International Journal of
Financial Studies

Article

Impacts of U.S. Stock Market Crash on South African Top Sector Indices, Volatility, and Market Linkages: Evidence of Copula-Based BEKK-GARCH Models

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Abstract: This paper examines the effects of the Standard and Poor's 500 (SP500) stock index crash during the global financial crisis and the COVID-19 pandemic periods on the South African top sector indices (basic materials, consumer goods, consumer services, financials, healthcare, industrials, technology, and telecommunication). The results of a copula-based BEKK-GARCH approach technique demonstrate the existence of price and volatility spillover during times of stock crashes. We discover that during a stock crisis, strong shocks and higher volatility spillover effects from the United States (U.S.) SP500 index to the top sector indices of the South African Johannesburg Stock Exchange (JSE) markets are more significant. However, there is no integrated economy, as the results did not show any spillover effects from South Africa to U.S. markets. Furthermore, the Gumbel copulas have higher dependence parameters, implying that extreme co-movements occur in the upper tails, suggesting the possibility of a large transmission of shocks from the SP500 to the eight top sector indices of the JSE and showing an asymmetric dependence between these markets. This result is important for investors willing to invest in the South African sector of equity markets to develop hedging strategies to prevent risk spillover from developed markets.

Keywords: volatility spillover; stock market crash; market linkages; global financial crisis; COVID-19; copulas; BEKK-GARCH

Citation: Mudiangombe, Benjamin Mudiangombe, and John Weirstrass Muteba Mwamba. 2023. Impacts of U.S. Stock Market Crash on South African Top Sector Indices, Volatility, and Market Linkages: Evidence of Copula-Based BEKK-GARCH Models. *International Journal of Financial Studies* 11: 77. https://doi.org/10.3390/ijfs11020077

Academic Editor: Duc Khuong Nguyen

Received: 14 March 2023
Revised: 24 May 2023
Accepted: 5 June 2023
Published: 10 June 2023

1. Introduction

During the 2008 financial crisis, the U.S. stock markets experienced a downward trend. After the global financial crisis (GFC), the U.S. market increased significantly. Nevertheless, in February 2020, a pandemic called COVID-19 began, and the U.S. stock market regime moved from an increasing to a decreasing trend. The Wilshire 5000 Total Market Index fell over the next five weeks with a 34.9 percent drop. The SP500 index, which fell from 3386.1 to 2237.4, lost 33.9% of its value in just a few weeks from February to March 2020 (Shu et al. 2021).

The stock market crash in the U.S. in 2020 had a significant impact on the lives and livelihoods of many people across the country, as well as permanently destroying the wealth of many investors, particularly those with little experience in risk management. During the COVID-19 pandemic, the U.S. unemployment rate increased dramatically from March 2020, with a rate of 4.4 percent, to April 2020, with a rate of 14.7 percent (FRED 2020). Until now, it appears that external shocks were the main causes of the 2020 stock market crash. The stock market crash was caused by the quick transmission of the novel coronavirus COVID-19 in January 2020, originating from China, and followed by lockdowns (Albuquerque et al. 2020). Moreover, the 2020 Russia–Saudi Arabia oil price war is believed to have caused the 2020 stock crash (Ma et al. 2021).

The significance of topics such as the impact of shocks on stock market co-movements and the nature of cross-country market dependencies has sparked considerable interest in international finance literature. A spillover effect arises when the variations in price in one market have a lagged effect on other markets (Hamao et al. 1990). Empirical analyses of shock transmission effects can help to demonstrate the nature of information spread and provide important policy implications of international portfolio diversification to support risk management strategies and investor decisions. During times of crisis, there is a perception of an increased probability of financial spillover because of shocks spreading from one stock market to another. These transmissible market effects typically harm the expected profits from the international diversification process (Ahmed and Huo 2019).

Meanwhile, as a result of the U.S. market crash, the interdependence of global financial markets has grown significantly. Researchers are interested in determining the nature and magnitude of relationships between various markets as well as the causes of financial market instability because of increased financial transmission. Empirical evidence of return and volatility transmission effects from the U.S. to other major economies has been detected in the Canadian, German, Japanese, and U.K. stock markets (Theodossiou and Lee 1993). The transmission of shocks in developed and emerging markets has piqued the interest of more researchers.

According to Bekaert and Harvey (1997), capital market liberalization frequently increases international relationships and improves the correlation of stock markets, influencing asset returns and risk sharing among investors. The U.S. stock market is a leading market in the world, and its role as a benchmark market is incontestable. Given the dominance and influence of the financial markets in the United States, their warnings may not go unheeded. Nevertheless, the literature on South African economic integration has considered integration between the top sector indices of JSE markets and developed U.S. markets. Therefore, it is crucial to look into how the U.S. market crisis affected the JSE top sector indices in South Africa. To evaluate the strength of the volatility spread between the South African national equities markets and the United States and provide insight into stock market co-movement patterns.

Stock price crashes, defined as sudden and dramatic drops in stock prices, have become an increasingly important topic in financial studies due to their impact on investment decisions, regulatory practices, risk management, and corporate governance. As a result, the literature on the causes and consequences of stock price crashes is expanding and reflecting various points of view. Several studies examine the relationship between managerial incentives to keep bad news a secret, which increases the risk of a stock price crash, and firm characteristics such as corporate social responsibility (Kim et al. 2014; Hunjra et al. 2020).

A stock price crash is defined as a significant drop in the stock price as a result of bad news (Jin and Myers 2006; Hutton et al. 2009). The theoretical framework for crash risk links to information structure. The managerial incentive to keep bad news hidden drives the accumulation of bad news. However, in some cases, managers cannot continue to keep bad news to themselves, and the unexpected disclosure of such information results in a significant drop in stock prices (Kim et al. 2011; Hutton et al. 2009).

It is critical to discuss the market risk posed by a rapid rise in stock prices, particularly during a financial crisis. The stock price becomes extraordinarily sensitive during a financial crisis, especially to unexpected information shocks, which can produce a significant price spike and usually have severe market repercussions (Jiang and Kim 2016). According to Savor (2012), price shocks and overall implied volatility are significantly correlated.

Liu et al. (2021) investigate the outbreak and risk of a stock crash in the Chinese stock market. Yet, he contends that a COVID-19 pandemic raises the danger of a stock market meltdown. A decline in market expectations for the companies is reflected in the stock prices. Although the COVID-19 outbreak is an exogenous shock to the economy, it affects practically every element of business operations at once, making it the perfect opportunity to study how pandemic crises increase the probability of stock price crashes. In addition, because of the simultaneous movements in all major stock markets, the value of global equities has decreased, along with market volatility (Dai et al. 2019, 2021; Wen et al. 2019, 2020).

We are aware that in the available literature, it is crucial to look at how the collapse of the SP500 index on the U.S. stock market affected the eight leading sector indices of the

South African JSE. The S&P Dow Jones Indices SP500 index, which gauges the performance of 500 large-capitalization stocks listed on U.S. stock exchanges, was chosen as the stock market index since it is the most widely used index. In this study, we tried to determine the impact of market linkages and volatility co-movement on South Africa's top sector indices during the crisis. To this end, the Copula-based BEKK-GARCH model will be used in three periods: the first period will cover the global financial crisis of 2008, the second period will cover the COVID-19 pandemic, and the third period will cover the entire sample.

Studies on the interdependencies between international stock markets focused on assessing how investor behaviour and market performance are affected by shocks from one stock market. Co-movement, market integration, and volatility spillovers spread risk across markets and remain a critical topic because we cannot predict but can prevent a crisis. Strong international trading relations most likely result in a higher level of market co-movement when considering economic integration.

In the last decade, there have been three specified destructive financial crises: the subprime crisis of 2008, the European debt crisis of 2009, and finally, the COVID-19 crisis of 2020. In this study, we only investigate the GFC and COVID-19. Since the emergence of the global financial crisis, the interdependence of various financial markets has unexpectedly increased, resulting in a significant contagion. The interdependence of equity or foreign exchange rates examines the spread of stock price and exchange rate shocks across markets. Moreover, it is necessary to determine whether the extent and nature of stock market integration in economic states become preoccupied.

Among the studies that inspired us on the impact of the stock market crash causing risk on financial variables are (Shu et al. 2021; Ahmed and Huo 2019; and Cui et al. 2022). Liu et al. (2021) look into the impact of the COVID-19 pandemic on the risk of a Chinese stock market crash. To that end, the conditional skewness of the return distribution from a GARCH with skewness (GARCH-S) model serves as a proxy for the Shanghai Stock Exchange's equity market crash risk. Chen and Haga (2021) investigate investor sentiment in the aftermath of the market crash. Following the 2008 stock market meltdown, Meric et al. (2012) looked into contemporaneous co-movements and time-series lead/lag links between international stock markets using time-varying correlation analysis, principle components analysis (PCA), and Granger-causality (G-C) statistical techniques. Gong et al. (2020) noticed Poor 2020 quarterly reports from several firms. Due to the epidemic's effects on the A-share market, the short-term market experienced significant fluctuations before stabilizing.

We note that it is crucial to consider the South African example by combining the top sector indices of the JSE with the SP500 stock indices. Here, we need to determine how the SP500 crash on the American stock market will affect the JSE's main sector indices during that period. To the best of our knowledge, this is the first study employing the Copula-based BEKK-GARCH model to account for the effects of the U.S. SP500 stock crash on the eight major sector indices of the South African JSE. In light of the aforementioned concerns, it is crucial to look at how the SP500 crash affected the major sector indices during the global financial crisis and the COVID-19 period.

The remainder of this study is organized as follows: Section 2 presents the literature review; Section 3 describes the methodology of the study; Section 4 presents the discussions of the empirical results; and Section 5 presents the conclusions and policy implications.

2. Literature Review

Kim et al. (2016) support the U.S. stock market's hegemonic position. Using Bayesian vector autoregressive (VAR) and BEKK-GARCH, Ahmed and Huo (2019) look at the effects of the Chinese stock market crash in 2015–2016. The findings demonstrate that price and volatility spillover behaviours change during stable and stressful periods. There is evidence of significant price spillovers from China to other regional markets during a bullish period, proving that good news from China has a significant effect on its neighbours. The bulk of Asia-Pacific stock markets saw higher volatility and severe shock spillover effects from

China during the crisis period. In four significant U.S. stock market indexes, each with a different degree of total market capitalization, Shu et al. (2021) analyze the 2020 stock market crash. The four indices lost more than a third of their value over the course of the 2020 U.S. stock market crash in less than five weeks. The results demonstrate that these four stock market index price paths before the 2020 stock market crash indicated a positive bubble regime using the log-periodic power law singularity (LPPLS). Contrary to common assumptions, it was shown that the COVID-19 pandemic was only a spark in the process of the 2020 U.S. stock market crash, which was brought on by the stock market's rising systemic instability.

Dai et al. (2022) examine the impact of the COVID-19 outbreak on China's commodity price surges using 5 min intraday high-frequency futures data from three Chinese commodity markets (energy, chemical, and metal) for the period of 23 January 2020 to 10 June 2022. The data show that the COVID-19 pandemic presents the most notable spike in the information spillover pattern to China's chemical price and that the information spillover from the COVID-19 transmission scenario to China's energy price jumps is quite moderate. In addition, its dependence on imports and exports is the primary cause of the sensitivity of its price increases during the COVID-19 pandemic. Wen et al. (2019) examine the effect of retail investor attention on the likelihood of a crash in the price of Chinese stocks. Data from a large sample of Chinese listed companies from 2007 to 2017 shows that companies that receive more attention from individual investors are less likely to experience future stock price crashes. Furthermore, improved auditing can lessen the impact of retail investor attention on a company's potential for a future fall. Wang et al. (2023) establish a link between firm-specific economic policy uncertainty (FEPU) and the risk of a stock price crash. The findings show that FEPU has a negative impact on crash risk, which remains true even after considering the endogeneity issue and differs depending on the firm's owner.

Liu et al. (2021) examine the impact of the COVID-19 pandemic on the likelihood of a Chinese stock market crash. A GARCH with skewness (GARCH-S) model was used to estimate the conditional skewness of the return distribution as a proxy for the risk of the Shanghai Stock Exchange's equity market collapsing. They developed a fear index for COVID-19 using information from the Baidu Index. The findings demonstrate that the pandemic increases the likelihood of a stock market crash by demonstrating that conditional skewness responds negatively to daily growth in total confirmed cases. Furthermore, the fear-based attitude makes these risks greater, especially in light of COVID-19's effects. In other words, the pandemic increases the probability of a stock market fall when fear levels are high. Kong et al. (2023) examine the effect of firms' exposure to COVID-19 sentiment on the likelihood of a stock market crash. According to the findings, being exposed to COVID-19 sentiment related to medical, travel, and unclear elements significantly raises the probability of a stock price fall, but being exposed to COVID-19 sentiment related to vaccinations significantly lowers the risk of a stock price crash.

Zhou et al. (2021) used a sample of all Chinese listed businesses from 2010 to 2017 to investigate the influence of three corporate social responsibility (CSR) dimensions on the risk of stock price crashes. The results show that CSR, particularly businesses' accountability to stakeholders and the environment, significantly decreases the likelihood of a stock market drop. CSR's primary method of lowering crash risk is by attracting institutional investors with long-term investment horizons. Savor (2012) concentrates on equities that experience substantial price fluctuations. Utilizing all days with active trading, meeting the requirements for both the analyst coverage and the main price movement. Evidence suggests that price occurrences with information are followed by drift, whereas those without information produce reversals. The findings also demonstrate that investors overreact to other shocks that change stock values while underreacting to fundamental news. Ho et al. (2022) look into how modern health pandemics affect a company's chance of a stock price fall. Early results suggest that pandemic crises reduce the likelihood of stock market crashes. The regulatory framework safeguards a more stable nation, and the pandemic's impact on crash risk is less dramatic. This statement looks to be opposed to the reality we have seen during the COVID-19 outbreak in the U.S. stock market.

Cui et al. (2022) investigate the potential of a stock price decrease and how positive information shocks influence investors' trading behaviour. Stock price shocks and higher risk emerge when positive information shocks are measured using cumulative positive jump returns. The effect of information shocks also varies according to business characteristics and overall state. In 22 emerging markets, Bai et al. (2021) examine the significant price decreases in particular stocks. By considering analyst reports as a proxy for information arrivals, the evidence suggests that the majority of crashes in emerging markets are not followed by information events and that all crashes are accompanied by price reversals. Additional studies show that short-term crashes are less common in nations with improved information environments or lower levels of openness, suggesting that characteristics such as market integration and information transparency may have a significant impact on huge swings in stock values in emerging markets. Alp et al. (2022) use firm data from Borsa Istanbul covering the years 2009–2019 to examine the effect of stock market liquidity on a stock price crash. According to the results, more stock liquidity makes stock price crashes more likely, but block holder ownership is not what causes this beneficial link. Akhtaruzzaman et al. (2021) examine how, during the COVID-19 period, financial transmission occurs between China and G7 nations via financial and non-financial enterprises. Empirical results show that listed companies in these nations, both financial and non-financial, experience a significant rise in conditional correlations between their stock performances. Nevertheless, during the COVID-19 outbreak, the magnitude of the increase in these correlations was significantly higher for financial firms, showing the importance of their role in the financial spread.

According to the interdependence theory, genuine ties and substantial integration serve as conduits for the transfer of shocks between markets during times of crisis and non-crisis. This idea emphasizes genuine connections and fundamental integration as a means for shocks to be distributed between two markets during unstable and booming times. Cheng and Yang (2017) investigate the interdependence between the stock markets and the government bond markets in the regions of 39 countries. Using the Markov-Switching approach, they discovered that during the financial crisis, the majority of investors preferred bonds over equities due to the riskier nature of equity markets. Depending on the relevant location, the current study on interdependence produced varying conclusions about the interconnectedness of the stock market. During the GFC and the EDC, Yang et al. (2016) concentrated on the interdependence and co-movement between exchange rate returns (EUR-USD, GBP-USD, and JPY-USD). At all frequencies and scales during the study period, applied wavelet analysis revealed considerable dependency between the pound sterling and the euro; at higher scales, there is a hint of covariation for the yen and the pound pairwise. Additionally, they discover that dependency is more obvious in times of crisis. Mensi et al. (2018) investigate the correlations between commodity prices (such as the prices of petroleum, Brent, and gold) and the developing BRICS stock markets. The outcomes of the wavelet technique show that at low frequencies, the BRICS index returns and the price of crude oil move in lockstep. Furthermore, there has been a strong co-movement during the GFC. Ahmed and Huo (2018) investigate the current volatility spread mechanisms between the Chinese and African stock markets. The results from the Bayesian VAR and BEKK-GARCH models strongly suggest that there are spillover effects in terms of price movement and volatility behaviour, suggesting that the two markets are integrated. The correlation between the Chinese and African stock markets raises the possibility of mutual influence. Jiang et al. (2017) explore the co-movement and interdependence of Asian stock markets using wavelet analysis and find a significant short-term dependency between these markets and some specific external shocks in select countries. Using wavelets and variational mode decomposition (VMD), Shahzad et al. (2016) investigate the interconnection of the Greek stock market and other European stock markets. According to the data, there is a long-term relationship between the Greek and European stock markets, indicating a growing dependency.

Strong international trading relations most likely result in a higher level of market co-movement when considering economic integration. Shamsuddin and Kim (2003) investigate on the Australian stock market's integration with the U.S. and Japanese markets. The findings demonstrate a stable long-run connection between the Australian, U.S., and Japanese markets compared to the Asian Crisis, but this relationship vanished after the Asian Crisis period. The vector error correction model (VECM) and VAR approaches were used to take into account the interdependence between stock prices and foreign exchange rates. Yang and Hamori (2015) investigate the bond market interdependence of Germany and the Central and Eastern European countries CEEC-3 (Poland, the Czech Republic, and Hungary). The results of the wavelet transform demonstrate that during the GFC and EDC, contagion occurred in these markets at various levels and in various directions. Moreover, prior to 2004, all samples from Hungary, Poland, and the Czech Republic had very high levels of bond market integration. In et al. (2001) established the presence of a reciprocal volatility spread between Korea and Hong Kong as well as unidirectional volatility spread between Korea and Thailand using a vector autoregressive exponential generalized autoregressive conditional heteroscedasticity (VAREGARCH) model. In addition, there is evidence of market integration. In order to explain the dependency resulting from the spread of the U.S. financial crisis, Samarakoon (2011) looks into the dynamic interdependence, market integration, and volatility transmission of a few selected Asian stock markets, specifically during the Asian financial crisis, creating shock models for partially overlapping and non-overlapping markets using the VAR framework. According to the findings, there is significant regional change as well as a bi-directional and asymmetric dependency in emerging markets. U.S. shocks drive interdependence, whereas contagion shocks are driven in emerging markets.

3. Methodology

3.1. Bivariate Copula Function

The 2-dimensional distribution forms a copula function, $C[u, v]$, defined in the interval $[0, 1]^2$ and the range of $[0, 1]$. The following properties might be satisfied.

Limitation: $\forall(u, v)\epsilon[0, 1]$ and Monotonic property: $\forall u_1, u_2, v_1, v_2\epsilon[0, 1]$, with $u_1 \leq u_2$ and $v_1 \leq v_2$;

$$C(u_2, v_2) + C(v_1, u_1) - C(u_2, v_1) - C(u_1, v_2) \geq 0$$

The theorem of Sklar (1959) revealed that the joint distribution function given $T(x, y) = P(X \leq x, Y \leq y)$ and the marginal distribution $F(x) = P(X \leq x)$ and $K(y) = P(Y \leq y)$. Then, the copula function is defined as C:

$$[0, 1]^2 \rightarrow [0,\ 1] \text{ such that, } T(x, y) = C(F(x), K(y)) \tag{1}$$

If the marginal functions are continuous, then the copula function is unique. Sklar's theorem has the main effect of decomposing a joint distribution into two univariate marginal distributions, $F(x)$ and $K(y)$.

3.2. Archimedean Copulas

Archimedean copulas are a large family of copulas with numerous useful properties and dependence structures. The majority have closed-form expressions, which are extremely convenient for estimation. Distinct from many other copulas, they are not derived from multivariate distributions using Sklar's theorem. First, identify the two concepts: the generator function denoted by ϑ and the pseudo-inverse of the generator function denoted by ϑ^{-1}. The generator of a bivariate Archimedean copula function is

$$C_{Arc}(u, v) = \vartheta^{-1}(\vartheta(u) + \vartheta(v)) \tag{2}$$

Several Archimedean copula functions can be generated with diverse assumptions of generator functions.

3.2.1. Gumbel Copula

Gumbel (1960) first suggested a Gumbel copula. The generator function is given by

$$\varphi_\delta(t) = (-lnt)^\delta \tag{3}$$

The bivariate Gumbel copula is an asymmetric copula and displays upper tail dependence. The Gumbel copula formula is expressed by

$$C_G(u, v; \delta) = \exp\left\{-((-lnu)^\delta + (-lnv)^\delta)^{\frac{1}{\delta}}\right\}. \tag{4}$$

with δ a parameter defining the degree of dependency, $\delta = 1$ define independence and perfect dependence when $\delta \to \infty$. The formula of the upper tail dependence is given by

$$\lambda_U = 2 - 2^{\frac{1}{\delta y}} \tag{5}$$

3.2.2. Clayton Copula

The Clayton copula is an asymmetric copula, suggested first by Clayton (1978). The Clayton copula exhibits a generator function given by

$$\varphi_{Cl}(t) = \frac{1}{\delta}(t^{-\delta} - 1) \tag{6}$$

The bivariate Clayton copula function is given by

$$C_{Cl}(u, v) = (u^{-\delta} + v^{-\delta} - 1)^{\frac{-1}{\delta}} \tag{7}$$

When $\delta \to 0$ reveals independence, and when $\delta \to \infty$ denotes a perfect tail dependence. It displays a lower tail dependence expressed by the following formula:

$$\lambda_L = 2^{-1/\delta} \tag{8}$$

3.2.3. Frank Copula

The Frank copula exhibits the property of radial symmetry and has no tail dependence. It is a symmetric copula, and it allows to capture of the full range of dependence. Indeed, the Frank copula was discovered to be the only Archimedean copula with radial symmetry. The generator function is given by

$$\varphi(t) = -\ln\left(\frac{e^{-\theta t} - 1}{e^{-\theta} - 1}\right) \tag{9}$$

where $\theta \neq 1$. The bivariate Frank copula is given by

$$C_{Fr}(u, v) = -\frac{1}{\theta}\ln(1 - \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1} \tag{10}$$

3.2.4. Plackett Copula

The Plackett copula is an Archimedean copula with an upper tail dependence θ goes to infinity and the lower tail dependence $\theta \to 0$, $\theta \in (0,\infty)$.

The bivariate Plackett copula is given by

$$C_{Pl}(u, v) = \frac{1}{2}(\theta - 1)\left[1 + (\theta - 1)(u + v) - \sqrt{\left[(1 + (\theta - 1)\left(u + v\right))^2 - 4\theta(\theta - 1)uv\right]}\right] \tag{11}$$

3.3. Elliptical Copulas

Elliptical copulas are merely elliptical distribution copulas that share several multivariate normal distribution properties and are used to model multivariate extreme events and non-normal dependencies. The use of elliptical copulas has the advantage of allowing the modeling of multivariate distributions in which the marginals are not assumed to be equal, but the dependence between the marginals is categorized by an elliptical distribution. The elliptical copulas are restricted to having radial symmetry.

3.3.1. Gaussian Copula

Gaussian copula does not have tail dependence for $\rho < 1$; it is simply derived from the bivariate normal distribution and has the distribution function given in the following expression:

$$C_{Gaus}(u,v) = \int_{-\infty}^{\vartheta^{-1}(u)} \int_{-\infty}^{\vartheta^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} e^{\left(-\frac{s^2-2\rho st+t^2}{2(1-\rho^2)}\right)} dsdt \tag{12}$$

where ρ denotes the linear correlation coefficient of the bivariate normal distribution. Kendall's tau is given by the following expression:

$$\tau = \frac{2}{\pi}\arcsin(\rho) \tag{13}$$

3.3.2. t-Copula

A t-copula is an elliptical copula that displays upper and lower tail dependence, with coefficients that are equal. The bivariate t-copula is given by

$$C_t(u,v) = \int_{-\infty}^{t^{-1}(u;v)} \int_{-\infty}^{t^{-1}(v;v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left(1 + \frac{s^2 - 2\rho st + t^2}{v(1-\rho^2)}\right)^{-\frac{v+2}{2}} dsdt \tag{14}$$

where v indicates the degrees of freedom of the bivariate t-distribution. The relationship between ρ and Kendall's tau is similar to the Gaussian copula. The tail dependence is given by

$$\lambda = 2\bar{t}_{v+1}\left(\frac{\sqrt{v+1}\sqrt{1-\rho}}{\sqrt{1+\rho}}\right) \tag{15}$$

3.3.3. Rotated Copulas

The copulas with asymmetric dependence structures are the only ones that can be rotated. These copulas are the survivors of Archimedean, but they are not Archimedean. We are limited to the rotated Gumbel and rotated Clayton copulas. It is indicated that the rotated Gumbel copula is defined when u and v have the Gumbel copula, and then the variables 1-μ and 1-v have the rotated Gumbel copula with lower tail dependence. If u and v have the Clayton copula, then the variables 1-μ and 1-v have the rotated Clayton copula, which displays stronger dependency in the upper tail instead of lower tail dependence.

3.4. BEKK-GARCH Model

Ross (1989) explains volatility spillovers using information transmission theory. He contends that because price and volatility are related to the rate of information flow, spillovers between financial markets could be used to explain the process of information transmission and market efficiency. Bollerslev (1986) suggested the Generalized Autoregressive Conditional Heteroscedastic (GARCH) techniques for forecasting volatility and market return dynamics. Because of the increased interdependence of international financial markets, univariate GARCH specifications have been extended to multivariate GARCH models, which can explain the dynamics of stock returns across financial markets. The multivariate GARCH model is used to investigate how the correlation and covariance between different variables vary over time by identifying the conditional variance and covariance equations (Li and Giles 2015; Majdoub and Mansour 2014). The mean equation is given by

$$r_t = \mu + \varepsilon_t \text{ with } \varepsilon_t \backslash \Omega_{t-1} / \sim N(0, H_t) \tag{16}$$

where r_t represents a vector of stock markets returns expressed as $r_t = (r_{us,t}, r_{i,t})'$, ε_t denotes a vector of Gaussian error given by $\varepsilon_t = (\varepsilon_{us,t}, \varepsilon_{i,t})$, and μ_t is a vector of constants defined as $\mu_t = (\mu_{us,t}, \mu_{i,t})$, with i = Basic Materials, Consumer Goods, Consumer Services, Financials, Healthcare, Industrials, Technology, and Telecommunication, respectively. The residue vector ε_t is assumed to be subject to the conditions of a zero mean and constant variance and is defined by numerous criteria.

$$\varepsilon_{i,t} = v_{i,t} h_{i,t} \quad v_{i,t} \sim N(0,1) \tag{17}$$

$$h_{i,t} = c_i + \alpha_i \varepsilon^2_{i,t-1} + \beta h_{i,t-1} \tag{18}$$

where $v_{i,t}$ follows the standard normal distribution.

Bollerslev et al. (1988) first suggested a general VECH GARCH in extending the univariate GARCH model as

$$V(H_t) = A_0 + \textstyle\sum_{i=1}^{q} A_i V(\eta_{t-i}) + \sum_{j=1}^{p} B_j V(H_{t-j}) \tag{19}$$

where H_t indicates conditional variance-covariance matrix, $\eta_t = (\varepsilon_t, \varepsilon'_t)$, $V(.)$ signifies operator of a lower triangular matrix that is symmetric $d \times d$ into $d(d+1)/2$ dimensional vector, Ai and Bj are $d(d+1)/2$ dimensional parameter matrices.

Engle and Kroner (1995) proposed a practical model called the BEKK (Baba–Engle–Kraft–Kroner) GARCH model to address the two limitations on the specification of the VECH GARCH. The quadratic forms are used by the BEKK-GARCH model to remove the positive constraint on the conditional variance matrix and to simplify the process of estimation by reducing the number of parameters. This model guarantees that the conditional variance and covariance matrices are not affected by parameter deferral or variable cross-interference (Lin et al. 2019). The conditional variance and covariance matrix of the BEKK-GARCH model is given by

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{20}$$

where C is a lower triangular matrix of intercept coefficients while A and B are two unrestrictive matrices. The conditional variance and volatility transmission can be expressed specifically by

$$h_{11,t} = c^2_{11} + c^2_{21} + a^2_{11}\varepsilon^2_{1,t-1} + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a^2_{21}\varepsilon^2_{2,t-1} + b^2_{11}h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b^2_{21}h_{22,t-1} \tag{21}$$

$$h_{22,t} = c^2_{22} + a^2_{12}\varepsilon^2_{1,t-1} + 2a_{22}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a^2_{22}\varepsilon^2_{2,t-1} + b^2_{12}h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b^2_{21}h_{22,t-1} \tag{22}$$

The off-diagonal parameters will be defined by the following hypothesis: The null hypothesis

H_0. *$a_{12} = a_{21} = b_{12} = b_{21} = 0$.*

There is no presence of volatility spillovers in this study and the alternative hypothesis

H_1. *$a_{12}, a_{21}, b_{12}, b_{21}$.*

At least one of these parameters is different from zero, implying evidence of the existence of volatility spillovers. To estimate the BEKK-GARCH model, the following logarithm likelihood function should be maximized, assuming that the residuals are normally distributed:

$$L(\theta) = \textstyle\sum_{t=1}^{T} L_t(\theta) \tag{23}$$

where θ and T indicate, respectively, the vector of parameters to be estimated and the number of observations. The following expression represents the sum of the logarithm likelihood functions of the conditional distributions:

$$L_t(\theta) = -ln2\pi - \frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1} \varepsilon_t \quad (24)$$

4. Empirical Results and Discussion

4.1. Data

This study empirically examines the impacts of the U.S. stock index crash on the top sector indices of the South African JSE. This empirical analysis uses daily data from Thomson Reuter's database, which consists of closing prices of the market of the U.S. (SP500) index and eight top sector indices of the firms of the South African JSE sampled by data availability (basic materials, consumer goods, consumer services, financials, healthcare, industrials, technology, and telecommunication). The data consist of the daily sample size starting from 2 January 2004 to 1 April 2022, which contains 4566 observations. The series of data were transformed into log-returns using the following formula:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) * 100 \quad (25)$$

This paper will employ the copulas-based BEKK-GARCH model, which is critical for estimating the effects of market crashes and co-movement, focusing on the bilateral U.S. stock market and top firm sector indices of the JSE. Copula families, as well as the process of selecting the best copula model in conjunction with the BEKK-GARCH modelling approach and some multivariate extreme value copula functions, are of particular interest because stock markets may exhibit common extreme variations. Furthermore, it allows capturing the nonlinearities in the relationships between the U.S. SP500 and the eight top sector indices of the South African firms, as well as some empirically stylized facts of return distributions such as volatility persistence, fat tail behaviour, and asymmetric effects of return innovations on volatility. The quadratic forms are used by the BEKK-GARCH model to remove the positive restriction on the conditional variance matrix and to simplify the estimation process by reducing the number of parameters.

4.2. Preliminary Results

Table 1 summarizes the descriptive statistics for the SP500 index and eight main sectors of the South African JSE return series during the sample period 2004–2022. The J-Bera test proposes the rejection of the normality assumption, which is consistent with the statistics for skewness and kurtosis. All the series display negative skewness and a higher kurtosis than normal. The negative skewness suggests that negative returns occur more often, and the distributions have longer left-hand tails than large positive returns. The excess kurtosis for all return series is greater than 3, suggesting that all return pairs have high peaks and fat tails, and their distributions are more leptokurtic, showing that significant fluctuations in daily prices are much more common than the normal distribution estimates. The standard deviation (Std. Dev) characterizes the volatility, which is the highest in the sectors of South African telecommunication, consumer services, and healthcare, suggesting dispersion in volatility across markets. Investors can expect frequent small gains and a few large losses in markets with negatively skewed parameters.

Table 1. Descriptive statistics of the log-return series.

Variables	SP500	BMat	CoGood	CoServ	Fin	Health	Ind	Techn	Telecom
Mean	0.0297	0.0178	0.0383	0.0016	0.0169	−0.0265	0.0111	0.0076	−0.0323
Median	0.0724	0.0691	0.0806	0.0861	0.0615	0.0720	0.0591	0.0494	0.0471
Std. Dev.	1.2055	2.2821	1.6643	3.95075	1.9568	3.8658	1.8632	2.1548	4.2250
Skewness	−0.5653	−0.6645	−0.6053	−44.30323	−0.6302	−45.4507	−0.6730	−0.7792	−36.1993
Kurtosis	17.4332	13.0515	12.6524	2597.596	10.3139	2687.674	9.5365	17.3451	1982.636
J-Bera	39,875.48	19,557.25	18,004.26	12,138.751	10,479.33	18,543.561	8473.310	39,612.00	18,767.881
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	4566	4566	4566	4566	4566	4566	4566	4566	4566

Notes: This table presents the summary statistics of the log-return of the U.S. SP500 index and the South African top sector indices: Basic materials (BMat), Consumer Goods (CoGood), Consumer Services (CoServ), Financials (Fin), Healthcare (Health), Industrials (Ind), Technology (Techn), and Telecommunication (Telecom). The Jarque-Bera (J-Bera) test to check normality.

4.3. Goodness-of-Fit of Copulas Selection

Further, there are a few model selection criteria that permit the ranking of the copulas according to their fit. The most commonly used criterion is the Akaike information criterion (AIC) or Bayesian information criterion (BIC). To assess the goodness of fit test to determine which copula is the best fit for the data, we use Genest et al. (2009), presented in Table 2, which summarizes the result of the tests. Each pair of copulas are ranked based on both AIC and BIC criterion. The AIC results are all consistent with the BIC results. This result indicates that among the selected copulas estimated for the pair of data, the smallest AIC or BIC is found first for the Gumbel copulas for the pairs SP500-BMat, SP500-CoGood, SP500-CoServ, SP500-Health, SP500_Ind, SP500_Techn. Additionally, the Rotated Clayton copula with the smallest AIC or BIC is found for the pair of SP500-Fin and SP500-Telecom. It is indicated that the copulas with the smallest AIC are Archimedean copulas with one right tail; this captures the dependence between the pair of series in the right tail.

Table 2. Model selection by AIC and BIC.

Copulas		Normal	Clayton	RClayt	Plackett	Frank	Gumb	RGumb	t-Stud
SP500-BMat	AIC	−3.5242	−8.4786	−39.9786	−1.3259	−1.1912	**−54.5846**	13.3373	−26.8594
	BIC	−3.5228	−8.4772	−39.9772	−1.3245	−1.1898	**−54.5832**	13.3401	−24.4304
SP500-CoGood	AIC	−14.8092	−17.6504	−55.5688	−12.4398	−11.3598	**−77.6290**	−15.8062	−27.9768
	BIC	−14.8078	−17.6490	−55.5674	−12.4384	−11.3584	**−77.6262**	−15.8034	−21.5478
SP500-CoServ	AIC	−10.4508	−13.9968	−43.2947	−6.9529	−6.4052	**−58.6374**	6.5561	−17.4917
	BIC	−10.4494	−13.9954	−43.2933	−6.9515	−6.4038	**−58.6360**	6.5589	−16.0627
SP500-Fin	AIC	−0.0870	−1.8158	**−23.1897**	−0.0590	0.0010	−13.8672	58.7474	−19.4787
	BIC	−0.0856	−1.8144	**−23.1883**	−0.0576	0.0024	−13.8658	58.7502	−18.0496
SP500-Health	AIC	−9.8860	−11.9377	−41.4210	−4.7482	−4.4250	**−56.0367**	19.6101	−15.2767
	BIC	−9.8846	−11.9363	−41.4196	−4.7468	−4.4236	**−56.0353**	19.6129	−13.8477
SP500-Ind	AIC	−9.0721	−14.8257	−45.6266	−5.1145	−4.6126	**−66.4758**	−4.6584	−22.8345
	BIC	−9.0707	−14.8243	−45.6252	−5.1131	−4.6112	**−66.4744**	−4.6556	−26.4055
SP500-Techn	AIC	−9.0721	−14.8267	−45.6266	5.1173	−4.6186	**−66.4758**	−4.6584	−15.3977
	BIC	−9.0707	−14.8239	−45.6252	−5.1243	−4.6451	**−66.4787**	−4.6456	−14.9686
SP500-Telecom	AIC	−0.0648	−1.1064	**−24.2659**	−0.4057	0.0038	−13.1253	70.3740	−17.6879
	BIC	−0.0634	−1.1050	**−24.2645**	−0.4043	0.0052	−13.1239	70.3768	−13.2235

Notes: This table presents the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). The bold value shows the smallest AIC and BIC representing the best copulas fitting the data.

Different copulas are used to estimate the best copula related to the smallest AIC or BIC in the SP500 and each of the eight South African top sector indices.

4.4. Results of Gumbel and Rotated Clayton Copula

The tail dependence coefficients for the Gumbel and rotated Clayton copulas are presented in Table 3. Our findings exhibit the best fit, corresponding to the Gumbel copula for the pair of (SP500-BMat, SP500-CoGood, SP500-CoServ, SP500-Health, SP500-Ind, and SP500-Techn) and the Rotated Clayton copula for the pair of (SP500-Fin and SP500-Telecom), respectively, suggesting asymmetric dependence between these pairs. The dependence parameters for each of the two copula functions are significant at the 1% and 5% levels for the pair of data, showing a high degree of interconnectedness between the SP500 and the eight main sector indices of the JSE. Moreover, we find that the Gumbel copulas have higher dependence parameters than the rotated Clayton copulas. This result demonstrates that more observations are in the tails, implying that extreme co-movements occur in the upper tails. This proves that the dependence structure of the SP500 and the eight main sector indices of the JSE exhibits right tail dependence, implying the possibility of a large transmission of shocks from the SP500 to the eight South African main sector indices of the JSE. There is confirmation of our expectations of an asymmetric dependence between the U.S. SP500 index and the main sector indices of the South African JSE during market stress periods, suggesting the presence of systemic risk. The Kendall tau coefficients for Gumbel copula show positive tail-dependence, which indicates that when the SP500 stock index experiences an extremely positive event, the six main sectors of the JSE are more likely to also experience an extremely positive event. In other words, it suggests that the two markets tend to move together in the upper tail of their distribution. This implies a stronger positive correlation during extreme market conditions. Market participants can gain insights into the joint behaviour of financial variables, understand the level of dependence during extreme events, and make more informed decisions regarding portfolio diversification, risk management, and hedging strategies.

Table 3. Estimates of the dependence parameter for best copulas.

	Gumbel Copulas						Rotated Clayton Copulas	
Par	**SP500-BMat**	**SP500-CoGood**	**SP500-CoServ**	**SP500-Health**	**SP500-Ind**	**SP500-Techn**	**SP500-Fin**	**SP500-Telecom**
θ	1.0254 *** (4.5627)	1.0356 *** (3.9538)	1.0267 *** (4.0154)	1.0345 *** (7.4510)	1.0283 *** (4.3429)	1.0148 ** (3.1762)	0.0649 ** 3.1051)	0.0658 ** (3.1278)
τ	0.04954	0.06875	0.05201	0.06669	0.05504	0.02916	-	-

Notes: This table presents the dependence parameters of Gumbel and Rotated Clayton Copulas estimation results. For each pair of data, values in parenthesis represent the t-statistic of the parameters. **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

4.5. Estimated Results of the BEKK-GARCH

Table 4 shows the parameter estimates based on the BEKK-GARCH model, which is known to accurately capture stock market conditional volatility and its interactions. The diagonal parameters of matrix A show the effect of their own past shocks on their conditional variance, while the diagonal elements of matrix B measure the impacts of the markets' past volatility on their own conditional variance. In this paper, A(1,1) and B(1,1) assess the impacts of the U.S. SP500 stock market's past shocks and volatility on its own conditional variance, respectively, whereas A(2,2) and B(2,2) assess the impact of each of the eight top sectors of JSE firms' stock markets' past shocks and volatility on its own conditional variance.

The estimated parameters A(1,1) in panel A show the coefficients as positive and statistically significant at a 1% level for the pairs Sp500-CoGood, Sp500-CoServ, and SP500-Ind, implying that the past shocks of SP500 have had significant effects on the sectors of CoGood, CoServ, and Ind. The volatility shocks of SP500 are significant for all the pairs except for the pair of SP500-CoServ, implying that B(1,1) plays a significant effect on the transmission of the past volatility in these sectors.

A(2,2) captures the ARCH effect for the basic materials, consumer goods, consumer services, financials, healthcare, industrials, technology, and telecommunications sectors of the JSE stock markets. In panel A, we observe that the ARCH effect is only seen for consumer goods, consumer services, healthcare, and industrials. At the same time, the GARCH effects captured by coefficient B(2,2) are significant in all the eight main sector indices of the JSE.

Table 4. Estimation of BEKK-GARCH model.

Panel A: Global Financial Crisis from 9 October 2007 to 9 March 2009								
Variables	**BMat**	**CoGood**	**CoServ**	**Fin**	**Health**	**Ind**	**Techm**	**Telecom**
μ_1	−0.2175 (−0.7557)	−0.1757 (−1.7746)	−0.2486 ** (−2.4829)	−0.2175 (−0.7635)	−0.1607 (−1.6923)	−0.1785 * (−1.9576)	−0.2175 (−0.7588)	−0.2175 (−0.7609)
μ_2	−0.2886 (−0.5553)	−0.2355 * (−1.9784)	−0.2059 (−1.5929)	−0.2819 (−0.7388)	−0.1528 (−1.3008)	−0.1769 (−1.3889)	−0.2412 (−0.5699)	−0.1811 (−0.3633)
C_{11}	2.5848 *** (6.9801)	1.4015 *** (10.8559)	1.3102 *** (7.2655)	2.3878 *** (4.7610)	0.4780 *** (9.5032)	0.4779 *** (4.2729)	2.4807 *** (5.9701)	2.5391 *** (9.5408)
C_{21}	−0.0139 (−0.0236)	0.0018 (0.0052)	0.0346 (0.0917)	−0.3437 (−0.7480)	0.0053 (0.7250)	0.0133 (0.6742)	−0.0677 (−0.1379)	−0.4095 (−0.7099)
C_{22}	4.2783 *** (6.0981)	1.8045 (0.8961)	1.9427 *** (10.3557)	3.1234 (0.9821)	0.6618 ** (2.6199)	2.3748 *** (12.0793)	3.4535 (0.8023)	4.1270 (0.8761)
A_{11}	0.3013 (1.3604)	0.4225 *** (5.2834)	0.4437 *** (5.6029)	0.1000 (1.3599)	0.0031 (0.0019)	0.1916 *** (3.0924)	0.1100 (1.3839)	0.1320 (1.3493)
A_{21}	0.0200 (0.1477)	−0.5050 (−0.7548)	−0.5080 (−1.2822)	0.0210 (0.2090)	−0.5200 (−1.4552)	−0.5100 (−1.1961)	0.0201 (0.1803)	0.0206 (0.1577)
A_{12}	0.2701 *** (6.4655)	−0.1992 *** (−4.1003)	−0.1881 *** (−4.2926)	0.2210 *** (5.3536)	−0.1766 *** (6.0359)	−0.2987 *** (8.6609)	0.1200 *** (4.3532)	0.1203 ** (2.4802)
A_{22}	0.1000 (1.4153)	0.4929 *** (6.8919)	0.5122 *** (6.6879)	0.1000 (1.4073)	0.1910 *** (3.5245)	0.3516 *** (3.8633)	0.1020 (1.3159)	0.1101 (1.4573)
B_{11}	0.9000 *** (15.2454)	0.0001 * (1.9345)	0.0011 (0.0014)	0.9040 *** (10.9209)	0.8311 *** (14.3637)	0.8819 *** (5.2478)	0.9100 *** (10.3810)	0.8932 *** (10.3469)
B_{21}	0.0511 (1.0887)	−0.5002 (0.8721)	−0.5000 (0.8654)	0.0513 (1.3018)	−0.5060 (−0.9609)	0.2019 (0.7981)	0.0510 (1.6595)	0.0517 (1.0384)
B_{12}	0.1100 *** (3.3492)	0.5000 *** (8.9899)	0.5100 *** (10.9252)	0.1401 *** (6.0466)	0.3816 *** (10.9479)	−0.1411 ** (2.0545)	0.1190 *** (4.1239)	0.1114 *** (5.3161)
B_{22}	0.9000 *** (119.7641)	0.2457 *** (3.6512)	0.1994 ** (2.5880)	0.9000 *** (13.5406)	0.7698 *** (23.5621)	0.8001 *** (14.0019)	0.9000 ***(11.3654)	0.9000 *** (14.1761)
Panel B: COVID−19 Stock market crash from 19 February 2020 to 23 March 2020								
Variables	**BMat**	**CoGood**	**CoServ**	**Fin**	**Health**	**Ind**	**Techn**	**Telecom**
μ_1	0.1387 (0.3746)	0.1285 (0.3887)	0.1477 (0.3871)	0.1394 (0.3766)	0.9566 (0.5817)	0.1287 (0.3822)	0.1264 (0.3844)	0.1568 (1.1129)
μ_2	−2.3602 (−0.8304)	−1.3029 (−0.7595)	−1.8792 (−1.0133)	−2.7783 (−1.1371)	−1.7518 * (−1.8415)	−2.3147 (−1.1594)	−1.2012 (−0.5658)	−3.4505 *** (−3.0241)
C_{11}	0.7783 ** (6.7661)	0.7884 *** (7.4109)	0.7683 *** (5.6590)	0.7981 *** (8.0045)	0.2060 ** (7.9324)	0.7783 *** (8.4304)	0.7783 *** (5.0923)	0.1557 * (1.93911)
C_{21}	−0.7374 (−0.2629)	−0.5004 (−0.2818)	−0.5235 (−0.2713)	−0.2770 (−0.1136)	0.4333 (0.9736)	−0.1729 (−0.0851)	−0.6126 (−0.2821)	0.9150 *** (7.0840)
C_{22}	7.1667 *** (5.2100)	4.1588 *** (6.9830)	4.5172 *** (7.8307)	6.0886 *** (7.0083)	4.5306 *** (6.1304)	4.9078 *** (10.7210)	5.1932 *** (7.5431)	5.2109 *** (4.7238)
A_{11}	0.1000 ** (2.3739)	0.1032 *** (5.3953)	0.1090 *** (3.3977)	0.1042 *** (4.4008)	0.5057 *** (8.4415)	0.1067 ** (2.4009)	0.1092 (0.3906)	0.5509 ** (2.2926)
A_{21}	0.0202 (0.0089)	0.0251 (0.0147)	0.0200 (0.0138)	0.0206 (0.0108)	−0.5000 (−0.2636)	0.0219 (0.0131)	0.0220 (0.0122)	−0.5081 (−0.1842)
A_{12}	0.2210 *** (5.5859)	0.2204 *** (5.3715)	0.2201 *** (8.4210)	0.2290 *** (4.5205)	0.2154 *** (3.3661)	0.2209 *** (5.4275)	0.2217 *** (4.4413)	−0.2401 ** (−2.9602)
A_{22}	0.1009 (0.3283)	0.0895 ** (2.3200)	0.1000 (0.3610)	0.1047 *** (7.3250)	0.1103 *** (6.0336)	0.1076 ** (0.3278)	0.1084 (0.3305)	0.3561 (1.0272)

Table 4. *Cont.*

B_{11}	0.9081 *** (19.0877)	0.9001 *** (12.5192)	0.9000 *** (19.6732)	0.9100 *** (19.8270)	0.7100 *** (4.5004)	0.9056 *** (20.3946)	0.9082 *** (19.3750)	0.7919 *** (5.2046)
B_{21}	0.0511 (0.0793)	0.0520 (0.1176)	0.0510 (0.1132)	0.0513 (0.0897)	0.5057 (0.3066)	0.0518 (0.1078)	0.0528 (0.0988)	0.0509 (0.3622)
B_{12}	0.1160 ** (2.3049)	0.1107 *** (3.8832)	0.1100 *** (3.0027)	0.1118 *** (4.5254)	0.2721 *** (6.2310)	0.1182 *** (4.0964)	0.1162 *** (5.2314)	0.1239 *** (6.3273)
B_{22}	0.9071 *** (17.2287)	0.9000 *** (18.5162)	0.9003 *** (18.4458)	0.9107 *** (17.8281)	0.8537 *** (8.0102)	0.9061 *** (18.5658)	0.9088 *** (18.0740)	0.8021 *** (7.9016)

Notes: 1 and 2 denote the SP500 Index and the main sectors of the JSE all-share index; Figures in parentheses indicate the t-statistics; *, **, and *** indicate the statistically significant level at 10%, 5%, and 1%, respectively.

In Panel B (COVID-19 stock crash), the ARCH effects are visible in the sectors of consumer goods, financials, healthcare, and industrials, whereas the GARCH effects are significant at a 1% level for all the sector indices of the JSE. We observe that most of the coefficients are statistically significant for all the pairs in the SP500: basic materials, consumer goods, consumer services, financials, healthcare, industrials, and telecommunication. The implication is that the transmission of the past shocks from the SP500 to all the main sector indices of the South African JSE is significant. In addition, the transmission of volatility from the SP500 to all eight sectors of the JSE during a stock crash is significant and plays a very important role in the spread of risk effects.

Shifting on to the transmission of shocks and volatility across stock markets, the off-diagonal elements of matrices A and B capture the shock and volatility spillover effects, respectively. In matrix A, coefficient A(1,2) indicates the overall shock spillover effect from the SP500 to each of the top sectors of the JSE stock indices. In panel A, the transmission of shocks from the SP500 to all the sector indices of the JSE was statistically significant during the GFC; there is an indication of a contagion effect and co-movement of shocks from the U.S. stock crash to the South African main sector of the JSE, and the reverse is not possible. We understand that the U.S., as a benchmark of the market in the world, has an important influence on the transmission of shocks, bringing a systemic risk effect to the economies of the world. In panel B, the crash of the U.S. stock market during COVID-19 also has a great implication for the main sector of the JSE. The result shows that all the coefficients A(1,2) are statistically significant at the 1% level, implying that the shock from the SP500 crash was transmitted significantly to South African main sector indices. It is also noted that none of the shocks from these sectors were transmitted to the U.S. SP500 stock index during COVID-19, as the results show that all the sectors were not significant during this period.

Table A1 in Appendix A represents panel C. We observe that the past shock and volatility are positive and statistically significant at the 1% level for all pairs. These findings suggest past shocks and past volatility in the U.S. SP500 stock market have had a significant impact on the eight sector indices of the JSE, as indicated by the coefficients A(1,1) and B(1,1). There is an indication of strong ARCH effects in all sector indices where the coefficients of A(2,2) are statistically significant at the 1% level for each sector selected. The GARCH effect captured by B(2,2) shows all of the JSE's selected sectors exhibit strong GARCH effects for the sample period. We find that all the coefficients A(1,2) are statistically significant, implying that the SP500 spreads shocks to South African main sector indices. Although these coefficients are statistically significant for all pairs in the sample period, the shock spillover effects from the U.S. SP500 stock index are significant for the selected main sectors of the South African JSE for the sample period of our study. This result suggests that all South African JSE Main Sector indices may not be immune to the effects of U.S. shocks in the short and long run. The coefficient A(2,1) captures the shock spillover effect from the South African JSE main sectors' stock indices to the U.S. SP500 in the opposite channel. We find that this effect has no effect because this coefficient is not significant in all sectors except for consumer goods, where the significance is 10%. When we compare the two directions, we can see that the U.S. with the SP500 has strong shock spillovers to the South

African JSE main sector indices but no shock spillovers from South African markets to the U.S. This evidence supports our conclusion that the U.S.'s impact on South African main sector indices has grown during the recent volatile period, the global financial stock crash, and the COVID-19 stock crash.

Moving on to the volatility spillover effect, which could be captured by the off-diagonal parameters of matrix B, we observe that volatility transmissions from the U.S. SP500 to South African main sector stock markets captured by the coefficient B(1,2) are stronger during the global financial crisis, COVID-19, and the full sample period of study. The significance of these transmissions is indicated by the statistical significance of the B(1,2) coefficients in all the pairs in Panels A, B, and C. For example, in Panel C, B(1,2) for basic materials is equal to 0.2417, meaning that volatility transmission from SP500 to basic materials amounts to 24.17% and that a 1% increase in conditional variance in the SP500 index transmits 24.17% volatility to the basic materials index. This result suggests that volatility originating in the United States can be easily transmitted to the JSE's main sector of stock indices, implying an important market signal during a crisis. It is consistent with Goldstein (1998), who proposed the so-called wake-up call theory of contagion. Because the United States is the world's largest trading partner, particularly with South Africa, a sharp slowdown in the United States GDP growth and changes in some key fundamental indicators will have a negative effect on the macroeconomic variables of its neighbours via the international trading channel.

The expectation to downgrade the South African economies is likely to cause investors to sell off in their equity markets when contagion occurs. This is also supported by the theoretical framework proposed by Pretorius (2002), which indicates that similar patterns in macroeconomic indicators will lead to significant market co-movements and volatility spillovers. Furthermore, a crisis in one country can lead to a loss of public trust in financial markets, and this dynamism can spread to other countries. As a result of the loss of confidence in the country experiencing the crisis, investors will continue to sell assets in another market, contributing to spillover effects. All of these effects were significant during the GFC stock crash, the COVID-19 stock crash, and for the entire sample period, showing a high level of consistency concerning the three periods considered.

5. Conclusions and Policy Implication

The relative importance of the U.S. SP500 stock market crash's impact on the South African JSE main sector indices is investigated in this paper. We examine the daily price and volatility spread across various market types during the SP500 stock crash that occurred during the global financial crisis of 2007–2009 and the COVID-19 pandemic of 2020 various market types during the SP500 stock crash that occurred during the global financial crisis of 2007–2009 and the COVID-19 pandemic of 2020. We use the goodness of fit test with different copulas to find the appropriate copula fitting the pair of data, and then the copula fitting the data is used for the estimation of the dependence structure and interdependence between the stock markets. The BEKK-GARCH model is used to investigate volatility spillovers and linkages between the U.S. SP500 and South African JSE main sector indices of stock markets. In Panels A, B, and C, the South African sectors of stock market indices are significantly affected by their own past shocks, with a strong autoregressive feature, except for financial, industrial, technology, and telecommunication in Panel A. The behaviour of volatility spillover of the South African main sector indices shows that, in panels A, B, and C, all stock market indices are substantially affected by their own past spillover with strong autoregressive, except for CoServ in Panel A.

Price spillover from the U.S. SP500 stock market crash to South African JSE main sector indices is particularly important during crisis periods, as most South African JSE main sector indices stock markets are substantially impacted by changes in the U.S. SP500's domestic prices. These findings suggest that during crash periods, 'good news' from the SP500 stock market has a substantial impact on the South African main sector indices. We also notice that the effects of the U.S. SP500 stock market on some South African main sector indices become much stronger during price volatility. Furthermore, the U.S. SP500 stock market adjusts to information flow from South African main sector indices markets, suggesting that the shock spread from these markets to the SP500 is negligible.

We find strong evidence of shock spillover effects from the U.S. SP500 to most South African main sector stock markets for both the GFC and COVID-19 periods in examining the spread of shocks and volatility spillovers. Moreover, most of the volatility transmission from the U.S. SP500 stock index is statistically significant for all South African main sector indices in panels A, B, and C. During stock crash periods and throughout the sample period, our results confirmed strong information transmission from the U.S. SP500 stock index to most South African major sector indices markets. During the stock market crash, insignificant price spillover effects from South Africa's main sector markets to the U.S. SP500 stock index were observed. As a result, our findings suggest that the South African main sector indices are not inextricably linked to the performance of the U.S. SP500 stock market. The absence of spillover effects is significant because it offers significant profits from portfolio diversification opportunities to investors during the turbulent period in the United States.

The diagonal elements of matrices A(1,2) and B(1,2) in majority pairs are statistically significant, implying that shocks in the U.S. will have a significant impact on the volatility of the other sectors of emerging markets. Furthermore, we saw increased volatility spillovers from the United States when the SP500 stock market crashed during the 2007–2009 global financial crisis and the COVID-19 pandemic in 2020. As a result, we conclude that South African main sector indices markets were responsive to U.S. shocks during the crisis, demonstrating the importance of the United States as a powerful financial center in the world. In the meantime, the U.S. SP500 stock market is not integrated with the South African main sector indices financial markets in this study, as the South African main sector indices markets may not serve as information transmission channels and thus are unable to influence the U.S. equity market. Nevertheless, the U.S.'s growing influence in the emerging South African main sector and increasing integration in the emerging South African main sector may reduce diversification opportunities in both the U.S. and South African main sector indices.

Our findings have significant practical and policy implications. We notice the increased volatility spillover effects from the United States to the South African main sector indices markets, which are convenient for investors and portfolio managers when designing asset allocation and portfolio optimizations against downside risk. Furthermore, because 'good news' from the United States has a significant impact on the South African main sector indices markets, the increasing trend movement in the U.S. stock market could serve as a significant "buy" signal for foreign investors. Because of the lack of increased integration between the U.S. and South African main sector indices stock markets, both U.S. and South African local and international investors must carefully manage market movement to avoid some systematic risk.

Given the increased dependencies between the U.S. stock index and the South African main sector indices, our evidence suggests that a U.S. stock crash increases the risk exposure and vulnerabilities of financial markets in the emerging markets sector, specifically the South African main sector. With the SP500 stock index crash, it appears that these economies may experience a sudden acceleration of systemic risk due to deteriorations in both capital flow and international trading activities. As a result, market co-movement between these markets appears to be high during times of financial crises. To attain the stability of the financial system, policymakers must devise plans to take deterrent measures in the event of a financial crisis, as well as work to improve market efficiency and long-term stability.

Author Contributions: Conceptualization, J.W.M.M. and B.M.M.; methodology, B.M.M.; software, B.M.M.; validation, J.W.M.M.; formal analysis, B.M.M.; investigation, J.W.M.M. and B.M.M.; resources, B.M.M.; data curation, B.M.M.; writing—original draft preparation, B.M.M.; writing—review and editing, J.W.M.M.; visualization, B.M.M.; supervision, J.W.M.M.; project administration, B.M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The dataset consists of daily closing prices of the market of the U.S. (SP500) index and 8 top sector indices (Basic Materials, Consumer Goods, Consumer Services, Financials, Health care, Industrials, Technology, and Telecommunication) of the firms of South African JSE taken from Thompson Reuter's database. Data are available at: https://eikon.thomsonreuters.com/index.html (accessed on 17 November 2022).

Conflicts of Interest: The authors declare no conflict of interest. The authors certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Appendix A

Table A1. Estimation of BEKK-GARCH model for the entire sample period.

Panel C: Full Sample Period: From 2 January 2004 to 1 April 2022								
Variables	**BMat**	**CoGood**	**CoServ**	**Fin**	**Health**	**Ind**	**Techn**	**Telecom**
μ_1	0.5171 *** (8.4767)	0.5018 *** (13.2713)	0.5016 *** (9.1472)	0.5410 *** (5.7297)	0.5014 *** (13.1775)	0.5020 *** (9.1393)	0.5014 *** (7.2888)	0.5453 *** (5.7449)
μ_2	0.4829 *** (7.0910)	0.4982 *** (7.5995)	0.4983 *** (6.8758)	0.4581 *** (8.7095)	0.4969 *** (16.7989)	0.4980 *** (5.9569)	0.4993 *** (12.7173)	0.4547 *** (8.7703)
C_{11}	0.0577 *** (3.8655)	0.0575 *** (6.1255)	0.0588 *** (6.0480)	0.2886 *** (4.2531)	0.0577 *** (6.5806)	0.0567 *** (6.2478)	0.0573 *** (5.5786)	0.2885 *** (3.7543)
C_{21}	0.0470 *** (3.6360)	0.0740 ** (2.9058)	0.0116 (0.2583)	−0.0140 (−0.0752)	0.0024 (0.0966)	0.1976 ** (2.70245	0.0665 ** (2.2769)	−0.0025 (−0.1986)
C_{22}	0.0634 *** (4.8764)	0.1601 *** (4.0653)	0.2388 *** (10.6594)	0.2886 *** (6.1343)	0.0913 *** (6.1232)	0.1600 *** (3.9056)	0.0589 *** (4.0054)	0.2889 *** (6.3421)
A_{11}	0.2691 *** (6.1408)	0.3100 *** (11.1622)	0.2814 *** (9.7069)	0.1380 *** (6.1353)	0.3033 *** (12.1798)	0.3040 *** (10.4696)	0.2388 *** (10.6593)	0.1653 *** (6.1343)
A_{21}	−0.1537 *** (−4.0988)	−0.0336 *** (−3.7021)	0.0892 (1.3661)	0.0210 (1.1268)	0.1620 *** (7.6233)	0.3199 *** (8.3996)	0.0441 (1.3823)	0.0283 (1.1276)
A_{12}	0.0293 (1.0597)	−0.0031 (−0.1253)	−0.0333 (−1.5007)	0.0280 (1.2058)	−0.0487 ** (−2.7447)	−0.0292 (−1.0676)	−0.0343 *** (−3.4851)	0.0232 (1.2073)
A_{22}	0.1722 *** (5.2701)	0.1808 *** (4.4175)	0.2001 *** (5.1174)	0.1204 *** (5.8111)	0.0707 *** (3.9478)	0.1591 *** (3.4097)	0.2446 *** (4.6633)	0.1732 *** (5.8222)
B_{11}	0.9380 *** (6.6866)	0.9304 *** (6.4136)	0.9381 *** (6.0332)	0.9180 *** (7.2464)	0.9299 *** (11.2845)	0.9313 *** (6.4266)	0.9496 *** (9.0599)	0.9201 *** (7.2972)
B_{21}	0.1301 *** (7.9254)	0.0257 *** (8.6420)	−0.0251 (−0.6846)	0.0510 *** (5.7373)	−0.0682 *** (−8.1398)	0.0824 *** (7.0942)	−0.0061 (−0.3676)	0.0510 *** (5.6796)
B_{12}	−0.0917 *** (−2.6298)	−0.0222 (−0.6204)	0.0148 * (2.0586)	0.0105 ** (3.2150)	0.0211 * (2.0281)	−0.0173 *** (−4.3992)	0.0621 *** (4.0401)	0.0182 ** (3.2170)
B_{22}	0.9379 *** (9.1044)	0.8095 *** (5.2189)	0.8797 *** (3.4097)	0.9134 *** (12.4400)	0.9314 *** (4.9865)	0.8149 *** (9.3215)	0.9470 *** (6.7654)	0.9308 *** (8.9483)

Notes: 1 and 2 denote the SP500 Index and the main South African sectors of the JSE all-share index; Figures in parentheses indicate the t-statistics; *, **, and *** indicate the statistically significant level at 10%, 5%, and 1%, respectively.

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