Atilgan et al., (2020), the VaR of every stock in each month is calculated by using the returns for the past one-year interval. In this setting, we calculate VaR as the 5th percentile (VAR5) and the 10th percentile VaR (VaR10), of monthly stock returns over the past 12 months (one year). According to Lui and Wang (2020), from theories of tail risk measures, for a given confidence level P Є [0, 1], VaR of X at level p is defined as the left p-quantile of F as follows:

$$VaR_p(x) = Inf\{x \in R, F_x(x) > P\} = F_x^{-1}(p), x \in L^0$$

Expected shortfall is defined as the expectation of a loss when the loss is beyond a certain probability level. It tells us how bad the losses will be if it exceeds the VaR level. In this paper, we use the average of observations that are below the 5th or the 10th percentile (denoted as ES5 and ES10 respectively) of daily stock returns during the past 12 months. We use Lui and Wang's (2020) approach to calculate Expected shortfall as follows:

$$ES_p(x) = \frac{1}{1-p}\int_p^1 VaR_q^r(x).d_q, x \in L^0$$

The downside loss, which represents monthly losses, is also used as an explanatory variable in this study. Following Farago and Tédongap (2018) and Ang et al. (2006), it represents the market loss experienced by an investor on a given stock. It is equal to the negative value of the market return and therefore takes the value zero if the return is positive or zero. This is how Ang et al. (2006) show that returns on assets should include a risk premium associated with downside risk exposure. Farago and Tédongap (2018) stated that the regular beta (standard CAPM beta) underestimates and overestimates the risk respectively for low- and high-beta stocks. It is therefore necessary to break down this risk into two components (upside and downside risk) because it allows investors to intelligently manage portfolio risk.

Skewness and kurtosis are another category of extreme (tail) risk measures known as "higher moments." Skewness represents the third standardized moment and a measure of the asymmetry or distortion of a symmetrical bell curve distribution (Yifan Li, 2020). It shows to what extent a given distribution varies from the normal distribution. Yifan Li (2020), Goyal and Santa-Clara (2003), Kim et al. (2011), and Farago and Tédongap (2018) used this variable to measure tail risk in asset pricing together with kurtosis. Kurtosis indicates how tailed a distribution is. Lui (2021), Chamadia et al. (2022), and others used kurtosis to predict stock returns in their studies. In this study, we follow the approach of Jordeau et al. (2019) to calculate the skewness and kurtosis of the stock return distribution.

Additionally, we control for other factors that have been shown to influence the relationship between tail risks and expected returns on the African stock markets. More specifically, we use illiquidity and second-order moments as control variables[5]. These variables are jointly or individually considered in the estimation models.

3.4 Estimation strategy

Different specifications of model 2 are estimated using the Generalized Least Square (GLS) method. As a robustness strategy, Fixed Effects (FE) results are also provided. Moreover, the price of a risk factor is determined using Fama and McBeth's (1973) sequential estimation technique.

Generalized Least Squares (GLS) is one of the most prominent methods for estimating unknown coefficients of a linear regression model when the independent variable is correlated with the residuals (serial correlation problem) or when the observation variances are biased (heteroscedasticity problem). This method thus takes into account serial correlations in the error terms in panel data, and tracks the problem of outliers and heteroscedasticity. Thus, the model has the property of being unbiased, efficient, consistent, and asymptotically normal. The GLS estimator is the generalization version of the Ordinary Least Square (OLS) estimator since it leads to the best estimator, which is BLUE (Best Linear Unbiased Estimator).

With the Fixed Effects (FE) estimation model in panel data, also known as the within estimator, the variations across individuals are fixed or identical. The FE model in panel data is used only when we are interested in analyzing the impact of time variation on variables. The aim of the FE model is to compute the common effect for the identified population, which in this study is the stocks listed on a given financial market. The model shows the relationship between the explained (expected returns) and explanatory

[5] Following Amihud (2002) and Hikouatchaet al. (2022), we define illiquidity (ILLIQ) as the absolute monthly stock return over monthly trading volume. The second-moment variable measures fluctuation around the mean, or the expected value of stock return. It measures dispersion, meaning it is a measure of how far a set of values is spread out from their average value. These variables are together or individually considered in the model for estimation.

(tail risk) variables within a company, with each one having its own characteristics that may or may not influence the dependent variable.

Fama and McBeth's (1973) regression (FM) is used to estimate the risk premium for different risk factors in the financial literature. It determines the price of risk and is the most widely used technique for this issue due to its undeniable merits of simplicity and clarity (Pasquariello, 1999). It is a sequential estimation method where the output of the first step is the input of the second stage. FM analysis is implemented following a three-step sequential estimation process. First, we run a time series regression to estimate the betas (systematic risk) using the OLS method. Second, we run periodic cross-sectional regressions to estimate gammas, which are the risk premiums from the previous betas obtained. Third, the gammas are aggregated and the hypotheses are tested. This procedure may look very simple, but it is of great importance in this estimation approach (Hikouatcha et al., 2022). Concerning this study, the first step is the estimation of the beta coefficients of the tail risk factors. This step corresponds to the first regression, where the systematic risk factors for each tail risk variable are obtained for each stock i at time t from equation (3) below.

$$ERET_{it} = \beta_0 + \beta_{1it}.DSR_t + \beta_{2it}.ES_t + \beta_{3it}.VaR_t + \beta_{4it}.Kurt_t + \beta_{5it}.Skew_t + \beta_{6it}.ILLQ_t + \beta_{7it}.SECM_t + \varepsilon_{it} \quad (3)$$

Contrarily to model (2) specification, the explained variable here is an excess return. The estimates are done using the OLS. The systematic risks obtained are used in the second step to estimate the risk premium following equation (4).

$$ERET_{it} = \delta_0 + \delta_1.\beta_{DSR_{it}} + \delta_2.\beta_{ES_{it}} + \delta_3.\beta_{VaR_{it}} + \delta_4.\beta_{Kurt_{it}} + \delta_5.\beta_{Skew_{it}} + \delta_6.\beta_{ILLQ_{it}} + \delta_7.\beta_{SECM_{it}} + \varepsilon_{it} \quad (4)$$

The aggregation of the output of this last regression is now the risk premium which explains the risk exposure of each tail risk factor. Hence, a stock with a high sensitivity to any of the factors should expect a higher return to compensate for the additional risk.

4. Empirical results

4.1 Summary statistics and correlations

Table 2: Descriptive statistics of variables

Variables	Mean	Std.Dev.	Minimum	Maximum
RET	-0.013	0.180	-6.624	8.354
ERET	-0.191	0.426	-6.639	8.339
DSR	-0.037	0.096	-6.624	0.000
ES10	-0.152	0.185	-6.624	1.202
ES5	0.022	0.164	-1.871	8.354
VAR10	-0.096	0.116	-5.930	3.416
VAR5	-0.137	0.153	-6.277	3.416
KURT	1.482	2.972	-5.997	12.00
SKEW	-0.028	1.157	-3.464	3.464
SECM	0.033	0.270	-0.553	15.98
ILLIQ	0.016	0.153	-22.70	8.745
	N = 111891 ; n = 741 ;T = 151			

Sources: Authors Notes: Std. Dev., Min and Max stands for standard deviation. RET stands for Expected Returns, ERET is Excess Returns, VaR5 is value at Risk at 5%, VaR10 is Value at Risk at 10%, ES5 is Expected Shortfall at 5%, ES10 is Expected Shortfall at 10%, SKEW stands for Skewness, KURT stands for Kurtosis, DSR risk stands for monthly loss, ILLIQ is Illiquidity and SECM stands for Second Moment

Table 2 reports the descriptive statistics of monthly stocks across 741 stocks in 12 African markets with a total of 111890 observations for all the variables used in the main analysis. For each variable, we present the mean, standard deviation, and minimum and maximum values. The average expected return for all stocks on the African market is -0.013, while the minimum and the maximum returns are -6.624 and 8.354 respectively. The overall variation is 0.180 for expected stock returns and it is quite different from that of excess returns which stands at 0.426. This implies that there are important excess returns in the market. The maximum and the minimum values are far from the arithmetic mean thus signaling the presence of tails in the distribution. This variation also means that the stocks are so volatile over time. The volatility of stocks is a typical feature of African stock markets. This result confirms the assertion made by Odera (2012). According to him, African stock markets are highly volatile due to weak regulatory institutions and high macroeconomic fluctuations. The mean of VaR5 is -0.137, suggesting that for a typical stock; there is a 5% likelihood that the average daily loss exceeds 1.37%. All the independent variables show great fluctuations away from the mean with the maximum and minimum values being far from the mean. Consequently, the descriptive statistics confirm the assumption that there exist tails on the African stock markets.

Table 3: Correlation matrix

	Return	ERET	DSR	ES10	ES5	VaRr10	VaRr5	KURT	SKEW	SECM	ILLIQ
ERET	0.360***	1									
	(0.000)										
DSR	0.612***	0.181***	1								

	(0.000)	(0.000)									
ES10	0.073***	0.056***	0.282***	1							
	(0.000)	(0.000)	(0.000)								
ES5	-0.020***	0.007***	-0.044***	-0.143***	1						
	(0.000)	(0.009)	(0.000)	(0.000)							
VaR10	0.126***	0.039***	0.324***	0.675***	-0.052***	1					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
VaR5	0.105***	0.052***	0.330***	0.923***	-0.128***	0.868***	1				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
KURT	-0.001	-0.096***	-0.021***	-0.269***	0.043***	0.083***	-0.159***	1			
	(0.889)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
SKEW	0.123***	0.155***	0.067***	0.249***	0.0620***	0.0365***	0.203***	-0.139***	1		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
SECM	0.193***	0.105***	-0.089***	-0.306***	0.194***	-0.234***	-0.295***	0.122***	0.112***	1	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
ILLIQ	0.089***	0.039***	-0.127***	-0.072***	0.001***	-0.065***	-0.076***	0.017***	0.015***	0.0736***	1
	(0.000)	(0.000)	(0.000)	(0.000)	(0.900)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Sources: Authors Notes: This table shows the correlation between this study's variables. P-values are in parentheses. ***, **, and *, indicate that the coefficient is significant at 1%, 5%, and 10% threshold levels, respectively.

Table 3 displays correlation coefficients among the variables. Overall, it seems to be strong correlations between tail risks expected returns on African stock markets. Globally, downside risk, value at risk, skewness, and the 10% expected shortfall are positively and significantly related to expected returns. The relationship between VaR and returns is consistent with our expectations and confirms the findings of Bali et al., (2011), Yang and Ma, (2021), and Lui and Wang (2021). The 5% expected shortfall is negatively and significantly associated with the expected returns. The positive relationship between Kurtosis and returns is not significant. Illiquidity and second-order moments are negatively correlated with returns.

4.2 Empirical investigation of the relationship between extreme risks and returns on African stock markets

4.2.1 Main results

In this section, we investigate the impact of tail risks on expected returns in African stock markets using Generalized Least Square (GLS) and Fixed Effects (FE) estimation approaches.

Table 4: Impact of Value at Risk on expected returns

Variables	GLS	FE	GLS	FE	GLS	FE
VAR10	0.186***	0.221***			0.289***	0.351***
	(0.009)	(0.009)			(0.004)	(0.005)
VAR5	0.092***	0.120***	0.215***	0.263***		
	(0.006)	(0.007)	(0.003)	(0.003)		
ILLIQ	0.101***	0.099***	0.101***	0.099***	0.099***	0.098***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SECM	0.159***	0.162***	0.161***	0.164***	0.154***	0.156***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Constant	0.023***	0.030***	0.022***	0.0288***	0.0208***	0.026***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)
Observations	111,891	111,891	111,891	111,891	111,891	111,891
R-squared		0.083		0.078		0.080
Number of stocks	741	741	741	741	741	741

*Sources: Authors Note: This table shows the estimation results of Value at Risk model. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Table 4 shows the main estimation results of the impact of value at risk on expected returns, using the Generalized Least Squares (GLS) and the Fixed Effects (FE) as estimation methods. Globally, the effect of VaR risk factor is positive and statistically significant at the 1% level. This implies that VaR positively influences monthly stocks' expected returns. In other words, stocks with a higher maximum likely loss yield higher returns. A stock with a high probability of loss will be compensated by a high-risk premium. This result implies that Value at risk positively influences monthly stock returns on African stock markets. This result is consistent with those of Yang and Ma, (2021), Bali and Cakici (2004), and Bali et al. (2009), who also find a positive relationship between VaR and expected stock returns. Iqbal and Azher (2014) also make suggestions that VaR has strong explanatory power for the cross-sectional and time-series variations of average returns in Pakistan. Atingan et al., (2020) instead obtain a negative relationship between VaR and expected returns.

The positive and significant coefficient of illiquidity means that illiquid stocks yield to higher expected returns. This result is in line with the clientele theory of Amihud and Mendelson (1986), which shows that illiquid assets command higher expected returns. Thus investing in an illiquid market or illiquid asset, with higher risk, must be compensated by a higher return. In deed, since African stock markets are still emerging, their level of liquidity is far below that of developed countries. As a result, their stock returns are higher than those of developed markets. Chordia et al. (2001b), Amihud et al. (2002), and Hikouatcha et al. (2018, 2022) empirically document a strong positive relationship between illiquidity and expected stock returns. Contrarily, Zhang and Li (2023) find a negative relationship between these two variables.

Concerning the second-moment risk variable, the relationship with the expected return is positive and significant. This means that an increase in variance will lead to an increase in future returns. This result is contrary to the conclusion of Sovbetov (2018), who found volatility to be a negatively significant determinant of returns.

Table 5: Impact of higher moment on expected returns

Variables	GLS	FE	GLS	FE	GLS	FE
SKEW	0.015***	0.016***	0.016***	0.016***		
	(0.0004)	(0.0004)	(0.0004)	(0.0004)		
KURT	-0.0005***	-0.001***			-0.001***	-0.002***
	(0.0001)	(0.0001)			(0.0001)	(0.0001)
ILLIQ	0.088***	0.090***	0.088***	0.090***	0.089***	0.090***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.00345)	(0.003)
SECM	0.119***	0.122***	0.118***	0.121***	0.127***	0.130***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Constant	-0.004***	-0.003***	-0.005***	-0.005***	-0.003***	-0.003***
	(0.0005	(0.001)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Observations	111,891	111,891	111,891	111,891	111,891	111,891
R-squared		0.052		0.052		0.043
Number of id	741	741	741	741	741	741

*Sources: Authors Note: This table shows the estimation results of the higher moment model. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Table 5 shows the results of examining the impact of higher-order moments on expected returns. These findings show that there is a positive relationship between skewness and returns for all specified models. Thus, high skewness leads to positive returns. Consequently, when there is a skewed distribution (implying high risk), investors may expect higher returns. This result is in line with Atilgan et al. (2020), Conine et al. (2017), and Barberis and Huang (2008), who also find a positive relation between skewness and stock returns.

Concerning Kurtosis, Table 5 shows that the associated coefficients are significantly negative for all model specifications. This means that, on African stock markets, a distribution with a large kurtosis has tails that exceed those of a normal distribution and is highly peaked. The negative relationship implies that high kurtosis associated with high risk will lead to lower expected returns. The degree of correlation between the two variables already predicts this finding. African stock markets are characterized by infrequent trading for most stocks, leading to low excessive returns and thus a large kurtosis (Azher and Iqbal, 2018). These results are contrary to those of Rehman et al. (2021), who instead find a positive relationship. The negative relation between kurtosis and returns is justified by the fact that at higher kurtosis, the tail of the distribution is skinny, causing the bulk of the data to fall within a narrow or skinny area, thus giving rise to extreme events that are then compensated by higher returns. Blau and Whitby (2018) claim that the lack of a positive relationship between kurtosis and expected returns is either a sign that nonstandard preferences predominate or that kurtosis is a poor measure of risk.

Table 6: Results of the downside risk model

Variables	1	2	3	4	5
Panel A: GLS results					
ES10		0.146***		0.142***	0.033***
		(0.002)		(0.002)	(0.002)
ES5	-0.065***			-0.050***	-0.046***
	(0.003)			(0.003)	(0.002)
DSR			1.226***		1.240***
			(0.004)		(0.004)
ILLIQ	0.088***	0.097***	0.182***	0.096***	0.180***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
SECM	0.133***	0.156***	0.160***	0.161***	0.159***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Constant	-0.004***	0.015***	0.037***	0.015***	0.033***

	(0.0005)	(0.0006)	(0.0004)	(0.0006)	(0.0005)
Panel B: FE results					
ES10		0.177***		0.173***	0.004*
		(0.003)		(0.003)	(0.002)
ES5	-0.070***			-0.058***	-0.057***
	(0.003)			(0.003)	(0.002)
DSR			1.261***		1.258***
			(0.004)		(0.004)
ILLIQ	0.089***	0.096***	0.180***	0.095***	0.179***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
SECM	0.136***	0.159***	0.155***	0.165***	0.162***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Constant	-0.004***	0.019***	0.038***	0.020***	0.040***
	(0.0005)	(0.0007)	(0.0004)	(0.0007)	(0.0005)
R-squared	0.045	0.066	0.471	0.068	0.473
Observations	111,891	111,891	111,891	111,891	111,891
Number of id	741	741	741	741	741

*Source: Authors Note: This table shows the estimation results of the downside risk model. In panel A the estimation method is GLS whereas in Panel B it is FE. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Based on the findings in Table 5, the kurtosis and skewness variables appear to be good explanatory variables for stock's expected returns on African stock markets. This finding is consistent with Mhiri and Prigent (2010) who that an investor aims to minimize kurtosis and maximize skewness.

Table 6 presents estimation results regarding the downside risk model (expected shortfall and monthly loss). Contrary to our expectations, these results show that expected shortfall is negatively and significantly associated with stock returns at the 95% confidence interval. Contrarily, at a 90% confidence level ES is positively and significantly associated with expected returns. The positive relation implies that high average losses on African stock markets are associated with higher future stock returns. Ang et al. (2006) and Bali et al., (2009) claimed that stocks with high downside risk measured by ES have high returns. In other words, ES has a positive impact on future returns.

Regarding monthly loss, Table 6 shows that the relationship with expected return is positive and significant. A higher monthly loss on African stock markets requires a higher expected return. It's also important to notice that this risk factor's coefficient has the greatest value of any of the others. This is in line with perspective and disappointment aversion theories, which state that investors are more sensitive to losses than gains.

These results are robust with respect to estimation methods (GLS in Panel A and FE in Panel B).

4.2.2 Robustness check

We conduct different robustness analyses including removing control variables, employing alternative model specifications, and analyzing regional and country specificities. Table 7 provides the results of the estimation of model 2, without considering the control variables.

Table 7: Impact of studied variables on future returns without control variables

VARIABLES	Panel A : GLS				Panel B : FE			
	Global	VaR	Skew & Kurt	Shortfall	Global	VaR	Skew & Kurt	Shortfall
VaR5	-0.266***	-0.020***			-0.243***	0.009		
	(0.014)	(0.007)			(0.015)	(0.007)		
VaR10	0.198***	0.220***			0.227***	0.254***		
	(0.010)	(0.009)			(0.011)	(0.009)		
SKEW	0.019***		0.019***		0.017***		0.0201***	
	(0.0003)		(0.0004)		(0.0004)		(0.0004)	
KURT	-0.001***		0.001***		-0.001***		0.0005***	
	(0.0001)		(0.0001)		(0.0001)		(0.0002)	
ES10	0.026***			0.007***	0.035***			0.018***
	(0.002)			(0.002)	(0.002)			(0.002)
ES5	-0.025***			-0.106***	-0.015*			-0.066***
	(0.007)			(0.002)	(0.008)			(0.002)
DSR	1.206***			1.206***	1.214***			1.225***
	(0.004)			(0.004)	(0.004)			(0.004)
CONSTANT	0.026***	0.018***	-0.001*	0.0287***	0.033***	0.025***	-0.0004	0.035***
	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0006)	(0.0005)
Observations	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891
R-squared					0.407	0.023	0.015	0.398

Number of id	741	741	741	741	741	741	741	741

*Sources: Authors Note: This table shows the estimation results of the global model taking into account various specifications and no control variables. In panel A the estimation method is GLS whereas in Panel B it is FE. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

The global model is estimated with all this study's considered variables on the one hand and, on the other hand, with individual previously estimated models (VaR, Higher-moment, and shortfall models). It appears that removing these variables did not have significant effects on the results. The positive and significant relationship regarding VaR10, skewness, ES10, and monthly loss, is still observed. Similarly, the negative and significant link associated with Var5 and ES5 still holds. The main exception here is kurtosis, which can have either a positive or a negative impact on return. Thus, the effect of this variable depends on the presence of control variables. Regardless of the estimation method used (GLS for Panel A and FE for Panel B), these findings remain qualitatively unchanged. This is also the case when several specifications of the model are considered, as highlighted by Table 8 and Table 9, for GLS and FE estimation strategies, respectively.

Table 8: Alternative specification with GLS estimation method

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VAR5	-0.240***		-0.030***	-0.120***	-0.266***		-0.066***	-0.191***	
	(0.013)		(0.008)	(0.013)	(0.014)		(0.002)	(0.003)	
VAR10	0.199***		0.320***	0.068***	0.198***	0.037***			0.302***
	(0.010)		(0.010)	(0.009)	(0.010)	(0.005)			(0.006)
SKEW	0.012***	0.010***	0.014***		0.019***	0.010***	0.009***	0.010***	0.013***
	(0.000)	(0.0003)	(0.0004)		(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
KURT	-0.002***	-0.001***	-0.002***		-0.001***	-0.001***	-0.0009***	-0.0003**	-0.002***
	(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ES5	-0.058***	-0.051***		-0.048***	-0.026***		-0.050***	-0.055***	
	(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.003)	
ES10	0.031***	0.060***		0.028***	0.025***	0.072***			0.015***
	(0.007)	(0.002)		(0.007)	(0.007)	(0.003)			(0.004)
DSR	1.239***	1.243***		1.243***	1.206***	1.238***	1.246***		
	(0.004)	(0.004)		(0.004)	(0.004)	(0.004)	(0.004)		
ILLIQ	0.178***	0.179***	0.098***	0.180***		0.180***	0.179***	0.098***	0.098***
	(0.002)	(0.002)	(0.003)	(0.002)		(0.002)	(0.002)	(0.003)	(0.003)
SECM	0.151***	0.151***	0.148***	0.159***		0.147***	0.152***	0.158***	0.148***
	(0.001)	(0.001)	(0.002)	(0.001)		(0.001)	(0.001)	(0.002)	(0.002)
CONSTANT	0.033***	0.032***	0.023***	0.033***	0.026***	0.033***	0.031***	0.020***	0.023***
	(0.0005)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)
Observations	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891
Number of id	741	741	741	741	741	741	741	741	741

*Sources: Authors Note: This table shows the estimation results of various specifications models when control variables are considered. The estimation method is GLS. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively*

Results shown in Table 8 consider an alternative specification for each of the models estimated previously (VaR, ES, DSR, and higher moment) using the GLS estimation approach. These outputs are shown in columns (2) to (9). The global model results are also provided (column 1) with all the explanatory variables and control variables. From there, it appears that irrespective of the scenarios, conclusions are similar to that of the main results. VaR10, skewness, illiquidity, variance, ES10, and monthly losses remain positively and significantly associated with returns for all the specifications. Kurtosis also maintains its negative and significant effect. Contrarily, VaR5 variable changes from positive to negative, as compared to the main findings. It is also the case when estimation technique is FE regarding results in Table 9.

Table 9: Alternative model specification with FE estimation strategy

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VAR5	-0.222***		0.0004	-0.131***	-0.243***		-0.005	0.239***	
	(0.014)		(0.008)	(0.013)	(0.015)		(0.003)	(0.004)	
VAR10	0.233***		0.341***	0.139***	0.227***	0.079***			0.337***
	(0.010)		(0.010)	(0.009)	(0.011)	(0.005)			(0.006)
SKEW	0.008***	0.006***	0.012***		0.017***	0.006***	0.006***	0.007***	0.011***

	(0.0004)	(0.0003)	(0.0005)		(0.0004)	(0.0003)	(0.0003)	(0.0005)	(0.0005)
KURT	-0.002***	-0.0006***	-0.002***		-0.001***	-0.001***	-0.0005***	0.0002	-0.002***
	(0.0001)	(0.0001)	(0.0002)		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
ES5	-0.068***	-0.059***		-0.062***	-0.035***		-0.058***	-0.062***	
	(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.003)	
ES10	0.049***	0.015***		0.048***	0.015*	0.045***			0.004
	(0.007)	(0.002)		(0.007)	(0.008)	(0.003)			(0.004)
DSR	1.246***	1.257***		1.251***	1.214***	1.246***	1.254***		
	(0.004)	(0.004)		(0.004)	(0.004)	(0.004)	(0.004)		
ILLIQ	0.178***	0.179***	0.098***	0.179***		0.180***	0.179***	0.097***	0.098***
	(0.002)	(0.002)	(0.003)	(0.002)		(0.002)	(0.002)	(0.003)	(0.003)
SECM	0.158***	0.157***	0.153***	0.163***		0.152***	0.159***	0.164***	0.154***
	(0.001)	(0.001)	(0.002)	(0.001)		(0.001)	(0.001)	(0.002)	(0.002)
Constant	0.042***	0.035***	0.030***	0.042***	0.033***	0.041***	0.039***	0.026***	0.030***
	(0.0006)	(0.0005)	(0.0007)	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0007)	(0.0007)
Observations	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891
R-squared	0.478	0.475	0.088	0.475	0.407	0.473	0.475	0.083	0.088
Number of stock	741	741	741	741	741	741	741	741	741

*Sources: Authors Note: This table shows the estimation results of various specifications models when control variables are considered. The estimation method is FE. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Table 9 shows the results when considering alternative specifications of the model with the FE estimation method. Here, the findings drawn previously in relation to Table 8 still hold. We thus globally conclude that, for the majority of the extreme risk factors, the major findings remain unchanged regardless of the model specification approach. We now turn to check the specificities of the country and region to which the financial market belongs.

In order to avoid checking if sample size matters, we repeat our analysis using the GLS estimation method by taking into consideration the region and country specificities of stock markets.

Table 10: Robustness by region

Variables	Eastern Africa	Northern Africa	Southern Africa	Western Africa
Panel A: VaR model				
VAR5	0.421***	0.333***	0.058***	0.259***
	(0.027)	(0.023)	(0.013)	(0.011)
VAR10	-0.164***	0.104***	0.477***	-0.078***
	(0.031)	(0.026)	(0.018)	(0.012)
ILLIQ	0.0014	0.027***	0.299***	-0.019***
	(0.003)	(0.005)	(0.007)	(0.006)
SECM	1.187***	1.498***	0.151***	0.372***
	(0.082)	(0.075)	(0.002)	(0.017)
Constant	0.014***	0.026***	0.037***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Skewness and kurtosis model				
SKEW	0.0093***	0.009***	0.0183***	0.017***
	(0.0008)	(0.0007)	(0.001)	(0.0006)
KURT	0.0005*	-0.0006**	-0.002***	0.0005**
	(0.0003)	(0.0003)	(0.0004)	(0.0002)
ILLIQ	0.001	0.026***	0.284***	0.041***
	(0.003)	(0.005)	(0.007)	(0.006)
SECM	-0.0361	-0.050	0.114***	0.021
	(0.057)	(0.057)	(0.002)	(0.013)
Constant	-0.0034***	-0.005***	-0.003**	-0.001
	(0.001)	(0.001)	(0.001)	(0.0009)
Panel C: Downside risk model				
ES5	0.001	-0.045***	-0.061***	-0.024***
	(0.007)	(0.005)	(0.004)	(0.004)
ES10	0.015*	0.046***	0.008*	0.026***
	(0.008)	(0.008)	(0.004)	(0.003)
DSR	1.185***	1.332***	1.273***	1.203***
	(0.011)	(0.008)	(0.008)	(0.005)

ILLIQ	0.007***	0.070***	0.353***	0.221***
	(0.002)	(0.003)	(0.006)	(0.004)
SECM	0.889***	1.385***	0.154***	0.261***
	(0.048)	(0.050)	(0.002)	(0.010)
Constant	0.021***	0.031***	0.045***	0.021***
	(0.0008)	(0.0007)	(0.001)	(0.0006)
Observations	7,701	16,760	41,676	32,012
Number of id	200	111	218	212

*Sources: Authors Note: This table provides results of the estimation by region. We consider the four main geographical areas of African region namely, Eastern, Western, Northern, and Southern regions. The estimation method is GLS. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Table 10 presents a robustness check by region concerning the relationship between extreme risk variables and returns. VaR5, downside risk, ES10, and skewness maintain a positive and significant relationship regardless of the regions. VaR10 has negative effects on Eastern and Western African stock markets. Kurtosis on its part has a positive and significant influence on returns in Eastern and Western Africa markets, contrarily in northern and Southern regions. These markets according to Okorie et al. (2021) are among those that are characterized by low expected returns. This justifies their negative relationship. Globally, these results reveal some region particularities concerning some risk factors. We try to explain it by considering the country's specificities.
(Insert Table 11 here)
We repeated our estimations considering the stock of each of the 12 African stock markets, and the results are in Table 11. From there, we observe that there are some country-specificities concerning some variables. The relationship between VaR10 and returns is significantly negative for seven of the 12 countries and non-significant for two countries in southern Africa (Mauritius and Namibia). The kurtosis effect is mostly negative and significant, but for Ghana, Mauritius, Morocco, and Namibia this effect is not significant. The effect is rather positive and significant for Egypt, Kenya, and Nigeria. Concerning ES variables at 95% and 90% confidence intervals, the relationship with return is disparate. Contrary to these differences, there are no country specificities concerning VaR5, Skewness, monthly loss, and control variables. These results can be explained by the fact that African stock markets are characterized by thin trading, an outcome of illiquidity, and also extreme deviations (Asongu, 2013). Rehman et al. (2021) concluded the same, regarding skewness, on the emerging stock market of Pakistan.

4.3 Investigating the Price of extreme risks on African stock markets
The analysis done so far demonstrated if tail risk has a positive or a negative impact on expected return. The concern now is whether these risk factors are likely to have a significant premium. To attain this objective, Fama and MacBeth's (FM, 1973) estimation method is applied. With this method, the dependent variable is excess returns. As before, we divide the robustness analyses from the main insights.

4.3.1 Main findings
In this subsection, we examine the risk premium (excess returns) associated with extreme risk on the African stock markets by running regressions according to Fama and MacBeth (1973) with normal standard error and with Newey-West (1987) standard errors that take into account the autocorrelation and heteroscedasticity of the slope coefficients. Model (4) allows us to estimate the price of risk for the different factors. The results of the global and individual model specifications are displayed in Table 12.

Table 12: Price of extreme risks on African stock markets: FM estimation results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A : FM with normal Standard Error				Panel B : FM with NW Standard Error			
VaR5	-0.397	0.608**			-0.397	0.608**		
	(0.275)	(0.283)			(0.357)	(0.260)		
VaR10	0.316	-0.322			0.316	-0.322		
	(0.208)	(0.338)			(0.252)	(0.318)		
SKEW	0.039***		0.031**		0.039***		0.031**	
	(0.004)		(0.008)		(0.005)		(0.009)	
KURT	0.221		0.291		0.221		0.291	
	(0.231)		(0.291)		(0.234)		(0.294)	
ES5	0.00846			0.0327	0.00846			0.0327
	(0.0188)			(0.0216)	(0.0198)			(0.0253)
ES10	0.208			0.267***	0.208			0.267***
	(0.130)			(0.0333)	(0.173)			(0.0464)
DSR	0.796***			0.853***	0.796***			0.853***
	(0.0337)			(0.0937)	(0.0325)			(0.0946)
ILLIQ	0.338***	0.126***	-0.226	0.359***	0.338***	0.126***	-0.226	0.359***
	(0.0496)	(0.0277)	(0.308)	(0.0426)	(0.0509)	(0.0312)	(0.310)	(0.0450)
SECM	0.306***	0.965***	-0.864	0.801***	0.306***	0.965***	-0.864	0.801***
	(0.0892)	(0.113)	(0.933)	(0.0958)	(0.114)	(0.156)	(0.935)	(0.135)

constant	-0.153***	-0.162***	-0.178***	-0.150***	-0.153***	-0.162***	-0.178***	-0.150***
	(0.0085)	(0.0093)	(0.0079)	(0.0083)	(0.0145)	(0.0158)	(0.0133)	(0.0141)
Observations	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891
Adj. R²	0.181	0.065	0.072	0.135	0.181	0.065	0.072	0.135
Number of groups	151	151	151	151	151	151	151	151

*Sources: Authors Note: this table displays the factor risk prices for all the considered extreme risk factors. The Fama and Macbeth's (1973) estimation method is used. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively. Panel A shows the results with normal standard while Panel B indicates the NW corrected standard errors.*

From table 12, we can confirm that some risk factors are important for asset pricing on African stock markets since related gammas (risk prices) are positive and significant. Regardless of the model under consideration (individual or global), the corresponding coefficient (risk price) is positive and significant, thus we may draw the general conclusion that the price of risk associated with skewness, monthly loss, liquidity, and return variance is significant. Thus, compared to owners of shares with the opposite characteristics, an investor receives a higher risk premium when he commits to the stocks of firms with skewed returns, monthly losses, low liquidity, and higher volatile returns. This means that these extreme risks are compensated, and any increase in their value is taken into account on the African stock markets. This can be supported by the fact that the African stock markets are extremely volatile and so, for an investor to venture in the market, he/she must earn a risk premium to compensate for this volatility. In line with the Extreme value theory, Bollerslev and Todorov (2011) reported that the fear of rare events is a possible explanation for the existence of a risk premium. The results are not surprising because the risk premium reflects the undesirable exposure to some risk factors (Farago and Tédongap, 2018). This conclusion is in line with Huang et al. (2012), Iqbal and Azher (2014), Lui and Wang (2020), and Hikouatcha et al. (2022) and against of Joher (2009) and Hughes and Liu (2005). The remaining factors are either not relevant (VaR10, ES5) or barely marginally significant (VaR5, ES10).

4.3.2 Extreme risk price: robustness check

The primary findings are submitted to robustness tests, which include country and region effects as well as an alternative model specification.

(Insert Table 13 here)

Outputs in Table 13 are results when several specifications of Model 4 are considered. A variable is removed from the model at each step of the analysis. The goal is to ensure that the results obtained before are not a function of a variable's inclusion or absence in the general model. From there, it appears that findings are similar to what is reported in Table 12. Skewness, monthly loss, liquidity, and return variance are the only priced risk factors.

We also verified if these outcomes changed from one region to another, and the results are in Table 14.

(Insert Table 14 here)

Panel A is the global model with all this study's variables. Panel B indicates the VaR model. Skewness-kurtosis and downside risk model results are in Panels C and D, respectively. In general, the results are similar to the main insights. The sole exception is in the western region, where the risk variables appear to be more important in individual models.

Risk pricing country specificities are also investigated and findings are in Tables 15 to 17.

(Insert Table 15 here)

Table 15 shows the outputs of the VaR model. It is interesting to note that the VaR5 variable is on average positively and significantly linked to excess returns on most individual stock markets. This implies that an increase in the VaR5 variable is compensated by a risk premium on the African stock markets. When specific models were taken into account, Table 12 already reflected this.

(Insert Table 16 here)

We examine the effect of higher-order moments (skewness and kurtosis) on risk prices in African markets. The results in Table 16 confirm that skewness is a price factor. Indeed, apart from the case of Ivory Coast, the risk price is significant in all other countries.

(Insert Table 17 here)

The expected shortfall at a 90% confidence interval and downside risk are equally priced globally on individual African stock markets, as shown in Table 17. Indeed, similar to the findings of Table 12, for most countries, the risk premium associated with these variables is positive and significant.

5. Concluding remarks and future research perspectives

This paper investigates the relationship between extreme risks and expected returns on African stock markets. More specifically, it was a question highlighting the effect of extreme risk (measured by Value at Risk, Expected Shortfall, skewness, kurtosis, and monthly loss) on the expected return of stocks listed on the African markets. Furthermore, we verify if these risks receive a significant premium in the market. Data used are from datastream and concerned 741 stocks of 12 financial markets, spread over four main regions in Africa. We use the GLS and the FE estimation methods to determine the relationship between risk factors and expected returns. Furthermore, we make use of Fama and Macbeth's (1973) estimation techniques with Newey-West's (1987) error correction, to examine if these risks are priced.

Globally, our results show that there is a significant relationship between most risk factors and expected returns, after controlling for illiquidity and second moment. Most extreme risk measures (skewness, monthly loss, expected shortfall, and Value at risk at

90% confidence level) have a positive and significant relation with expected returns. This is in line with general risk theory. The results further indicate that some risk variables (kurtosis, expected shortfall at 95% confidence level) negatively impacted expected return. Thus, the existence of asymmetric or non-normal distributions caused by the occurrence of rare scenarios significantly explains the expected returns in the African stock market. Furthermore, we find a significant risk premium on the African stock market after controlling for illiquidity and second moment. Overall, skewness and monthly loss are variables for which the premium remains significant whatever the situation. All these results did not change after several robustness checks including alternative model specifications, and consideration of country and region specificities.

The implication of such risk can be difficult, especially in frontier markets which are generally too volatile due to economic and political conditions as well as noisy market makers and speculators (Iqbal, 2012). However, investors are compensated in terms of excess returns due to their exposure to such high and infrequent extreme risks. Consequently, investors are encouraged to invest in the African stock markets characterized by the occurrence of rare and extreme events since there is compensation for taking such risk. Additionally, increasing the volume of transactions, information flow, and number of listed companies on the African financial markets is essential and consequently, they are able to make better investment and diversification decisions. Likewise, institutions and investors now better understand the extreme risk behavior on African stock markets and consequently, they are able to make better investment and diversification decisions. In the same vein, investment decisions on these financial markets should consider extreme risks. It will be interesting for further research to investigate causality relationships between extreme risks and returns as well as a mediation analysis between the two sets of variables both on stock and cryptocurrency markets.

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Appendices

Table 1: Number of stock per country and per region

Country/Regions	Eastern	Northern	Southern	Western	Total
Botswana	/	/	15	/	15
Ivory Coast	/	/	/	33	33
Egypt	/	91	/	/	91
Ghana	/	/	/	49	49
South Africa	/	/	132	/	132
Kenya	51	/	/	/	51
Mauritius	/	/	58	/	58
Morocco	/	60	/	/	60
Namibia	/	/	21	/	21
Nigeria	/	/	/	130	130
Tunisia	/	51	/	/	51
Zimbabwe	/	/	50	/	50
Total	51	202	276	212	741

Notes: This table shows details about the repartition of companies among country's stock market and by region.

Table 11: Robustness by country

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	BOT	COI	EGY	GHA	JSE	KEN	MAU	MOR	NAM	NIG	TUN	ZIM
VAR5	0.519***	0.283***	0.304***	0.379***	0.174***	0.421***	0.393***	0.378***	0.361***	0.247***	0.295***	0.030
	(0.039)	(0.030)	(0.0230)	(0.032)	(0.018)	(0.027)	(0.025)	(0.030)	(0.048)	(0.014)	(0.045)	(0.039)
VAR10	-0.363***	-0.092***	-0.180***	0.099***	0.904***	-0.164***	-0.004	0.073**	-0.055	-0.100***	0.126**	0.174***
	(0.068)	(0.030)	(0.026)	(0.034)	(0.025)	(0.031)	(0.029)	(0.032)	(0.061)	(0.015)	(0.052)	(0.048)
ILLIQ	-0.068	-0.002	0.040***	0.027***	0.173***	0.0014	0.042***	0.019***	0.466***	0.167***	0.055***	0.648***
	(0.042)	(0.013)	(0.009)	(0.006)	(0.008)	(0.003)	(0.008)	(0.006)	(0.087)	(0.016)	(0.011)	(0.022)
SECM	0.765***	0.439***	0.508***	1.622***	0.146***	1.187***	1.279***	1.664***	0.508***	0.332***	1.385***	0.338***
	(0.058)	(0.042)	(0.044)	(0.126)	(0.002)	(0.082)	(0.082)	(0.120)	(0.069)	(0.021)	(0.098)	(0.015)
CONSTANT	0.009***	0.024***	0.012***	0.032***	0.0750***	0.014***	0.022***	0.030***	0.028***	0.013***	0.021***	0.009*
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.005)
SKEW	0.011***	0.026***	0.020***	0.011***	0.001	0.009***	0.013***	0.011***	0.017***	0.019***	0.009***	0.025***
	(0.001)	(0.001)	(0.001)	(0.00)	(0.001)	(0.0008)	(0.0007)	(0.0009)	(0.002)	(0.0008)	(0.001)	(0.003)
KURT	-0.001**	-0.003***	0.001***	1.710	-0.011***	0.0005*	0.0002	0.0002	-0.0005	0.001***	-0.001***	-0.005***
	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0008)	(0.0003)	(0.0003)	(0.0004)	(0.001)	(0.0003)	(0.0005)	(0.001)
ILLIQ	0.102**	-0.011	-0.042***	0.027***	0.166***	0.001	0.038***	0.020***	0.492***	-0.235***	0.043***	0.634***
	(0.043)	(0.013)	(0.009)	(0.007)	(0.009)	(0.003)	(0.008)	(0.006)	(0.089)	(0.015)	(0.011)	(0.022)
SECM	0.124***	0.116***	0.033	-0.324***	0.114***	-0.036	-0.114*	-0.346***	-0.043	0.003	0.221***	0.268***

	(0.031)	(0.029)	(0.030)	(0.085)	(0.002)	(0.057)	(0.059)	(0.082)	(0.063)	(0.017)	(0.081)	(0.018)
CONSTANT	-0.0004	0.003	-0.008***	0.0009	-0.003*	-0.003***	-0.002***	8.230	-0.005**	-2.310	-0.011***	-0.008
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0009)	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)
ES5	-0.019	0.018	0.003	0.024***	0.055***	0.001	0.015*	-0.022***	-0.018**	0.042***	-0.060***	0.088***
	(0.027)	(0.012)	(0.006)	(0.008)	(0.005)	(0.007)	(0.008)	(0.007)	(0.007)	(0.005)	(0.007)	(0.010)
ES10	0.032*	-0.040***	-0.019***	0.075***	0.112***	0.015*	0.055***	0.077***	-0.043***	-0.004	0.017	-0.082***
	(0.016)	(0.009)	(0.007)	(0.011)	(0.006)	(0.008)	(0.008)	(0.010)	(0.009)	(0.003)	(0.013)	(0.012)
DSR	1.132***	1.165***	1.274***	1.293***	1.264***	1.185***	1.202***	1.292***	1.676***	1.394***	1.396***	1.290***
	(0.019)	(0.014)	(0.007)	(0.011)	(0.012)	(0.011)	(0.010)	(0.010)	(0.013)	(0.007)	(0.013)	(0.020)
ILLIQ	0.373***	0.147***	0.096***	0.063***	0.230***	0.007***	0.086***	0.051***	2.707***	0.825***	0.127***	0.673***
	(0.027)	(0.008)	(0.005)	(0.004)	(0.007)	(0.002)	(0.005)	(0.003)	(0.041)	(0.011)	(0.006)	(0.018)
SECM	0.267***	0.163***	0.356***	1.464***	0.153***	0.889***	0.865***	1.566***	0.115***	0.295***	1.255***	0.315***
	(0.030)	(0.027)	(0.023)	(0.079)	(0.002)	(0.048)	(0.051)	(0.075)	(0.033)	(0.012)	(0.068)	(0.012)
CONSTANT	0.013***	0.022***	0.043***	0.032***	0.069***	0.021***	0.023***	0.032***	0.029***	0.0186***	0.029***	0.031***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.0008)	(0.0007)	(0.0009)	(0.001)	(0.0008)	(0.001)	(0.004)
Observations	2,265	4,983	13,741	7,399	19,932	7,701	8,758	9,060	3,171	19,630	7,700	7,550
Number of stocks	15	33	91	49	132	51	58	60	21	130	51	50

*Note: This table provides results of the estimation by country. We carry out estimations on the stock of each of the 12 countries. The estimation method is GLS. Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectivel*

Table 13: Extreme risk prices on African stock markets: Alternative model specification

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VaR5	-0.397		0.100	0.218	-0.109	-0.578	0.0875	-0.290	-0.319	-0.476
	(0.357)		(0.166)	(0.338)	(0.349)	(0.365)	(0.243)	(0.353)	(0.377)	(0.357)
VaR10	0.316	0.219*		-0.171	-0.0816	0.485*	-0.0216	0.390	0.236	0.327
	(0.252)	(0.129)		(0.241)	(0.241)	(0.276)	(0.243)	(0.245)	(0.262)	(0.250)
SKEW	0.0392***	0.0223	0.0337***		0.0403***	0.0371***	0.0386***	0.0401***	0.0469***	0.0398***
	(0.0054)	(0.0147)	(0.0047)		(0.0050)	(0.0072)	(0.0048)	(0.0056)	(0.0066)	(0.0113)
KURT	0.221	0.184	0.190	0.220		0.0740	0.474	0.210	0.218	0.176
	(0.234)	(0.192)	(0.200)	(0.232)		(0.0868)	(0.488)	(0.224)	(0.233)	(0.187)
ES5	0.00846	0.00144	0.0127	0.0324	0.0264		0.0135	0.00453	0.00194	0.0181
	(0.0198)	(0.0200)	(0.0207)	(0.0219)	(0.0199)		(0.0284)	(0.0218)	(0.0205)	(0.0162)
ES10	0.208	-0.0432	-0.0254	0.125	0.220	0.229		0.215	0.169	0.190
	(0.173)	(0.0657)	(0.139)	(0.170)	(0.175)	(0.174)		(0.175)	(0.187)	(0.176)
DSR	0.796***	0.788***	0.804***	0.796***	0.797***	0.804***	0.893***		0.738***	0.814***

	(0.0325)	(0.0337)	(0.0328)	(0.0336)	(0.0340)	(0.0331)	(0.0945)		(0.0289)	(0.0341)
ILLIQ	0.338***	0.403***	0.338***	0.354***	0.331***	0.347***	0.322***	0.139***		0.358***
	(0.0509)	(0.109)	(0.0514)	(0.0450)	(0.0437)	(0.0525)	(0.0461)	(0.0462)		(0.0515)
SECM	0.306***	0.540***	0.525***	0.818***	0.306***	0.302**	0.324***	0.372***	0.360***	
	(0.114)	(0.115)	(0.120)	(0.140)	(0.115)	(0.117)	(0.110)	(0.117)	(0.116)	
cons	-0.153***	-0.149***	-0.153***	-0.140***	-0.171***	-0.153***	-0.153***	-0.156***	-0.152***	-0.160***
	(0.0145)	(0.0141)	(0.0141)	(0.0145)	(0.0156)	(0.0147)	(0.0143)	(0.0148)	(0.0146)	(0.0150)
Observations	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891	111,891
R-squared	0.181	0.171	0.171	0.164	0.169	0.176	0.172	0.114	0.172	0.169
Number of groups	151	151	151	151	151	151	151	151	151	151

*Note: this table displays the risk prices for all the considered extreme risk factors and for alternative model specifications. The Fama and Macbeth's (1973) estimation method is used. NW Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Table 14: Extreme risk price on African stock markets: region specificities

VARIABLES	Panel A : Global Model				Panel B : VaR model				Panel C : Skew-Kurt model				Panel D: Shortfall model			
	East	North	South	West	East	North	South	West	East	North	South	West	East	North	South	West
VAR5	1.447	-0.507	-0.188	-0.380	0.086	4.543	0.203	1.24***								
	(1.145)	(2.240)	(0.175)	(0.686)	(0.155)	(3.228)	(0.126)	(0.207)								
VAR10	-0.079	-2.030	0.106	0.640	0.187	-4.529	0.130	-0.431***								
	(0.183)	(1.844)	(0.156)	(0.628)	(0.173)	(3.126)	(0.139)	(0.164)								
SKEW	0.003***	0.031***	0.008***	0.027***					0.006***	0.045***	0.019***	0.055***				
	(0.001)	(0.007)	(0.002)	(0.001)					(0.001)	(0.011)	(0.002)	(0.010)				
KURT	-0.001***	-0.002	-0.001	0.689					9.27e-05	-0.00444	0.00101	0.586				
	(0.0002)	(0.005)	(0.001)	(0.709)					(0.001)	(0.006)	(0.001)	(0.597)				
ES5	-0.0127	0.103	-0.0122	0.0118									-0.005	0.009	-0.036	0.185***
	(0.012)	(0.094)	(0.015)	(0.060)									(0.012)	(0.075)	(0.024)	(0.060)
ES10	-1.432	2.315	0.094	0.398**									-0.0159	0.372	0.0315	0.458***

	(1.018)	(1.763)	(0.072)	(0.182)									(0.020)	(0.319)	(0.022)	(0.064)
DSR	1.507***	1.037***	1.377***	0.303***									1.501***	0.888***	1.362***	0.481***
	(0.051)	(0.087)	(0.041)	(0.057)									(0.057)	(0.092)	(0.033)	(0.106)
ILLIQ	0.892***	0.335***	1.071***	0.173***	0.253**	0.226***	0.416***	0.0665	0.110	0.262***	0.327***	-0.530	0.940***	0.376***	1.137***	0.227***
	(0.126)	(0.050)	(0.087)	(0.047)	(0.123)	(0.045)	(0.103)	(0.044)	(0.120)	(0.049)	(0.105)	(0.479)	(0.134)	(0.051)	(0.093)	(0.053)
SECM	1.010***	5.881**	0.536***	-0.616**	1.110***	7.338**	0.674***	1.197**	-0.402*	-1.212	-0.136*	-1.610***	1.162***	5.388***	0.428***	0.115
	(0.229)	(2.863)	(0.101)	(0.281)	(0.304)	(3.063)	(0.110)	(0.460)	(0.228)	(1.814)	(0.076)	(0.271)	(0.224)	(1.848)	(0.075)	(0.294)
CONS	0.006***	-0.263***	-0.027***	-0.278***	0.003**	-0.257***	-0.031***	-0.289***	-0.006***	-0.242***	-0.060***	-0.313***	0.006***	-0.232***	-0.024***	-0.303***
	(0.001)	(0.026)	(0.007)	(0.022)	(0.001)	(0.025)	(0.007)	(0.024)	(0.002)	(0.017)	(0.006)	(0.021)	(0.001)	(0.023)	(0.005)	(0.023)
Observations	7,701	30,501	41,676	32,012	7,701	30,501	41,676	32,012	7,701	30,501	41,676	32,012	7,701	30,501	41,676	32,012
Adj. R²	0.842	0.260	0.352	0.234	0.367	0.153	0.130	0.127	0.303	0.116	0.098	0.148	0.809	0.205	0.326	0.140
Number of groups	151	151	151	151	151	151	151	151	151	151	151	151	151	151	151	151

*Note: this table displays the risk prices for all the considered extreme risk factors and considering region specificities. We consider global and individual models. The Fama and Macbeth's (1973) estimation method is used. NW Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Table 15: Extreme risk prices on African stock markets: VaR model with country specificities

VARIABLES	BOT	COI	EGY	GHA	JSE	KEN	MAU	MOR	NAM	NIG	TUN	ZIM
VAR5	0.0392	0.262***	0.320***	0.479***	0.065	0.0860	0.320***	1.830***	1.207***	1.691***	0.374***	0.260***
	(0.199)	(0.044)	(0.052)	(0.080)	(0.106)	(0.155)	(0.060)	(0.573)	(0.283)	(0.292)	(0.081)	(0.074)
VAR10	0.239	0.073	-0.00263	-0.056	0.329***	0.187	0.092	-0.377	-0.113	-0.578**	0.154**	-0.017
	(0.213)	(0.077)	(0.055)	(0.084)	(0.115)	(0.173)	(0.062)	(0.509)	(0.245)	(0.253)	(0.076)	(0.061)
ILLIQ	0.467*	0.093	0.204	0.0406	0.285*	0.253**	0.080**	-0.036	-0.920*	-0.028	0.217***	0.347
	(0.269)	(0.151)	(0.130)	(0.029)	(0.161)	(0.123)	(0.040)	(0.022)	(0.503)	(0.091)	(0.061)	(0.257)
SECM	2.844**	1.004***	1.197***	2.604***	0.691***	1.110***	2.923***	6.810***	3.323***	2.107***	2.304***	0.535***
	(1.129)	(0.187)	(0.192)	(0.516)	(0.171)	(0.304)	(0.594)	(1.149)	(0.667)	(0.251)	(0.337)	(0.113)
CONS	-0.000	0.008***	0.019***	0.020***	0.029***	0.003**	0.012***	-0.625*	-0.582*	-0.509*	0.019***	0.020**

	BOT	COI	EGY	GHA	JSE	KEN	MAU	MOR	NAM	NIG	TUN	ZIM
	3							**	**	**		
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.001)	(0.002)	(0.050)	(0.048)	(0.035)	(0.002)	(0.008)
Observations	2,265	4,983	13,741	7,399	19,932	7,701	8,758	9,060	3,171	19,630	7,700	7,550
R-squared	0.584	0.519	0.323	0.325	0.328	0.367	0.310	0.189	0.395	0.195	0.285	0.439
Number of groups	151	151	151	151	151	151	151	151	151	151	151	151

*Note: this table displays the risk prices for all the considered extreme risk factors and considering countries specificities. Here the VaR model is estimated. The Fama and Macbeth's (1973) estimation method is used. NW Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Table 16: Extreme risk prices on African stock markets: Skewness and Kurtosis model with country specificities

VARIABLES	BOT	COI	EGY	GHA	JSE	KEN	MAU	MOR	NAM	NIG	TUN	ZIM
SKEW	0.004***	0.156	0.010***	0.007***	0.004*	0.006***	0.008***	0.007***	0.023**	0.0419***	0.007***	0.045***
	(0.001)	(0.134)	(0.002)	(0.001)	(0.002)	(0.0008)	(0.001)	(0.001)	(0.010)	(0.005)	(0.001)	(0.015)
KURT	0.0001	0.129	-0.0005	-0.0007	-0.0001	9.27e-05	0.0001	-0.003***	0.002	-0.013***	-0.002***	-0.005
	(0.0003)	(0.130)	(0.0008)	(0.0005)	(0.0007)	(0.0004)	(0.0004)	(0.0008)	(0.003)	(0.003)	(0.0006)	(0.004)
ILLIQ	0.360	11.83	0.124	0.021	0.170	0.110	0.073	-0.054*	-1.441***	-0.944*	0.173***	0.209
	(0.281)	(11.78)	(0.132)	(0.030)	(0.166)	(0.120)	(0.045)	(0.027)	(0.402)	(0.483)	(0.063)	(0.257)
SECM	-0.852	-0.160	0.050	-0.248	-0.218**	-0.402*	0.245	-2.479***	-1.229***	-1.722***	0.047	-0.0622
	(1.060)	(0.257)	(0.123)	(0.350)	(0.101)	(0.228)	(0.354)	(0.536)	(0.327)	(0.238)	(0.213)	(0.061)
CONS	-0.008***	-0.001	-0.015***	-0.004*	-0.002	-0.006***	-0.008***	-0.706***	-0.656***	-0.537***	-0.016***	0.0001
	(0.001)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.002)	(0.055)	(0.053)	(0.035)	(0.002)	(0.007)
Observations	2,265	4,983	13,741	7,399	19,932	7,701	8,758	9,060	3,171	19,630	7,700	7,550
R-squared	0.560	0.484	0.280	0.271	0.271	0.303	0.255	0.099	0.293	0.148	0.224	0.404
Number of groups	151	151	151	151	151	151	151	151	151	151	151	151

*Note: this table displays the risk prices for all the considered extreme risk factors and considering countries' specificities. Here the skewness-Kurtosis model is estimated. The Fama and Macbeth's (1973) estimation method is used. NW Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*

Table 17: Extreme risk prices on African stock markets: Downside risk model with country specificities.

VARIABLES	BOT	COI	EGY	GHA	JSE	KEN	MAU	MOR	NAM	NIG	TUN	ZIM
ES5	0.001	-0.0002	-0.010*	-0.002	-0.014***	-0.005	-0.004	-0.055*	-0.099**	0.090**	-0.013	-0.007
	(0.020)	(0.022)	(0.006)	(0.011)	(0.005)	(0.012)	(0.008)	(0.028)	(0.048)	(0.036)	(0.009)	(0.010)
ES10	0.023	0.008	0.05***	0.073***	0.019	-0.015	0.079***	1.302***	1.349***	0.658***	0.063**	-0.014
	(0.023)	(0.011)	(0.016)	(0.025)	(0.018)	(0.020)	(0.025)	(0.143)	(0.170)	(0.056)	(0.024)	(0.016)
DSR	1.722*	1.412*	1.612*	1.454*	1.735*	1.501*	1.358*	-	1.163	0.097	1.535*	1.612

	**	**	**	**	**	**	**	0.121*			**	***
	(0.106)	(0.072)	(0.053)	(0.031)	(0.032)	(0.057)	(0.035)	(0.064)	(0.718)	(0.107)	(0.044)	(0.065)
ILLIQ	1.800***	1.506***	1.029***	0.154***	2.317***	0.940***	0.243***	-0.047**	-0.842	-0.322***	0.538***	2.868***
	(0.203)	(0.168)	(0.102)	(0.026)	(0.129)	(0.134)	(0.037)	(0.021)	(0.714)	(0.121)	(0.062)	(0.197)
SECM	1.166**	0.384***	0.799***	2.302***	0.182	1.162***	2.500***	6.620***	4.796***	0.551***	1.714***	0.273***
	(0.563)	(0.099)	(0.124)	(0.341)	(0.130)	(0.224)	(0.491)	(1.097)	(0.790)	(0.159)	(0.266)	(0.062)
CONS	0.003**	0.003*	0.027***	0.022***	0.028***	0.006***	0.014***	-0.638***	-0.555***	-0.528***	0.019***	0.016**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.050)	(0.045)	(0.036)	(0.002)	(0.007)
Observations	2,265	4,983	13,741	7,399	19,932	7,701	8,758	9,060	3,171	19,630	7,700	7,550
R-squared	0.912	0.856	0.777	0.752	0.861	0.809	0.718	0.196	0.455	0.181	0.757	0.848
Number of groups	151	151	151	151	151	151	151	151	151	151	151	151

*Note: this table displays the risk prices for all the considered extreme risk factors and considering countries specificities. Here the downside risk model is estimated. The Fama and Macbeth's (1973) estimation method is used. NW Standard errors are in parentheses and ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10% threshold respectively.*