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COVID-19 crisis and risk spillovers to developing economies: Evidence from Africa

Md Akhtaruzzaman[1] | Ramzi Benkraiem[2] | Sabri Boubaker[3,4] | Constantin Zopounidis[2,5]

[1]FinArchitect Australia Pte Ltd, Sydney, Australia

[2]Audencia Business School, Nantes, France

[3]EM Normandie Business School, Métis Lab, Paris, France

[4]International School, Vietnam National University, Hanoi, Vietnam

[5]Financial Engineering Laboratory, Technical University of Crete, Chania, Greece

Correspondence
Ramzi Benkraiem· Audencia Business School, 8 Route de la Jonelière, 44312 Nantes, France.
Email: rbenkraiem@audencia.com

Abstract

This study provides new evidence on how risk spillovers occur from the United States to developing economies in Africa during the COVID-19 pandemic. The results show that downside risk exposures of African markets, financial firms and banks particularly increased during Phase I (30 January to 30 April 2020). The nature and magnitude of downside risk exposures of African financial markets were similar to those of the United States. Our results also reveal that the United States is a net transmitter of risk spillovers while Nigeria, South Africa, Egypt and Morocco are net recipients. Our conclusions offer guidance to risk managers, policymakers and investors.

KEYWORDS

Africa, COVID-19, developing economies, risk spillovers, spectral risk measure, value at risk

1 | INTRODUCTION

The COVID-19 pandemic spread quickly worldwide, recording more than 118 million confirmed cases and more than 2.62 million deaths (WHO, 2021). Economies across the globe have suffered severe economic and financial consequences of the pandemic. Global financial markets, in particular, developed markets, plummeted in March 2020 (World Economic Forum, 2020). However, economic uncertainties continue amidst the introduction, roll-out, and efficacy of the COVID-19 vaccine. Due to the pandemic, the world economy is expected to have negative growth of 4.4% in 2020 (IMF, 2020). Developing economies were hard-hit by the pandemic and are projected to have negative growth of 5.6% in 2020 (The UN, 2021). Governments across the world adopted unprecedented monetary and fiscal stimulus packages to boost pandemic-inflicted economies. The UN estimated the global fiscal response of USD 12.7 trillion, amounting to 15.8% of the world GDP in 2020 (The UN, 2021). African economies are not immune to the pandemic. They are expected to register a negative growth of 3.4% in 2020 (The UN, 2021). Nigeria and

South Africa, the two largest economies in Africa, are expected to have negative growth of 4.3% and 8.0%, respectively, in 2020 (IMF, 2020).

Literature shows that financial risk spillovers occur through financial linkages (Damijan et al., 2013; Fan et al., 2020; Kaminsky & Reinhart, 2000; Kodres & Pritsker, 2002), trade linkages (Ali & Imai, 2015; Barrot et al., 2018; Fontaine et al., 2018; Glick & Rose, 1999; Goldstein, 2001; Haile & Pozo, 2008), investors behaviours (Bikhchandani et al., 1992; Broner et al., 2006; Calvo & Mendoza, 2000) and regional effects (Bucci et al., 2019; De Gregorio & Valdés, 2001; Thang et al., 2016). There are extensive studies regarding the COVID-19 pandemic effects on developed and developing economies (Akhtaruzzaman, Boubaker, & Sensoy, 2021; Banerjee, 2021; Bottan et al., 2021; Guo et al., 2021; Janssens et al., 2021; Kansiime et al., 2021; Narayan et al., 2020). There is literature on the risk spillovers to African markets during the global financial and European debt crises (Atenga & Mougoué, 2020; Belcaid & El Ghini, 2019; Fosu, 2013; Gurara & Ncube, 2013; Sugimoto et al., 2014). However, there is a paucity in the literature on how risk spillovers occur from developed to developing African economies during the pandemic. Our study fills the literature void by examining the risk spillovers from the United States to the four largest African developing economies, namely, Nigeria, South Africa, Egypt and Morocco, during the pandemic.[1]

Examining Africa's pandemic effect is critical since Africa has a disproportionate burden of disease and poverty (Ataguba, 2020). Adam et al. (2020) argue that early and stringent lockdowns disrupted Africa's domestic economic activities, and second-wave lockdowns will dramatically increase economic shocks. Bisong et al. (2020) argue that the remittance flows to African countries will be reduced due to the host countries' lockdown measures. Given the literature gap, we attempt to examine how the four of the five largest African developing economies—Nigeria, South Africa, Egypt and Morocco—were affected by the pandemic compared to the US market.[2]

Our study has several contributions to the literature. First, it examines the financial risk spillovers to the developing African economies at the aggregate market and sectorial levels: financial firms and banks. Analysing the spillovers at aggregate and sectorial levels helps investors and policymakers devise appropriate strategies for safeguarding financial portfolios. Second, we use downside risk measures of African financial markets and compared those with the United States. We have included both Value at Risk (VaR) and Conditional VaR (CVaR). We have supplemented the downside risk analysis using the historical (back simulation), which overcomes the normality assumption problem of the RiskMetrics approach.[3] We have also used the spectral risk measure to overcome the problem of incoherence in the downside risk measure (see Acerbi, 2002, 2004). Third, our study contributes to the literature on the increased integration of the African economies to the global financial markets and their higher exposition to financial shocks during the crisis. For instance, Giovannetti and Velucchi (2013) find that African economies had been severely hit by the global financial crisis in 2008–2009, despite the claim that Africa is not integrated into the globalization process and, hence, it is not expected to be exposed to global shocks.

Our study makes several interesting findings. First, the downside risk exposures of African markets, financial firms and banks increased significantly during Phase I (30 January to 30 April 2020) of the pandemic compared to the pre-COVID-19 (2 January 2017 to 29 January 2020) and Phase 2 (1 May to 30 October 2020) of the COVID-19 period. The nature and magnitude of downside risk exposures of African financial markets appear similar to those of the US market. This result implies that African financial markets are equally affected by the pandemic. Second, we provide evidence that the United States is the net transmitter of risk spillovers while Nigeria, South Africa, Egypt, and Morocco are net recipients during the pandemic. Third, our results show that the dynamic conditional correlations (DCCs) between the US and South African markets, financial firms and banks increased during Phase I, which echoes Diebold and Yilmaz's (2012) spillover model. Similarly, DCCs between the US and Nigerian financial firms and

[1]The United Nations has classified Nigeria, South Africa, Egypt, and Morocco as developing economies (see The UN, 2021).

[2]The five largest economies in Africa are Nigeria, South Africa, Egypt, Morocco and Algeria. Due to the unavailability of required data, we have not included Algeria in our study.

[3]JP Morgan first introduced the RiskMetrics model to measure VaR in 1994.

banks increased during Phase I. Higher DCCs between the United States and South Africa (Nigeria) provide evidence that spillovers occurred between the United States and the African two largest economies.

The rest of the paper proceeds as follows. Section 2 presents our empirical design. Section 3 presents the literature review on risk spillover measures. Section 4 provides data and the empirical results. Section 5 checks robustness. Section 6 concludes.

2 | LITERATURE REVIEW

Literature has evolved to analyse international spillovers, although the focus was primarily on the equity markets in the early 1990s. For example, Hamao et al. (1990), King et al. (1994) and Lin et al. (1994) find return and volatility spillovers from the United States to the Japanese and UK equity markets. Bekaert et al. (2009) find return spillovers across 23 developed equity markets. Diebold and Yilmaz (2009) introduce a spillover index based on forecast error variance decompositions from vector autoregression (VAR) models to measure the spillovers or connectedness of asset returns and/or volatilities for 19 global equity markets. Diebold and Yilmaz (2009) find evidence of divergent behaviour in return and volatility spillovers dynamics. In particular, they show that return spillovers appear to be increasing over time with a burst. However, the volatility spillovers do not have any trend but with significant bursts. Following Diebold and Yilmaz's (2009) seminal work, literature on the spillover measure significantly evolved (McMillan & Speight, 2010; Zhou et al., 2012). However, Diebold and Yilmaz's (2009) spillover index model depends on the Cholesky-factor identification of VAR, and thus, the resulting forecast error variance decompositions can be influenced by order of variables. Also, Diebold and Yilmaz's (2009) model measures only the total spillovers and does not examine the directional spillovers from/to a particular market. Diebold and Yilmaz (2012) propose the spillover index model based on the generalized VAR framework that removes the order of the variables that could influence return and volatility spillover results. Extensive literature applies Diebold and Yilmaz's (2012) model to measure the total and directional spillovers among equity markets as well as among different asset classes (Akhtaruzzaman, Boubaker, Lucey, & Sensoy, 2021; Akhtaruzzaman, Abdel-Qader, et al., 2021).[4] We apply the Diebold and Yilmaz (2012) model to examine spillovers across the United States and developing African economies: South Africa, Nigeria, Egypt and Morocco.

3 | EMPIRICAL MODEL

To investigate how risk spillovers occur from the United States to developing African economies, we apply state-of-the-art methodologies. First, we apply Value at Risk (VaR) and Conditional VaR (CVaR) to measure downside risk exposure of market indices, financial firms, and banks in African developing economies compared to their US counterparts during the pandemic. Second, we apply the asymmetric DCC (ADCC) model of Cappiello et al. (2006) built on the DCC-GARCH model of Engle (2002) to assess how the risk spillovers are transmitted from the US to African developing economies during the COVID-19 pandemic. Finally, we apply Diebold and Yilmaz's (2012) spillover index model to examine the source of risk spillovers during the pandemic.

3.1 | VaR and CVaR

The VaR measures the downside risk of a portfolio. A two-moment VaR is calculated as[5]

[4]Recent literature has extended Diebold and Yilmaz's (2012) spillover index model to the time-varying parameter Vector Autoregressive model (TVP–VAR) to measure spillovers (for details, see Akhtaruzzaman, Boubaker, & Umar, 2021; Bouri et al., 2021)

[5]We have followed Hong et al. (2009) for the specification of the VaR equation.

$$VaR_{p(\alpha)} = -\mu_p + z_\alpha \sigma_p \tag{1}$$

where μ_p and σ_p are the mean and standard deviation of the daily returns of the portfolio p, respectively. z_α is the α quantile of the standard normal distribution. VaR in Equation 1 assumes the normal distribution of returns. However, during the crisis periods, return distribution is most likely non-normally distributed. To overcome the assumption underlying the VaR measure in the RiskMetrics model (JP Morgan, 1995), we use the historical (back simulation) approach that does not assume an a priori distribution of returns. Our empirical results also demonstrate that our return series are generally not distributed.

Although VaR is now a standard risk measure for downside risk, it has several problems (Yamai & Yoshiba, 2005). For instance, it does not consider any loss beyond the VaR level known as 'Tail risk.' VaR is also a subadditive method, which concerns the situation when the total risk of a portfolio should not be higher than the sum of each portfolio's risk element (Artzner et al., 1999). Conditional Value at Risk (CVaR) (also known as an expected shortfall) overcomes these problems. CVaR, a loss expectation if the loss is larger than the VaR level, is calculated as follows:

$$[CVaR]_p = E\left(r_p | r_p > VaR_{p(\alpha)}\right) \tag{2}$$

where $[CVaR]_p$ is an average of returns exceeding the VaR level at the α quantile.

3.2 | DCCs

Building on the DCC–GARCH model of Engle (2002), prior studies (Alexakis & Pappas, 2018; Kenourgios et al., 2011; Kocaarslan et al., 2017; Kocaarslan et al., 2018; Zhang, 2017) apply the Asymmetric DCC model of Cappiello et al. (2006) to account for the non-linearities and asymmetries in return distribution. Engle (2002) applies a two-step estimation process to compute the dynamic conditional correlation (DCC). First, the univariate GARCH model is estimated. Second, DCC is estimated through a variance–covariance matrix.

Let r_t be an $n \times 1$ vector of assets returns with covariance matrix H_t:

$$r_t | \Omega_{t-1} \tilde{N}(0, H_t) \tag{3}$$

where $\Omega_{i,t-1}$ is the information set at $t-1$.

$$H_t \equiv D_t R_t D_t \tag{4}$$

where $D_t = diag\left(h_{11,t}^{1/2} ....h_{nn,t}^{1/2}\right)$ is an $(n \times n)$ diagonal matrix. $\sqrt{h_{ii,t}}$ is the ith diagonal with $i = 1, 2, 3 ....n$.

R_t is an $(n \times n)$ correlation matrix as below:

$$R_t \equiv Q_t^{*-1} Q_t \, Q_t^{*-1} \tag{5}$$

Equation 5 presents the correlation matrix with $Q_t = (q_{ij,t})$ as the conditional variance–covariance matrix of the standardized residuals, and $Q_t^* = \left(q_{ii,t}^*\right) = \sqrt{q_{ii,t}}$ as a diagonal matrix. Q_t is expressed as

$$Q_t = (1 - a - b)\overline{Q} + a(u_{t-1} u_{t-1}^{\prime}) + bQ_{t-1} \tag{6}$$

where $\overline{Q}$ is the unconditional variance matrix of standardized residuals, $u_{i,t}$ and a and b are nonnegative scalars with $(a+b) < 1$.

A typical element of R_t is of the form:

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}} i,j = 1,2,\ldots n,\ and\, i \neq j \tag{7}$$

In Equation 7, $\rho_{ii,t}$ represents the time-varying conditional correlations between the US and African markets, financial and bank stock returns. $q_{ii,t}$ and $q_{jj,t}$ are the conditional variance of the US and African markets, financial and bank stock returns, respectively.

Cappiello et al. (2006) introduce an Asymmetric DCC model by combining the DCC model (Engle, 2002) and asymmetric GARCH model (Glosten et al., 1993) as below:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma I[\varepsilon_{t-1} < 0] \varepsilon_{t-1}^2 \tag{8}$$

In Equation 8, the indicator function $I[\varepsilon_{t-1} < 0]$ equals one if ε_{t-1}<0 and zero otherwise.

The DCC model of Engle (2002) does not allow for asset-specific news and asymmetries. Cappiello et al. (2006) modify the correlation equation described by Equation 6 to be

$$Q_t = \left(\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{N}G\right) + A'u_{t-1}u_{t-1}'A + G'n_{t-1}n_{t-1}'G + B'Q_{t-1}B \tag{9}$$

where A, B and G are $k \times k$ parameter matrices, $n_t = I[u_t < 0] \text{o}\, u_t$ ($I[u_t < 0]$ is a $k \times 1$ indicator function that takes the value of one if $u_t < 0$ and zero otherwise, 'o' indicates the Hadamard product, and $\overline{N} = E\left[n_t n_t'\right]$).

Equation 9 is an asymmetric generalized DCC (AG-DCC) model. The ADCC model is obtained as a particular case of the AG-DCC model if the matrices A, B, and G are replaced by scalars. Cappiello et al. (2006) propose the scalar ADCC as

$$Q_t = \left(\overline{Q} - a^2\overline{Q} - b^2\overline{Q} - g^2\overline{N}\right) + a^2 u_{t-1}u_{t-1}' + g^2 n_{t-1}n_{t-1}' + b^2 Q_{t-1} \tag{10}$$

A sufficient condition for Q_t to be positive definite is that the matrix in the parentheses is positive semi-definite, and a necessary and sufficient condition for this to hold is $a^2 + b^2 + \delta g^2$ where $\delta = maximum\ eigenvalue \left[\overline{Q}^{-1/2}\overline{N}\overline{Q}^{-1/2}\right]$.

3.3 | Directional spillover model

We apply the Diebold and Yilmaz (2012) model to examine spillovers across the United States and developing African economies: South Africa, Nigeria, Egypt, and Morocco. The Diebold and Yilmaz (2012) model applies a generalized vector autoregression (VAR) framework instead of using Cholesky factor orthogonalization to measure spillover (see Diebold & Yilmaz, 2009).

Assume an N-variable VAR(p), $y_t = \sum_{i=1}^{p} \varphi_{y_{t-i}} + \varepsilon_t$, where $\varepsilon(0,\tilde{\Sigma})$ is a vector of i.i.d. residuals.

$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ is a moving average with A_i, an $N \times N$ matrix A_i in a recursive pattern:

$A_i = \omega_1 A_{i-1} + \omega_2 A_{i-2} + \ldots + \omega_p A_{i-p}$ with $A_{i-p} = 0$ for $i < 0$.

The H-step-ahead Forecast Error Variance Decompositions (FEVD) are calculated as below:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\left(e_i' A_h \sum e_j \right) \right)^2}{\sum_{h=0}^{H-1} \left(\left(e_i' A_h \sum A_h' e_i \right) \right)^2} \tag{11}$$

where σ_{jj} is the standard deviation of error terms and e_i is a selection vector, with one as the i^{th} element, and 0 otherwise. $\sum_{j=1}^{N}\theta_{ij}^{g}(H) \neq 1$. Each element is normalized by the row sum.

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{12}$$

with $\sum_{j=1}^{N}\theta_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H) = N$.

The spillover index is calculated from Equation 13 as

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H)}\cdot 100 = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\widetilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{13}$$

Directional spillover to market i from all other markets j is measured in Equation 14

$$S_{i\cdot}^{g} = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H)}\cdot 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\widetilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{14}$$

Directional spillover from market i to all other markets j is calculated in Equation 15

$$S_{\cdot i}^{g} = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ji}^{g}(H)}\cdot 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\widetilde{\theta}_{ji}^{g}(H)}{N}\cdot 100 \tag{15}$$

Net spillover from market i to all markets j is estimated in Equation 16.

$$S_{i}^{g} = S_{\cdot i}^{g} - S_{i\cdot}^{g} \tag{16}$$

4 | DATA AND EMPIRICAL RESULTS

4.1 | Data and descriptive statistics

Our sample period covers both the pre-COVID-19 period (2 January 2017 to 29 January 2020) and COVID-19 period (30 January to 30 October 2020). The COVID-19 period started on 30 January 2020, when the WHO declared a public health emergency of international concern over a novel coronavirus outbreak.[6] We have taken 2 January 2017, as the start of the period to not overlap with other financial crises.

Data on market indices, financial firms, and banks are from DataStream. We include major developing economies in Africa, namely Egypt, Morocco, Nigeria and South Africa (The UN, 2021). Together, these countries contributed to

[6]See https://www.who.int/director-general/speeches/detail/who-director-general-s-statement-on-ihr-emergency-committee-on-novel-coronavirus-(2019-ncov)

TABLE 1 Descriptive statistics

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations	Q (10)	ADF
Panel A: Total period (2 January 2017 to 30 October 2020)											
US market	0.0004	0.0005	0.0895	−0.1291	0.0128	−1.3167	25.63	21630***	1000	313***	−8.9***
US financial firms	0.0001	0.0002	0.1174	−0.1428	0.0156	−1.0547	24.24	18984***	1000	279***	−10.5***
US banks	−0.0001	0.0001	0.1280	−0.1593	0.0198	−0.6693	16.64	7830***	1000	171***	−9.0***
South Africa market	0.0001	0.0001	0.0656	−0.0989	0.0133	−1.0111	12.90	4252***	1000	30.3***	−36.6***
South Africa financial firms	−0.0002	0.0002	0.0825	−0.1455	0.0178	−0.8071	12.70	4028***	1000	15.0	−32.0***
South Africa banks	−0.0001	0.0002	0.0949	−0.1720	0.0208	−0.6497	11.92	3383***	1000	14.0	−32.0***
Egypt market	0.0001	0.0002	0.0419	−0.0731	0.0100	−1.3143	10.67	2740***	1000	64.9***	−24.8***
Egypt financial firms	0.0000	0.0001	0.0405	−0.0721	0.0103	−0.9023	8.99	1633***	1000	56.5***	−25.2***
Egypt banks	0.0001	0.0001	0.0389	−0.0681	0.0102	−0.6555	8.39	1284***	1000	45.3***	26.0***
Nigeria market	0.0001	0.0001	0.0508	−0.0522	0.0108	0.2934	7.19	745***	1000	37.1***	−27.5***
Nigeria financial firms	0.0007	0.0003	0.0683	−0.1202	0.0154	−0.7175	11.57	3144***	1000	120.6***	−24.6***
Nigeria banks	0.0007	0.0002	0.0705	−0.1251	0.0159	−0.7377	11.77	3298***	1000	120.7***	−24.7***
Morocco market	0.0001	0.0002	0.0458	−0.0853	0.0078	−1.7864	25.88	22343***	1000	65.4***	−26.4***
Morocco financial firms	−0.0001	0.0001	0.0590	−0.0997	0.0087	−2.0596	30.56	32355***	1000	39.2***	−19.0***
Morocco banks	−0.0001	0.0001	0.0652	−0.1018	0.0094	−1.7824	26.81	24148***	1000	32.1***	−19.5***
Panel B: Pre-COVID−19 period 1 (2 January 2017 to 29 January 2020).											
US market	0.0005	0.0005	0.0475	−0.0401	0.0077	−0.6946	8.59	1109***	803	24.1***	−28.0***
US financial firms	0.0005	0.0005	0.0451	−0.0449	0.0084	−0.7177	7.42	722***	803	20.8**	−28.6***
US banks	0.0003	0.0001	0.0462	−0.0561	0.0116	−0.4563	5.46	230***	803	10.4	−28.1***
South Africa market	0.0002	0.0001	0.0422	−0.0412	0.0101	−0.1048	4.41	68***	803	15.1	−29.2***
South Africa financial firms	0.0001	0.0002	0.0581	−0.0464	0.0124	0.0958	4.32	59***	803	12.0	−28.7***
South Africa banks	0.0003	0.0002	0.0762	−0.0629	0.0150	0.1017	4.40	67***	803	11.4	−29.2***
Egypt market	0.0003	0.0001	0.0301	−0.0496	0.0086	−0.7593	6.23	425***	803	42.0***	−23.3***
Egypt financial firms	0.0003	0.0001	0.0297	−0.0419	0.0091	−0.3160	4.51	90***	803	33.8***	−23.6***
Egypt banks	0.0006	0.0001	0.0339	−0.0407	0.0091	−0.0472	4.59	84***	803	28.2***	−24.1***

TABLE 1 (Continued)

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations	Q (10)	ADF
Nigeria market	0.0000	0.0000	0.0455	−0.0485	0.0104	0.3760	6.26	375***	803	12.1	−25.9***
Nigeria financial firms	0.0007	0.0002	0.0629	−0.0430	0.0125	0.4999	5.72	281***	803	66.4***	−21.7***
Nigeria banks	0.0007	0.0002	0.0648	−0.0444	0.0128	0.5025	5.70	278***	803	61.6***	−21.9***
Morocco market	0.0003	0.0002	0.0255	−0.0255	0.0059	0.1353	5.64	235***	803	31.6***	−24.6***
Morocco financial firms	0.0001	0.0001	0.0332	−0.0298	0.0062	0.0732	6.15	333***	803	24.1***	−27.3***
Morocco banks	0.0002	0.0001	0.0288	−0.0313	0.0068	0.0949	5.60	227***	803	20.0**	−28.1***
Panel C: COVID–19 period (Phase 1: 30 January to 30 April 2020)											
US market	−0.0018	0.0001	0.0895	−0.1291	0.0380	−0.4472	4.7150	10.29***	66	59.1***	−12.3***
US financial firms	−0.0041	0.0000	0.1174	−0.1428	0.0465	−0.2384	4.2606	5.00*	66	47.1***	−11.5***
US banks	−0.0053	−0.0003	0.1280	−0.1593	0.0540	−0.1541	3.9250	2.61	66	39.7***	−10.7***
South Africa market	−0.0022	0.0002	0.0656	−0.0989	0.0334	−0.7790	4.1883	10.56***	66	11.8	−8.5***
South Africa financial firms	−0.0051	−0.0013	0.0744	−0.1455	0.0431	−0.7478	4.3080	10.86***	66	12.1	−8.6***
South Africa banks	−0.0063	0.0003	0.0949	−0.1720	0.0483	−0.6905	4.6927	13.12***	66	10.9	−8.4***
Egypt market	−0.0033	−0.0002	0.0419	−0.0731	0.0208	−1.1710	5.4462	31.54***	66	13.2	−5.5***
Egypt financial firms	−0.0040	−0.0009	0.0337	−0.0721	0.0199	−1.1230	5.6359	32.98***	66	11.5	−5.7***
Egypt banks	−0.0041	−0.0020	0.0355	−0.0681	0.0190	−0.9719	5.5988	28.96***	66	10.3	−5.9***
Nigeria market	−0.0035	−0.0015	0.0401	−0.0522	0.0159	−0.4828	4.4454	8.31*	66	17.7*	−5.8***
Nigeria financial firms	−0.0046	0.0005	0.0643	−0.1202	0.0354	−0.9679	4.1531	13.96***	66	29.2***	−6.2***
Nigeria banks	−0.0047	0.0005	0.0673	−0.1251	0.0368	−0.9665	4.1522	13.93***	66	29.4***	−6.2***
Morocco market	−0.0037	−0.0037	0.0458	−0.0853	0.0205	−1.1067	6.9239	55.81***	66	9.8	−6.6***
Morocco financial firms	−0.0047	−0.0022	0.0590	−0.0997	0.0232	−1.2264	7.7025	77.36***	66	9.6	−7.0***
Morocco banks	−0.0048	−0.0019	0.0652	−0.1018	0.0246	−1.0963	7.2382	62.62***	66	9.3	−7.2***

(Continues)

TABLE 1 (Continued)

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations	Q (10)	ADF
Panel D: COVID–19 period (Phase 2: 1 May to 30 October 2020).											
US market	0.0011	0.0036	0.0320	−0.0605	0.0133	−1.2460	6.1868	89***	131	17.7*	−12.9***
US financial firms	0.0004	0.0001	0.0517	−0.0824	0.0185	−0.4854	5.5403	40***	131	21.4**	−11.5***
US banks	−0.0001	0.0002	0.0738	−0.0960	0.0267	−0.0908	4.1455	7**	131	17.1*	−11.2***
South Africa market	0.0005	0.0005	0.0361	−0.0373	0.0132	0.0570	3.4229	1	131	10.7	−10.8***
South Africa financial firms	−0.0001	0.0002	0.0825	−0.0512	0.0233	0.4795	3.7050	8**	131	11.3	−10.6***
South Africa banks	0.0004	0.0002	0.0945	−0.0572	0.0275	0.4945	3.6144	7**	131	10.0	−10.8***
Egypt market	0.0003	0.0002	0.0319	−0.0319	0.0096	−0.2214	4.6012	15***	131	6.9	−9.9***
Egypt financial firms	−0.0001	0.0001	0.0405	−0.0414	0.0098	0.2007	6.8096	80***	131	9.6	−9.8***
Egypt banks	−0.0003	−0.0002	0.0389	−0.0470	0.0100	−0.0470	7.5604	114***	131	10.1	−10.2***
Nigeria market	0.0021	0.0009	0.0508	−0.0217	0.0098	2.2569	13.4285	705***	131	5.2	−9.8***
Nigeria financial firms	0.0029	0.0004	0.0683	−0.0369	0.0146	1.1596	6.9890	116***	131	7.5	−10.4***
Nigeria banks	0.0031	0.0004	0.0705	−0.0389	0.0152	1.1358	6.9878	115***	131	7.5	−10.4***
Morocco market	0.0011	0.0002	0.0319	−0.0182	0.0063	0.7573	6.9250	97***	131	17.6*	−9.7***
Morocco financial firms	0.0007	0.0002	0.0374	−0.0250	0.0082	0.7218	6.8077	91***	131	12.1	−9.7***
Morocco banks	0.0007	0.0001	0.0392	−0.0280	0.0090	0.5980	6.2484	65***	131	11.9	−9.7***

Note: The Jarque–Bera test is used to check whether the return distribution is normal. The Box–Pierce–Ljung statistic, Q (10) statistic is distributed as χ^2 with 10 degrees of freedom. The augmented Dickey–Fuller (ADF) is used to check the unit root of the return series.

*Significance at the 10% level.

**Significance at the 5% level.

***Significance at the 1% level.

50.26% of the African GDP in 2019 (African Development Bank Group, 2021). We choose the United States as a source of risk spillovers given that it is the largest economy in the world and the most affected country by the COVID-19 pandemic. We use local currency-denominated return series to calculate daily returns.[7] Daily returns were computed from the return index: $r_t = ln(RI_t/RI_{t-1})$, where r_t is return and RI_t is the return index obtained from DataStream.

Table 1 presents the descriptive statistics for the daily stock returns for equity indices, financial firms, and banks from 2 January 2017 to 30 October 2020. Panel B provides the descriptive statistics of the pre-COVID-19 period while Panels C and D present those of Phase I and Phase 2, respectively.

During Phase I, all returns across markets were negative, with South African banks presented the highest negative return, followed by US banks. These statistics indicate that not only the US market was affected by the pandemic, but also African markets were affected. Similarly, US banks' volatility appears to be the highest during Phase 2, followed by South African banks. Most indices exhibit positive returns during Phase 2 of the pandemic except US banks, South African and Egyptian financial firms, and Egyptian banks. It is evident that the volatility is the highest during Phase I of the pandemic for African markets and the US market (see Figures SA1 and SA2). This provides evidence that African markets were not immune to the pandemic.

The skewness of portfolio returns deviates from zero, and the kurtosis is over 4 in all cases, indicating a non-normal distribution of returns. The Jarque–Bera test also indicates that the return series do not follow a normal distribution. The augmented Dickey-Fuller and Phillips–Perron tests reject the unit root hypothesis for all return series. The Box–Pierce–Ljung portmanteau test provides evidence of autocorrelation in returns. The presence of autocorrelation is consistent with Jegadeesh (1990).

4.2 | Empirical results

4.2.1 | Downside risk

Table 2 presents the downside risk exposure of the US, Egypt, Morocco, Nigeria and South Africa markets, financial firms, and banks. Our primary variable of interest is how African markets perform during Phase I of the COVID-19 pandemic compared to the US. Panel C results show that the downside risk exposures of African markets, financial firms, and banks increased significantly during Phase I compared to other phases in our study. More interestingly, the United States has the highest downside risk exposure during Phase I. Another interesting observation is that the magnitude of downside risk exposures using the Historic (Back Simulation) approach is much higher than that of the RiskMetrics (Variance–Covariance) approach. This happens because returns were not normally distributed and had tail risks during Phase I of the pandemic.[8] For example, South African banks could lose 8.97% or more of their equity value in Phase 1 compared to 3.47% or more during the pre-COVID-19 period using the Variance–Covariance approach at the 1% confidence level. However, this measure for South African banks jumped to 14.34% using the historical approach, which supports the presence of tail risks during Phase 1.

To check the robustness of the downside risk exposure, we present the results from the CVaR approach. Previous literature shows that CVaR is a better downside risk measure than a fixed-level quantile of VaR (Meng & Taylor, 2020; Taylor, 2019, 2020; Zoia et al., 2018). Results from CVaR demonstrate that the downside risk exposures of equity indices increased significantly notably in the period of our interest (e.g., Phase I). Another interesting finding is that the nature and magnitude of downside risk exposure of African markets, financial firms, and banks are similar to those of the United States. This result again reinforces our conclusion that African financial markets were

[7]Mink (2015) favours the use of domestic currency returns than USD returns. Literature (Akhtaruzzaman et al., 2021; Forbes & Rigobon, 2002) shows similar results for financial contagion using domestic currency or USD returns.

[8]The descriptive statistics show that returns are not normally distributed.

TABLE 2 Downside risk

	RiskMetrics (Variance–Covariance) Approach				Historic (Back Simulation) Approach			
	VaR (5%)	VaR (1%)	CVaR (5%)	CVaR (1%)	VaR (5%)	VaR (1%)	CVaR (5%)	CVaR (1%)
Panel A: Total period (2 January 2017 to 30 October 2020)								
US market	2.07	2.94	3.67	4.68	1.78	3.70	3.39	6.52
US financial firms	2.55	3.61	4.59	6.31	2.16	4.40	4.05	8.16
US banks	3.27	4.62	5.34	7.41	2.90	6.05	5.11	9.42
South Africa market	2.18	3.09	3.59	5.20	2.00	3.73	3.29	6.34
South Africa financial firms	2.95	4.16	5.13	6.93	2.60	4.66	4.24	8.14
South Africa banks	3.44	4.86	5.67	7.96	3.00	5.22	4.88	9.09
Egypt market	1.64	2.33	2.72	3.85	1.54	3.28	2.63	4.84
Egypt financial firms	1.69	2.39	2.31	3.92	1.51	3.24	2.56	4.53
Egypt banks	1.67	2.37	2.72	4.04	1.47	2.82	2.41	4.45
Nigeria market	1.77	2.51	2.60	3.41	1.70	3.05	2.53	3.89
Nigeria financial firms	2.46	3.51	4.04	5.95	2.25	4.09	3.67	7.03
Nigeria banks	2.54	3.62	4.15	6.35	2.30	4.19	3.78	7.29
Morocco market	1.27	1.80	2.45	3.40	0.93	2.19	1.86	3.94
Morocco financial firms	1.45	2.04	2.74	3.80	1.05	2.52	2.12	4.71
Morocco banks	1.55	2.19	3.19	3.85	1.17	2.80	2.26	5.53
Panel B: Pre-COVID–19 period 1 (2 January 2017 to 29 January 2020).								
US market	1.21	1.74	2.01	2.45	1.30	2.52	2.12	3.13
US financial firms	1.33	1.91	2.14	2.71	1.44	2.67	2.00	3.37
US banks	1.87	2.66	2.93	3.73	1.85	3.74	2.54	4.30
South Africa market	1.63	2.32	2.27	2.76	1.66	2.65	2.32	3.10
South Africa financial firms	2.02	2.87	2.61	2.89	2.10	2.89	3.48	3.40
South Africa banks	2.44	3.47	3.08	n/a	2.51	3.44	4.50	4.25
Egypt market	1.39	1.98	1.90	2.03	1.34	2.58	2.21	3.50
Egypt financial firms	1.46	2.08	1.69	n/a	1.42	2.39	2.26	3.40
Egypt banks	1.44	2.06	1.72	n/a	1.35	2.10	1.87	3.47
Nigeria market	1.71	2.41	2.83	3.74	1.64	2.74	n/a	3.42
Nigeria financial firms	1.98	2.83	2.84	n/a	1.97	3.11	2.51	3.60
Nigeria banks	2.03	2.90	2.92	n/a	1.97	3.07	2.19	3.68
Morocco market	0.93	1.33	2.07	0.57	0.86	1.59	1.37	1.93
Morocco financial firms	1.01	1.43	2.11	2.98	0.94	1.60	1.49	2.13
Morocco banks	1.10	1.56	1.63	3.12	0.96	1.64	1.59	2.32

TABLE 2 (Continued)

	RiskMetrics (Variance–Covariance) Approach				Historic (Back Simulation) Approach			
	VaR (5%)	VaR (1%)	CVaR (5%)	CVaR (1%)	VaR (5%)	VaR (1%)	CVaR (5%)	CVaR (1%)
Panel C: COVID–19 period (Phase 1: 30 January to 30 April 2020)								
US market	4.19	5.86	6.90	10.38	5.55	11.09	9.21	12.91
US financial firms	5.47	7.57	9.16	11.50	8.57	12.41	11.49	14.28
US banks	6.79	9.38	10.89	13.97	8.37	15.23	12.65	15.93
South Africa market	3.85	5.35	6.59	7.34	6.46	9.49	8.73	9.89
South Africa financial firms	5.67	7.81	9.53	11.42	9.55	12.23	11.42	14.55
South Africa banks	6.53	8.97	11.31	12.23	9.61	14.34	12.52	17.20
Egypt market	2.70	3.68	4.93	5.35	4.90	6.81	6.20	7.31
Egypt financial firms	2.72	3.68	4.59	5.39	3.96	6.96	5.85	7.21
Egypt banks	2.67	3.61	4.33	5.07	3.54	6.73	5.50	6.81
Nigeria market	2.39	3.24	3.61	4.34	3.20	4.55	4.18	5.21
Nigeria financial firms	4.38	6.01	7.72	8.04	7.15	10.29	9.28	12.02
Nigeria banks	4.55	6.24	8.01	8.28	7.26	10.63	9.61	12.51
Morocco market	2.52	3.41	4.91	6.67	3.19	7.08	5.80	8.53
Morocco financial firms	2.96	3.99	5.27	7.86	3.49	8.10	6.77	9.97
Morocco banks	3.14	4.24	5.24	8.19	3.90	8.50	7.11	10.18
Panel D: COVID–19 period (Phase 2: 1 May to 30 October 2020).								
US market	3.07	2.97	3.18	4.38	2.43	3.61	3.45	4.87
US financial firms	3.00	4.26	4.37	8.24	2.69	4.09	4.14	6.25
US banks	4.40	6.22	6.44	7.53	3.80	6.54	5.77	8.10
South Africa market	2.12	3.02	2.83	3.41	2.09	2.99	2.81	4.00
South Africa financial firms	3.84	5.44	4.42	n/a	3.53	4.68	4.32	4.91
South Africa banks	4.48	6.35	5.24	n/a	4.19	5.54	4.96	5.69
Egypt market	1.55	2.21	2.85	2.85	1.71	2.74	2.27	3.00
Egypt financial firms	1.62	2.29	2.29	4.14	1.28	2.18	2.15	3.20
Egypt banks	1.68	2.37	2.49	4.71	1.49	1.98	2.22	3.35
Nigeria market	1.39	2.06	1.59	2.31	0.94	1.97	1.62	2.08
Nigeria financial firms	2.10	3.10	2.53	3.69	1.85	2.51	2.46	3.12
Nigeria banks	2.19	3.22	2.67	3.89	1.98	2.56	2.59	3.23
Morocco market	0.93	1.37	1.56	1.74	0.73	1.51	1.37	1.74
Morocco financial firms	1.28	1.83	1.87	2.20	1.09	1.81	1.56	2.20
Morocco banks	1.41	2.03	2.04	2.50	1.27	2.04	1.74	2.50

Note: The values of VaR (1% and 5%) and CvaR (1% and 5%) represent a potential loss for each asset category at the 99% and 95% confidence levels, respectively. Equations (1) and (2) have been used to estimate VaR and CVaR, respectively. n/a means not computable for that asset category.

not immune to the COVID-19 pandemic. These results offer risk managers, policymakers, and investor guidance to consider a coherent downside risk measure such as CVaR during crisis periods.

4.2.2 | DCCs

Table 3 presents the dynamic conditional correlation (DCC) between the US and African financial markets. The mean DCC correlation coefficients between the US and South African markets, financial firms, and banks increased during Phase I of the pandemic. For example, the mean DCC between the US and South African markets rose to 0.4234 in Phase I from the value of 0.3111 in the pre-COVID-19 period. DCCs between the US and South African markets, financial firms, and banks increased during Phase I. Similarly, DCCs between the US and Nigerian financial firms and banks increased during Phase I. Higher DCCs between the United States and South Africa (Nigeria) provide evidence

TABLE 3 DCCs between the US and African equity indices, 2 January 2017 to 30 October 2020

	South Africa	Egypt	Nigeria	Morocco
Panel A: Between market indices				
Mean DCC				
Total Period	0.3187	0.1574	0.0147	0.0994
Pre-COVID–19 Period	0.3111	0.1569	0.0147	0.0993
COVID–19 Phase 1	0.4234	0.1797	0.0147	0.0994
COVID–19 Phase 2	0.3120	0.1490	0.0147	0.1002
Diagnostic Test:				
Tse (2000) test	19.27***	12.91***	n/a	44.14***
Panel B: Between financial firms				
Mean DCC				
Total Period	0.2892	0.1204	0.0630	0.1042
Pre-COVID–19 Period	0.2763	0.1218	0.0539	0.1012
COVID–19 Phase 1	0.3638	0.1021	0.1276	0.1357
COVID–19 Phase 2	0.3305	0.1208	0.0862	0.1071
Diagnostic Test:				
Tse (2000) test	14.99***	66.15***	34.11***	59.67***
Panel C: Between banks.				
Mean DCC				
Total Period	0.2550	0.0794	0.0917	0.0905
Pre-COVID–19 Period	0.2445	0.0767	0.0857	0.0868
COVID–19 Phase 1	0.2970	0.1104	0.1680	0.1313
COVID–19 Phase 2	0.2985	0.0808	0.0902	0.0927
Diagnostic Test:				
Tse (2000) test	13.48***	26.21***	2.32**	56.84***

Note: 1. Tse (2000) tests the null hypothesis of constant correlation: H_0: $\rho_{ij} = 0$ for the equation: $\rho_{ij,t} = \rho_{ij} + \delta_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1}$, where $\varepsilon_{i,t-1}$ and $\varepsilon_{j,t-1}$ are the standardized residuals of i (United States) and j (South Africa, Egypt, Nigeria and Morocco) returns from a GARCH (1,1) process. 2. Total Period: 2 January 2017 to 30 October 2020; Pre-COVID–19 Period: 2 January 2017 to 29 January 2020; COVID–19 Phase 1: 30 January to 30 April 2020, and COVID–19 Phase 2: 1 May to 30 October 2020.

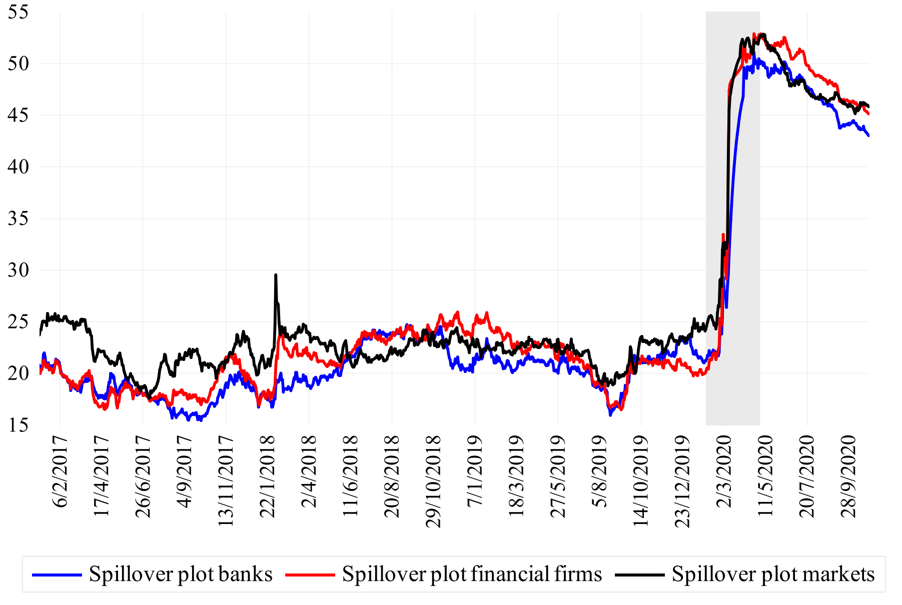

FIGURE 1 Spillover plots, 2 January 2017 to 30 October 2020. *Notes*: Diebold and Yilmaz's (2012) spillover model has been used to generate return spillover plots for the United States and developing African economies: South Africa, Nigeria, Egypt, and Morocco. The return spillover index uses a 200–day rolling window with a forecast horizon of 10 days. The shaded area represents Phase I of the COVID–19 pandemic (30 January to 30 April 2020)

that financial spillovers occurred between the United States and African two largest economies. Higher DCC between them could result from higher trade intensity, and capital flows between these countries. Higher DCCs during the crisis are consistent with the literature (Chiang et al., 2007; Hwang et al., 2013). These results offer investors and policymakers guidance on designing strategies to cope with the financial spillover from overseas.

4.2.3 | Spillovers

We measure the return spillovers using a 200–day rolling window to examine the magnitude and type of spillovers during the pre- COVID-19 and COVID-19 periods. The spillover plots show that return spillovers are the highest at mid-March when markets worldwide, mainly developed markets, experienced significant drops (see Figure 1). Higher return spillover plots during the height of the pandemic reflect similar results from DCCs and volatilities (see Figures SA2–SA4). We find an interesting result that the United States is a net transmitter of spillovers to developing African economies in all three levels: market indices, financial firms and banks, while African economies are net recipients of spillovers during the pandemic (see Table 4). To further examine the source of spillovers between developed and developing countries, we have generated net spillover plots using Equation 16. The results from the net spillover plots show that the United States is a dominant source of spillovers to African countries during the COVID-19 pandemic (see Figures SA5 and SA6). The net spillover plots further show that Nigeria and South Africa are dominantly net receivers of spillovers during the pandemic. Our results are consistent with those where the United States is the source of financial spillovers to developing economies during the global financial crisis (Kim et al., 2015). These results are critical to policymakers, regulators, investors, and other market participants to understand spillovers from developed to developing economies.

TABLE 4 Return spillover index, 2 January 2017 to 30 October 2020

	United States	South Africa	Egypt	Nigeria	Morocco	From Others	Net	Conclusion
Panel A: Between market indices								
United States	78.44	17.60	2.07	0.29	1.61	21.56	6.56	Net Contributor
South Africa	19.12	75.72	2.99	0.39	1.78	24.28	−0.33	Net Recipient
Egypt	4.96	4.00	89.09	0.13	1.82	10.91	−3.60	Net Recipient
Nigeria	1.76	1.17	0.90	95.85	0.32	4.15	−3.13	Net Recipient
Morocco	2.29	1.18	1.35	0.21	94.97	5.03	−0.50	Net Recipient
Contribution to others	28.12	23.95	7.30	1.02	5.53	65.92	Spillover Index (65.92/500)	
Contribution including own	106.56	99.67	96.40	96.87	100.50	13.18		13.18%
Panel B: Between financial firms								
United States	73.73	12.61	3.75	3.00	6.93	26.27	9.00	Net Contributor
South Africa	14.83	73.43	4.28	2.75	4.71	26.57	−6.05	Net Recipient
Egypt	5.58	3.14	86.90	1.12	3.26	13.10	−0.16	Net Recipient
Nigeria	5.17	2.66	1.88	88.20	2.09	11.80	−1.47	Net Recipient
Morocco	9.70	2.12	3.04	3.46	81.69	18.31	−1.33	Net Recipient
Contribution to others	35.28	20.53	12.94	10.33	16.98	96.06	Spillover Index (96.06/500)	
Contribution including own	109.00	93.95	99.84	98.53	98.67	19.21		19.21%
Panel C: Between banks								
United States	75.48	11.39	3.34	3.69	6.10	24.52	7.48	Net Contributor
South Africa	12.08	76.38	2.89	3.30	5.35	23.62	−5.31	Net Recipient
Egypt	4.61	2.57	88.47	1.55	2.80	11.53	−1.49	Net Recipient
Nigeria	6.27	2.36	0.76	88.03	2.58	11.97	−0.57	Net Recipient
Morocco	9.05	1.99	3.06	4.00	81.91	18.09	−1.26	Net Recipient
Contribution to others	32.00	18.31	10.04	12.54	16.83	89.73	Spillover Index (89.73/500)	
Contribution including own	107.48	94.69	98.51	100.57	98.74	107.48		17.95%

Note: Diebold and Yilmaz's (2012) spillover model has been used to identify the net contributor and recipients of spillover. The return spillover index uses a 200–day rolling window with a forecast horizon of 10 days.

TABLE 5 Spectral risk measures

	Total period (2 January 2017 to 30 October 2020)			Pre-COVID–19 period (2 January 2017 to 29 January 2020)			COVID–19 period (Phase 1: 30 January 2020 to 30 April 2020)			COVID–19 period (Phase 2: 1 May to 30 October 2020)		
	$R=20$	$R=100$	$R=200$	$R=20$	$R=100$	$R=200$	$R=20$	$R=100$	$R=200$	$R=20$	$R=100$	$R=200$
US market	3.84	5.77	7.42	2.27	2.88	3.26	9.55	11.32	12.10	3.50	4.34	4.93
US financial firms	4.62	7.07	9.08	2.39	3.10	3.58	11.62	12.83	13.47	4.17	5.40	6.34
US banks	5.72	8.32	10.43	3.11	3.97	4.46	13.16	15.00	15.58	5.92	7.33	8.17
South Africa market	3.70	5.49	6.93	2.45	2.93	3.23	8.95	9.53	9.71	2.78	3.17	3.40
South Africa financial firms	4.79	7.15	9.08	2.80	3.28	3.65	11.43	12.74	13.54	4.38	4.74	4.91
South Africa banks	5.47	8.04	10.19	3.36	4.04	4.55	12.70	14.83	15.94	5.06	5.49	5.64
Egypt market	2.96	4.26	5.20	2.32	3.15	3.71	6.29	6.85	7.08	2.35	2.78	2.98
Egypt financial firms	2.85	4.03	4.93	2.26	2.90	3.30	6.08	6.85	7.08	3.25	2.80	2.18
Egypt banks	2.69	3.86	4.77	2.08	2.72	3.20	5.75	6.54	6.75	2.22	2.88	3.45
Nigeria market	2.74	3.53	4.05	2.52	3.17	3.61	4.25	4.70	4.93	1.69	1.97	2.07
Nigeria financial firms	4.13	6.09	7.66	2.85	3.39	3.73	9.43	10.63	11.26	2.47	2.87	3.15
Nigeria banks	4.26	6.30	7.94	2.90	3.47	3.82	9.77	11.03	11.69	2.61	2.99	3.28
Morocco market	2.16	3.45	4.56	1.39	1.79	2.06	6.04	7.31	7.89	1.19	1.53	1.69
Morocco financial firms	2.46	3.97	5.28	1.50	1.97	2.28	9.16	8.48	7.05	1.61	1.98	2.19
Morocco banks	2.63	4.21	5.56	1.59	2.12	2.50	7.40	8.80	9.44	1.79	2.21	2.47

Note: A spectral risk measure ($\boldsymbol{M}_\emptyset$) is defined as follows: $\boldsymbol{M}_\emptyset = \int_0^1 \emptyset(\boldsymbol{p})\boldsymbol{q}_{\boldsymbol{p}}\boldsymbol{dp}$ (17), where $\emptyset(p)$ is a weighting function that reflects the user's risk aversion with the properties: $\emptyset(p) > 0$ for $p \in [0,1]$; $\int_0^1 \emptyset(p)dp = 1$; $\emptyset(p_1) \leq \emptyset(p_2)$ for all $0 \leq p_1 \leq p_2 \leq 1$ and q_p is the p loss quantile (see Acerbi, 2002, 2004; Adam et al., 2008; Cotter & Dowd, 2006). $\emptyset(p)$ is determined from the following exponential utility risk-aversion function: $\emptyset(p) = \frac{Re^{-R(1-p)}}{1-e^{-R}}$ (18), where $R \in (0, \propto)$ is the user's coefficient of absolute risk-aversion. In our estimation, absolute risk-aversion, R is 20,100, and 200, and the cumulative probability, p starts at 95%.

5 | ROBUSTNESS

In the baseline analysis, we have estimated the downside risk using VaR and Conditional VaR. However, these measures could be biased and not coherent (Artzner et al., 1999). To overcome the potential problem of incoherence, spectral risk measure is proposed as a weighted average of the quantiles of the portfolio returns with a non-increasing weight function. A spectral risk measure ($\boldsymbol{M}_{\emptyset}$) is defined as follows:

$$\boldsymbol{M}_{\emptyset} = \int_{0}^{1} \emptyset(\boldsymbol{p}) \boldsymbol{q}_{\boldsymbol{p}} \boldsymbol{dp} \tag{17}$$

where $\emptyset(p)$ is a weighting function that reflects the user's risk aversion with the properties: $\emptyset(p) > 0$ for $p \in [0,1]$; $\int_0^1 \emptyset(p)dp = 1$; $\emptyset(p_1) \leq \emptyset(p_2)$ for all $0 \leq p_1 \leq p_2 \leq 1$ and q_p is the p loss quantile (see Acerbi, 2002, 2004; Adam et al., 2008; Cotter & Dowd, 2006). $\emptyset(p)$ is determined from the following exponential utility risk-aversion function:

$$\emptyset(p) = \frac{Re^{-R(1-p)}}{1-e^{-R}} \tag{18}$$

where $\boldsymbol{R} \in (\boldsymbol{0}, \propto)$ is the user's coefficient of absolute risk-aversion.[9] The absolute risk function is presented in Figure SA7 with varying coefficients of absolute risk aversion (i.e., $\boldsymbol{R} \in (\boldsymbol{20}, \boldsymbol{100}, \boldsymbol{200})$). Figure SA7 shows that a weighting function $\emptyset(\boldsymbol{p})$ in Equation 17 rises with the cumulative probability $\boldsymbol{p}$ and rises exponentially for a more risk-averse user with higher absolute risk aversion values $\boldsymbol{R}$.

Table 5 presents the results from the spectral risk measure. The results show that the downside risk measures from the spectral risk measure are qualitatively similar to those from the VaR and Conditional VaR for the African markets, financial firms and banks. These results provide further support to our main findings.

To check the robustness of our results, we have estimated the conditional stock volatility as the conditional variance of daily stock returns from a GARCH (1,1), GARCH (2,2) and GARCH (3,3) process, respectively. The results are presented in Figure SA2 in the online appendices and show that the pattern of the conditional volatility remains similar at the different lag structures of the GARCH process.

6 | CONCLUSION

Our study examines how the risk spillovers occur between the United States and developing African economies during the COVID-19 pandemic. It considers the largest four developing economies (i.e., Nigeria, South Africa, Egypt and Morocco) that account together for more than half of the continent's GDP. It investigates the spillovers to the developing African economies at the aggregate market and sectoral levels: financial firms and banks. It uses both VaR and CVaR to measure the downside risk exposure of African financial markets and compared those with the United States. Additionally, it uses a spectral risk measure to overcome the potential incoherence in the downside risk measure. The results show that the downside risk exposures of African markets, financial firms, and banks increased significantly during Phase I (30 January to 30 April 2020). The nature and magnitude of downside risk exposures of African financial markets are similar to those of the US market, implying that African financial markets are likewise affected by the pandemic. Our results provide evidence that the United States is a net transmitter of risk spillovers while developing African economies are net recipients during the pandemic. Our findings offer risk managers, policymakers and investors guidance to consider a coherent downside risk measure such as CVaR during the crisis period. Our results are also important to investors, risk managers, and policymakers to understand financial

[9]The details of the absolute risk-aversion function are available at Acerbi (2004).

spillovers that originated from the COVID-19 pandemic and devise appropriate strategies to cope with the spillovers from overseas.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the authors. The data are not publicly available due to privacy or ethical restrictions.

ORCID

Ramzi Benkraiem https://orcid.org/0000-0002-3931-0546

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