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Financial contagion effects of major crises in African stock markets

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ABSTRACT

This study examines financial contagion effects in African stock markets during major crises over the period 2005 to 2020. We investigate contagion effects in individual stock markets and from a regional perspective using dynamic conditional correlations during the global financial crisis, European debt crisis, Brexit, and COVID-19. The empirical evidence confirms contagion effects in some individual markets. However, significant evidence of contagion is found only during the global financial crisis from the regional perspective. Our findings suggest that the regional impacts of crises differ due to the nature of those crises. We also find financial contagion increases in the country-level risk, market capitalization and export to GDP and decreases in corruption.

1. Introduction

Studies on financial contagion are becoming increasingly popular given the recent waves of crises. Evidence suggests recurring financial events within every 15 to 20-year cycle (Burks, Fadahunsi, & Hibbert, 2021; Choudhry, 1996; Kenourgios, Samitas, & Paltalidis, 2011; King & Wadhwani, 1990; Mink & De Haan, 2013; Mitchell, 2010; Patel & Sarkar, 1998; Sachs, Tornell, & Velasco, 1996; Samitas, Kampouris, & Umar, 2020; Yang & Bessler, 2008). In this paper, we investigate four recent crises in African stock markets including the global financial crisis (GFC), European debt crisis (EDC), the UK's vote to leave the European Union (Brexit) and the coronavirus pandemic (COVID-19).

The source of the GFC was the subprime credit crisis in the US, causing the values of stocks tied to the US real estate to plunge and substantially damage financial institutions globally. The crisis inevitably spread throughout the world. The EDC was caused by several Eurozone members, in particular Greece, which is unable to repay its government debt and has considerable deficits. Brexit has caused economic uncertainty, entangling domestic politics, migration and trade relationships between the UK and EU. Regarding COVID-19, March 2020 saw one of the most severe stock market crashes in history. In four trading days, the Dow Jones index plummeted nearly 6500 bps. This phenomenon was also widely observed in other stock markets across the globe. The crash was mainly caused by governments' reactions to the novel coronavirus (e.g., local, and national lockdowns and quarantines), which was originated in the Chinese city of Wuhan in December 2019 and quickly and widely spread throughout the world.

While many studies have been carried out within the context of developed and emerging markets, little research seems to have been undertaken in African markets. This is primarily because international portfolio investments in frontier markets including African markets, have surged only in recent decades as the sharply rising number of mutual funds and exchange traded funds launches that explicitly focus on frontier market equity investment (e.g., De Groot, Pang, & Swinkels, 2012). Much of this popularity stems from low correlations of those markets with global markets (Alagidede, 2009). The author notes that African markets are uniquely distinctive from other regional markets due to both institutional and regulatory circumstances. With the exception of South Africa, African markets remain segmented from global markets, and exhibit weak stochastic trends at global and regional levels which may offer potential diversification benefits.

A large number of studies show that African markets exhibit a partial segmentation from global stock markets (e.g., Agyei-Ampomah, 2011; Boako & Alagidede, 2017a; Boako & Alagidede, 2017c; Boamah, Watts, & Loudon, 2017; Hearn, Piesse, & Strange, 2010; Kodongo & Ojah, 2011; Sugimoto, Matsuki, & Yoshida, 2014). Both practitioners and academic researchers have argued that African markets are a “safe haven” for foreign investors that provide considerable diversification benefits to them.

Furthermore, these markets are experiencing substantial developments, becoming increasingly attractive for both local and international investors (Adams & Opoku, 2015; Agbloyor, Abor, Adjasi, &

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Yawson, 2013). For example, dramatic growth is observed in the number of African stock markets from 8 (in 2002) to 29 (in 2013) (African Development Bank, 2014); market capitalization from US$260,222.4 million (in 2000) to US$738,753.2 million (in 2011); and foreign direct investment (FDI) inflow from $9363.7 million (in 2000) to $46,552.8 million (in 2011).[1] Thus, our choice of the period 2005–2020 for this study, is informed by the substantial development of African stock exchanges that corresponds with recent major financial crises. In addition, we could not study earlier financial crises as most of the markets were established in the 1980s and 1990s.[2]

Overall, African stock markets are becoming integrated and interdependent (particularly during crisis periods) through globalization and international financial integration. This could potentially eliminate diversification benefits for foreign investors. However, some studies argue that the development of African stock markets does not translate into stock market maturity, suggesting African markets could still be relatively isolated (e.g., Yartey & Adjasi, 2007). Therefore, it is worth exploring these issues by studying the impact of financial crises on those markets.

We focus only on the recent global crises, for several reasons. First, it allows an examination of whether diversification benefits in recent years still exist in African markets, thus extending previous literature that focuses on the pre-2007 crises while providing new insights into the financial systems of African markets and their vulnerability to global shocks. Second, the majority of African markets are relatively new (Allen, Otchere, & Senbet, 2011), established in the late 1980s and early 1990s and experience substantial growth in recent decades as discussed above. Third, due to data availability, studying pre-2007 financial crises[3] on majority African markets will produce ungeneralizable outcomes. The prominent and older markets (such as Egypt, South Africa, Morocco and Nigeria which have data as far back as at least the 1960) have been already widely studied (see, e.g., Forbes & Rigobon, 2002; Rigobon, 2003; Collins & Biekpe, 2003; Fratzscher, 2003; Han, Lee, & Suk, 2003; Wang, Yang, & Bessler, 2003; Caramazza, Ricci, & Salgado, 2004; Gande & Parsley, 2005; Lagoarde-Segot & Lucey, 2009). Earlier contagion literature documents strong evidence of contagion as more of a regional than global phenomenon (Calvo & Reinhart, 1996; Frankel & Schmukler, 1998; Glick & Rose, 1999; Kaminsky & Reinhart, 1998) and intraregional rather than interregional (Diwan & Hoekman, 1999). Fourth, the recent crises are more likely to have global bearings. This is due to the rapid impact of globalization in recent decades (Asongu & De Moor, 2017; Inci, Li, & McCarthy, 2011; Jones & Knaack, 2019; Martin, Tyler, Storper, Evenhuis, & Glasmeier, 2018; Mendoza & Quadrini, 2010; Morales & Andreosso-O'Callaghan, 2014; Schmukler, 2004; van Treeck & Wacker, 2020) and the potential global nature of each crisis. Finally, several African markets are excluded due to missing data and issues relating to thin market effects of low trading volume. Therefore, our sample consists of 11 African markets.

Our study contributes to the literature by investigating the impact and nature of four major crises in individual African stock markets and the whole African region, over a recent 15-year period. While the GFC and EDC have received considerable attention in the literature, Brexit and COVID-19 have provided new opportunities to investigate contagion in African markets, given the nature of each crisis is significantly different. Policymakers would be able to improve market stability and efficiency of financial regulation systems if they better understand the mechanisms and nature of different financial crises, while investors would be in a better position to hedge financial shocks. It also helps to understand the interconnectivity of markets for the purpose of rescue packages and portfolio diversification (Alagidede, Panagiotidis, & Zhang, 2011; Aloui, Aïssa, & Nguyen, 2011).

The remainder of the paper is as follows. Section 2 presents methodology. Section 3 provides data and summary of statistics. We provide empirical results and discussions in Section 4, while Section 5 concludes the paper.

2. Methodology

The aim of this study is to investigate the evidence of contagion effects of major financial crises in African stock markets. We thereby adopt the definition of contagion as the significant increase in cross-market correlations following a shock to one country or group of countries (Forbes & Rigobon, 2002). This definition provides a direct means for testing contagion effect by examining pre-crisis and during crisis correlations between the origin of crisis and second markets. It also provides insights into the effectiveness of policy intervention.[4]

The empirical literature on contagion identifies four commonly cited methodologies for investigating financial contagion and markets' co-movements: 1) cross-market correlation coefficient analysis (King & Wadhwani, 1990); 2) time-varying correlation techniques such as DCC – GARCH approach (Engle, 2002); 3) cointegration technique (Longin & Solnik, 1995); and 4) transmission mechanism approach (Eichengreen, Rose, & Wyplosz, 1996). The first three techniques focus on the strength of linkages between markets as in the case of this study, while the last technique identifies pathways of financial contagion. The cross-markets correlation analysis forms the basis of contagion test modeled and popularized by Forbes and Rigobon (2002). However, the test requires adjustment for heteroscedasticity bias as it is based on changes in static correlation coefficients between markets before and after crisis. The cointegration procedure checks for changes in the cointegrating vector between markets in the long run, which implies that the test could be problematic if contagion event is short-lived or where market data is scarce.

In this paper, we utilize the DCC – GARCH model based on the method proposed by Engle (2002) to test for contagion. This model, which accounts for heteroskedasticity by estimating correlations of standardized residuals, has been widely used in contagion literature to capture the changing nature of correlations and structural shifts in data over time (Akhtaruzzaman, Boubaker, & Sensoy, 2021; Chiang, Jeon, & Li, 2007; Kenourgios, 2014; Samitas & Tsakalos, 2013; Syllignakis & Kouretas, 2011).

Our analysis begins with computing basic returns from all indices over the full period calculated as:

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where R_t is the return of a stock market index, and P_t and P_{t-1} are the daily closing prices of the market index at time t and $t-1$, respectively. Following Forbes and Rigobon (2002), we utilize two-day rolling averages of returns to account for different opening times of the exchanges, and an unrestricted vector autoregressive (VAR) model with five lags to control for serial correlations and any within-week variations in trading patterns. The unrestricted VAR consists of all variables including the return series of both markets (r_{it} and r_{jt}) up to five lags. The VAR

[1] The data are from World bank: Africa Development Indicators | DataBank (worldbank.org).

[2] More details are documented in the Appendix A.

[3] Those include the US market crash of 1987, the collapse of the European exchange rate mechanism in 1992, the Mexican economic crisis in 1994, the 1997 Asian financial crisis, the 1998 Russian financial crisis, and the Brazilian crisis of 1999.

[4] The argument is that for countries that exhibit historical strong links (referred to as interdependence in Forbes & Rigobon, 2002), intervention will not be as effective during a crisis. Where a country is affected by the crisis of another country for a short period (commonly referred to as shift contagion), government intervention such as short-term loans could be effective if there exist few linkages through trade, finance and other channels of transmission (Claessens & Forbes, 2004).

framework is given as:

$$r_{it} = \mu_i + \sum_{k=1}^{5} \alpha_k r_{it-k} + \sum_{k=1}^{5} \beta_k r_{jt-k} + \varepsilon_{it} \quad (2)$$

$$r_{jt} = \mu_j + \sum_{k=1}^{5} \alpha_k r_{jt-k} + \sum_{k=1}^{5} \beta_k r_{it-k} + \varepsilon_{jt} \quad (3)$$

where r represents returns, in which r_{it} is the return of the crisis market, and r_{ij} is the return of a second market, in this case an African market.

The next step is to obtain time-varying variances from the residuals of the VAR using GARCH (1,1) model and GJR–GARCH (1,1) model of Glosten, Ravi, and David (1993), which accounts for potential asymmetric responses of volatility to positive and negative shocks. The respective variance equations are specified below:

$$\sigma_{kt}^2 = \alpha_{k0} + \alpha_{k1}\, \varepsilon_{kt-1}^2 + \beta_{k1}\sigma_{kt-1}^2 \quad (4)$$

$$\sigma_{kt}^2 = \alpha_{k0} + \alpha_{k1}\, \varepsilon_{kt-1}^2 + \beta_{k1}\sigma_{kt-1}^2 + g\, \varepsilon_{kt-1}^2\, I_{kt-1} \quad (5)$$

where $\sigma_t{}^2$ is the conditional variance, α_0 the intercept, ε_t the standardized residual, α_1 the ARCH parameter, and β_1 the GARCH parameter. The subscript k takes the value of i for the crisis market and j an African market. I_{t-1} in the GJR – GARCH model (Eq. 5) is a dummy variable to capture the impact of negative shocks that takes the value of 1 if $\varepsilon_{t-1}<$ 0 and 0 otherwise. The non-negative scalars in this model are α_0, α_1 and β. A positive and statistically significant g indicates that negative shocks will have a larger effect on the conditional variance. GARCH models capture volatility clustering of the data, which is quantified in the persistence parameter. The persistence is computed as $\alpha_{k1} + \beta_{k1}$ for GARCH and $\alpha_{k1} + \beta_{k1} + Kg$ for GJR – GARCH.[5] It measures the persistence of the volatility and the rate at which the volatility decays over time. For brevity, we only report the results using GJR – GARCH (1,1) model as it accounts for the asymmetries in the correlation dynamics, which are indeed the case for African and crisis markets as shown in Table 4.[6] We then estimate conditional variance and conditional covariance terms as:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \quad (6)$$

$$D_t = diag\left(\sigma_{it}^2 \ldots\ldots \sigma_{Nt}^2\right) \quad (7)$$

$$R_t = diag\left(q_{ii,t}^{-1/2}, \ldots q_{NN,t}^{-1/2}\right) Q_t\, diag\left(q_{ii,t}^{-1/2}, \ldots, q_{NN,t}^{-1/2}\right) \quad (8)$$

$$\mathrm{Q_t} = (1 - \alpha - \beta)\overline{\mathrm{Q}} + \alpha \nu_{t-1} \nu_{t-1}^{'} + \beta \mathrm{Q_{t-1}} \quad (9)$$

where H_t is the conditional covariance matrix of the residuals, D_t is the diagonal matrix with square roots of the conditional variance obtained by GARCH (1,1) model. The significant α coefficient value in the DCC equation indicates that correlation will vary appreciably over time. α and β are non-negative scalars satisfying the constraint $\alpha + \beta < 1$ (which ensures models mean-revert). Q_t represents the covariance matrix, $Q_t = [\mathrm{q_{ij,\,t}}]$, and ν_t represents the residuals standardized by their conditional standard deviation. $\overline{Q}$ is the unconditional NxN variance/covariance matrix of ν_t. Next, we derive the estimates of conditional correlation from the covariance matrix as:

$$\rho_{ij,t} = \frac{\text{Conditional Covariance}_{ij,t}}{\sqrt{\text{conditional variance}_{it}}\text{conditional variance}_{jt}} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad (10)$$

where i=crisis country and j= an African country. We also denote the average of conditional correlation ($\rho_{ij,\,t}$) as the DCC coefficient.

We examine financial contagion by regressing the time-varying correlation against the dummy variables of the GFC, EDC, Brexit, or COVID-19 crises as follows.

$$\rho_{ij,t} = \gamma_1 + \gamma_2 Crisis + \nu_{ij,t} \quad (11)$$

where $\rho_{ij,\,t}$ is the conditional correlation between the crisis market and an African market at time t. *Crisis* equals to 1 in the presence of *GFC*, *EDC*, *Brexit,* and *COVID-19* crises, respectively and 0 otherwise. A positive and statistically significant dummy variable parameter from a one-tailed test indicates the evidence of contagion during the crisis period.

3. Data and summary statistics

To select our sample periods for each major crisis, we closely follow the literature. According to Mollah, Quoreshi, Shahiduzzaman, and Zafirov (2016), we define the GFC pre-crisis period as from the 1st of January 2005 to the 8th of August 2007 and the GFC crisis period from the 9th of August 2007 to the 31st of December 2009. For the EDC, the pre-crisis period is from the 1st of January 2010 to the 1st of May 2010 and the crisis period is from the 2nd of May 2010 to the 9th of June 2013. For Brexit, we follow Aristeidis and Elias (2018) to choose the pre-crisis period from the 1st of January 2016 to the 23rd of June 2016, while the crisis period is defined as the 24th of June 2016 to the 30th of September 2017. This period also corresponds with major economic events associated with Brexit, including the outcome of the vote and the beginning of the revocation of Article 50. Finally, for COVID-19, we follow Okorie and Lin (2021) to select the 1st of January 2020 to the 31st of March 2020 as the COVID-19 crisis period. The pre-crisis period is defined as the 1st of October 2019 to the 31st of December 2019. A short crisis window is chosen to avoid the impact of exogenous events. The full sample period incorporating all crises under investigation is from the 1st of January 2005 to the 31st of March 2020.

Our full sample consists of 11 major African stock market indices,[7] including Côte d'Ivoire (CXCOMP), Egypt (EGX30), Ghana (GGSECI), Kenya (NSEASI), Morocco (MOSENEW), Mauritius (SEMDEX), Nigeria (NGSEINDX), Tunisia (TUSISE), Tanzania (DARSDSEI), South Africa (JALSH), and Zambia (LUSEIDX). The US (S&P 500), the UK (FTSE All Share Index), Greece (Athens Stock Exchange General Index), and China (Shanghai Stock Exchange A-Share Index) are selected as sources of contagion from which the four major crises originated. We examine daily data of all indices obtained from Bloomberg in local currencies from January 2005 to March 2020.

Stock market index data are not available for some African markets prior to 2005. For example, data are available from January 2009 for Botswana, December 2010 for Ghana, February 2008 for Kenya, and November 2006 for Tanzania. As a result, we have 7 African stock markets for the GFC, 9 for the EDC, and 11 for both Brexit and COVID-19. Daily closing prices collected from Bloomberg provide 261 daily observations per year. This accounts for weekends, but not national holidays where the previous value is repeated. For each crisis under investigation, an equal number of observations is obtained between the crisis origin market and each African market.

Table 1 presents the descriptive statistics of returns over the pre-

[5] K is the expected value of the standardized residuals below zero. In the case of symmetric distributions, the value of K is simply 0.5.

[6] The results are qualitatively similar to those using GARCH (1,1) which are reported in the Appendix B.

[7] ICXCOMP is the Index for Bourse Régionale des Valeurs Mobilières (BRVM), which serves the eight West African French-speaking countries of Benin, Burkina Faso, Côte d'Ivoire, Guinea Bissau, Mali, Niger, Senegal, and Togo; EGX30 represents the Egyptian Stock Exchange; GGSECI is the Ghana Stock Exchange Composite index; NSEASI is the Nairobi Securities Exchange All Share index; MOSENEW is a free-float index on the Casablanca Stock Exchange; SEMDEX represents the Stock Exchange of Mauritius; NGSEINDX is the Nigeria Stock Exchange All Share Index; TUSISE represents the Tunis Stock Exchange; DARSDSEI is the Tanzania All Share Index; JALSH represents the Johannesburg Stock Exchange All Share Index; and LUSEIDX represents the Lusaka Stock Exchange All Share Index.

Table 1
Descriptive statistics pre-crisis and during crisis.

Panel A		Pre GFC									GFC						
Country	Code	Stock market	N	Mean	Median	Std	Skew	Kurt	Min	Max	N	Mean	Median	Std	Skew	Kurt	Min	Max
Côte d'Ivoire	CIV	ICXCOMP	656	0.001	0.000	0.009	−0.327	18.397	−0.060	0.061	620	0.000	0.000	0.007	0.591	3.257	−0.023	0.036
Egypt	EGY	EGX30	657	0.002	0.002	0.013	−0.811	5.330	−0.087	0.050	608	0.000	0.002	0.017	−1.393	7.472	−0.127	0.060
Morocco	MAR	MOSENEW	672	0.001	0.002	0.008	−0.733	4.083	−0.042	0.029	617	0.000	0.000	0.008	−0.717	5.791	−0.042	0.034
Mauritius	MUS	SEMDEX	669	0.001	0.001	0.008	−0.934	83.884	−0.108	0.098	621	0.000	0.000	0.010	−0.006	6.276	−0.062	0.055
Nigeria	NGA	NGSEINDX	637	0.001	0.000	0.007	0.360	5.315	−0.040	0.036	606	−0.002	−0.001	0.012	0.062	1.274	−0.049	0.037
Tunisia	TUN	TUSISE	650	0.001	0.001	0.004	0.278	2.393	−0.016	0.017	617	0.001	0.001	0.005	−0.325	10.553	−0.037	0.031
South Africa	ZAF	JALSH	672	0.001	0.002	0.008	−0.635	2.688	−0.041	0.035	621	0.000	0.001	0.013	0.060	1.718	−0.048	0.059
Panel B		Pre EDC									EDC							
Côte d'Ivoire	CIV	ICXCOMP	83	0.001	0.001	0.005	−0.497	1.082	−0.014	0.012	786	0.000	0.000	0.006	0.309	7.370	−0.030	0.033
Egypt	EGY	EGX30	82	0.002	0.004	0.010	−0.820	0.956	−0.032	0.020	750	0.000	0.000	0.013	−0.838	6.746	−0.087	0.067
Kenya	KEN	NSEASI	83	0.003	0.002	0.006	0.445	0.950	−0.010	0.022	802	0.000	0.000	0.005	−0.072	3.870	−0.029	0.033
Morocco	MAR	MOSENEW	83	0.002	0.001	0.005	1.340	3.211	−0.011	0.020	796	0.000	0.000	0.005	−0.162	2.507	−0.024	0.018
Mauritius	MUS	SEMDEX	83	0.000	0.000	0.004	−0.251	0.350	−0.010	0.008	800	0.000	0.000	0.003	−0.647	9.008	−0.027	−0.027
Nigeria	NGA	NGSEINDX	83	0.003	0.002	0.015	0.334	5.996	−0.049	0.059	792	0.001	0.000	0.006	0.249	1.323	−0.019	0.027
Tunisia	TUN	TUSISE	83	0.001	0.001	0.003	1.657	5.132	−0.004	0.017	783	0.000	0.000	0.006	−0.918	13.137	−0.038	0.038
South Africa	ZAF	JALSH	83	0.000	0.001	0.007	−0.593	0.669	−0.022	0.013	801	0.000	0.001	0.007	−0.254	1.007	−0.023	0.024
Zambia	ZMB	LUSEI	79	0.001	0.001	0.009	0.118	1.900	−0.023	0.030	790	0.001	0.000	0.006	0.105	3.526	−0.026	0.036

Country	Code	Stock market	N	Mean	Median	Std	Skew	Kurt	Min	Max	N	Mean	Median	Std	Skew	Kurt	Min	Max
Panel C		Pre Brexit									Brexit							
Côte d'Ivoire	CIV	ICXCOMP	123	0.000	0.000	0.005	−0.083	0.512	−0.016	0.012	332	−0.001	−0.001	0.005	0.164	1.288	−0.018	0.020
Egypt	EGY	EGX30	121	0.000	0.001	0.013	−0.470	2.299	−0.049	0.042	318	0.002	0.001	0.010	1.518	8.173	−0.025	0.068
Ghana	GHA	GGSECI	120	−0.001	0.000	0.003	−0.533	0.368	−0.008	0.004	331	0.001	0.000	0.005	−0.062	4.946	−0.020	0.021
Kenya	KEN	NSEASI	122	0.000	0.000	0.004	0.162	0.872	−0.013	0.014	330	0.000	0.001	0.007	−1.315	6.588	−0.041	0.019
Morocco	MAR	MOSENEW	123	0.001	0.001	0.005	0.350	0.982	−0.011	0.017	327	0.001	0.001	0.005	0.984	6.700	−0.020	0.029
Mauritius	MUS	SEMDEX	123	0.000	0.000	0.003	0.885	1.465	−0.006	0.009	332	0.001	0.000	0.002	0.528	1.788	−0.007	0.011
Nigeria	NGA	NGSEINDX	122	0.001	0.001	0.012	−0.496	1.394	−0.036	0.029	325	0.001	0.000	0.008	0.796	3.965	−0.025	0.036
Tunisia	TUN	TUSISE	123	0.001	0.000	0.004	0.443	0.543	−0.010	0.013	328	0.000	0.000	0.002	0.160	0.438	−0.006	0.008
Tanzania	TZA	DARSDSEI	122	0.000	0.000	0.008	−0.039	−0.032	−0.020	0.023	325	0.000	0.000	0.011	−0.669	3.137	−0.047	0.047
South Africa	ZAF	JALSH	122	0.001	0.001	0.008	0.060	−0.337	−0.017	0.025	330	0.000	0.000	0.006	−0.534	3.819	−0.034	0.018
Zambia	ZMB	LUSEIDX	108	−0.002	0.000	0.004	−4.093	20.948	−0.029	0.003	275	0.000	0.000	0.005	−0.296	6.707	−0.026	0.026
Panel D		Pre COVID-19									COVID-19							
Côte d'Ivoire	CIV	ICXCOMP	61	0.002	0.001	0.006	2.328	8.471	−0.008	0.030	60	−0.003	−0.004	0.006	−0.303	1.257	−0.022	0.012
Egypt	EGY	EGX30	64	−0.001	0.000	0.006	−0.047	−0.200	−0.014	0.014	65	−0.006	−0.001	0.022	−2.064	6.945	−0.098	0.044
Ghana	GHA	GGSECI	64	0.000	0.000	0.004	0.955	3.244	−0.011	0.015	63	−0.001	0.000	0.004	0.482	1.225	−0.009	0.013
Kenya	KEN	NSEASI	63	0.002	0.002	0.007	0.591	4.393	−0.020	0.029	66	−0.004	−0.002	0.013	−1.219	2.941	−0.055	0.018
Morocco	MAR	MOSENEW	64	0.001	0.001	0.003	0.087	−0.263	−0.004	0.008	66	−0.003	−0.001	0.016	−1.128	3.666	−0.062	0.034
Mauritius	MUS	SEMDEX	63	0.000	0.000	0.002	0.506	−0.056	−0.004	0.006	57	−0.006	−0.001	0.016	−1.787	3.546	−0.057	0.029
Nigeria	NGA	NGSEINDX	63	0.000	−0.001	0.004	0.159	0.814	−0.010	0.010	66	−0.003	−0.003	0.012	−0.691	3.631	−0.042	0.032
Tunisia	TUN	TUSISE	64	0.000	0.000	0.002	1.173	2.042	−0.004	0.007	66	−0.001	0.000	0.009	−2.539	8.980	−0.040	0.014
Tanzania	TZA	DARSDSEI	61	0.001	0.001	0.014	0.468	23.289	−0.068	0.074	66	−0.003	−0.001	0.007	−1.160	1.284	−0.024	0.008
South Africa	ZAF	JALSH	63	0.001	0.002	0.005	−0.270	−0.487	−0.012	0.012	66	−0.004	−0.002	0.019	−0.133	2.514	−0.055	0.062
Zambia	ZMB	LUSEIDX	41	−0.001	0.000	0.002	−1.469	3.235	−0.007	0.002	49	0.000	0.000	0.001	−0.278	1.826	−0.002	0.002

This table reports the descriptive statistics of returns pre-crisis and during crisis. GFC, EDC, Brexit, and COVID-19 represent the global financial crisis, European debt crisis, the UK vote to leave the European Union and the coronavirus pandemic crisis, respectively. The pre-crisis period for the GFC is defined as 1st January 2005 to 8th August 2007; the crisis period is defined as 9th August 2007 to 31st December 2009. The pre-crisis period for EDC is defined as 1st January 2010 to 1st May 2010; the crisis period is defined as 2nd May 2010 to 9th June 2013. The pre-crisis period for Brexit is defined as 1st January 2016 to 23rd June 2016; the crisis period is defined as 24th June 2016 to 30th September 2017. The pre-crisis period for COVID-19 is defined as 1st October 2019 to 31st December 2019; the crisis period is defined as 1st January 2020 to 31st March 2020. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. N, Std, Skew and Kurt represent sample size, standard deviation, skewness and kurtosis respectively.

crisis and crisis periods for all the crises studied. Egypt has the highest standard deviation for the GFC, EDC, and COVID-19 crises, while Tanzania has the largest standard deviation during Brexit. As expected with high frequency data, none of the series are normally distributed across all periods. This is demonstrated by high or low kurtosis and negative or positive skewness.

Table 2 presents the Pearson correlations of returns between crisis origin and African markets before and during each crisis. The results suggest that African markets are merely correlated with the US prior to the GFC. Negative correlations are observed in the pre-crisis periods of the EDC, Brexit, and COVID-19. South Africa is found to have the highest correlations across all crises. However, correlation does not necessarily imply causation; they can be simply spurious or meaningless. In essence, the existence of a relationship between variables does not prove causality or the direction of influence (Gujarati & Porter, 2009).

To investigate the direction of causalities between crisis origin and African markets, the Granger's (1969) causality (GC) test is conducted. Causality is implied when past values of a particular series is recorded over time; say $Y_{2,\,t}$ has explanatory power in a regression of another variable $Y_{1,\,t}$ upon its own lagged values and those of $Y_{2,\,t}$. Causality is argued to exist if $Y_{1,\,t}$ can be predicted with greater accuracy by using past values of $Y_{2,\,t}$ than by not using such past values, all other factors being equal. If this is the case, then $Y_{2,\,t}$ is argued to be *Granger cause* $Y_{1,\,t}$. In the two-variable case, the application of the GC test involves the following pair of regressions:

$$Y_{1,t} = \sum_{i=1}^{k} \alpha_i Y_{2,t-i} + \sum_{j=1}^{k} \beta_j Y_{1,t-j} + e_{1,t} \tag{12}$$

$$Y_{2,t} = \sum_{i=1}^{k} \lambda_i Y_{2,t-i} + \sum_{j=1}^{k} \delta_j Y_{1,t-j} + e_{2,t} \tag{13}$$

where it is assumed that the two error terms $e_{1,\,t}$ and $e_{2,\,t}$ are uncorrelated. k is the number of lags employed. Both variables $Y_{1\,t}$ and $Y_{2\,t}$ are assumed to be stationary. Eq. 13 postulates that $Y_{1,\,t}$ depends on previous values of itself as well as those of $Y_{2,\,t}$ and the second equation requires a similar behaviour for $Y_{2,\,t}$. The null hypothesis is that $Y_{2,\,t}$ does not Granger cause $Y_{1,\,t}$ in Eq. 12 and $Y_{1,\,t}$ does not Granger cause $Y_{2,\,t}$ in Eq. 13.

Table 3 reports the Granger causality test results for all stock markets. Regarding the GFC, the bi-directional causality is observed between the US and Egypt, and the US and South Africa during the pre-crisis period. The unidirectional causality from several African markets (e.g., Morocco, Mauritius, and Nigeria) to the US is statistically significant during the pre-crisis period. The unidirectional causality from Morocco to the US is also observed during the crisis period. In case of the EDC, the bi-directional causality is found between Greece and Morocco, and between Greece and South Africa during the pre-crisis period. Unidirectional causality from two African markets (e.g., Kenya and Nigeria) to Greece is found to be statistically significant during the pre-crisis period. No bi-directional causality is found to be statistically significant either pre- Brexit or during the Brexit period. However, unidirectional causality is observed from two African markets (e.g., Nigeria and South Africa) to the UK and from the UK to Kenya during Brexit. Finally, during the pre-COVID-19 period, unidirectional causality is observed only between China and several African markets (e.g., Egypt, Mauritius, and South Africa). No causality is observed during the COVID-19 period.

4. Empirical results and discussions

4.1. DCC–GARCH analysis

In this section, we begin by discussing the GARCH model outlined in the methodology section. We then present the tests for contagion effect and conclude with a discussion of findings based on the nature of different crises studied.

Table 4 reports pair-wise estimates of the conditional variances in Eq. 5. We observe that the coefficient of volatility (β) is highly significant for all African markets during the GFC, EDC and Brexit, but insignificant for Ghana, Tanzania, and Zambia during COVID-19. The picture is mixed in respect to α and g parameters across different crises. It can be observed from Table 4 that all three parameters of the GJR model are significant for South Africa during the GFC; Egypt, Morocco, Tunisia, and Zambia during the EDC; Kenya, Mauritius, and Nigeria during Brexit; and Côte d'Ivoire and Egypt during COVID-19. The results for GARCH (1,1), presented in Table B1, show significant β for all markets except Ghana and Tanzania during the COVID-19. The ARCH parameter (α) is also significant for all markets during the GFC and EDC; a few insignificant values are observed during Brexit, while COVID-19 shows limited evidence of ARCH effects.

Table 5 presents the conditional correlation results from Eqs. 9 and 10. It can be observed that the sum of α and β for all markets during all crises is <1, suggesting the model for all cases is mean-revert. We also report the average conditional correlation (DCC coefficient) estimated from GJR–GARCH (1,1) in the last column of each panel. The significance of the DCC coefficient is against a two-tailed test in which the null hypothesis is that the DCC coefficient equals to zero. During the GFC and Brexit crisis periods, the correlations between the origin markets (the US for the GFC and UK for Brexit) and Egypt, Mauritius and South Africa are high and significant. During the EDC, only the correlation between Greece and South Africa is positive and significant. The finding indicates that only a few markets are affected by those crisis shocks. During COVID-19, the correlation between China and Kenya, Mauritius, Morocco, Nigeria, and South Africa is positive and significant.

Table 6 reports results for contagion tests on the conditional correlations using the GJR model from Eq. 11. Positive and significant t-statistics from a one-tailed test indicate contagion, while any insignificant value indicates no sign of contagion. Fig. 1 plots the time-varying conditional correlations for each crisis at the regional level.

For the GFC period, seven African markets are investigated, and evidence of contagion in individual stock markets is found in Egypt, Morocco, Tunisia, and South Africa. The regional contagion test also confirms evidence of contagion. As can be seen from Panel A of Fig. 1, the dynamic conditional correlation increases considerably and peaks at the end of 2008. This is not surprising as the GFC is considered the worst financial crisis since the Great Depression. Unlike the 1987 market crash, 1994 Mexican crash and 1997 Asian crisis, the GFC also saw the growth of contagion studies in African stock markets. Although this group of markets was reported to be shielded from the crisis in its early stages, its long multi-year nature saw their eventual crash (Ahmadu-Bello & Rodgers, 2016; Dimitriou, Kenourgios, & Simos, 2013). Several studies purport that the source, length, interconnected financial systems, market integration and events prior and during the GFC culminated in making it the worst crisis since the Great Depression (Crotty, 2009; Drezner & McNamara, 2013; Pyun & An, 2016; Roy & Kemme, 2020). The GFC is analyzed by Morales and Andreosso-O'Callaghan (2014) as an important crisis that could see correlation patterns among markets suffering jumps. They also show that the South African stock market is strongly influenced by the US stock market, and interlinkages exist among African markets. As such, shocks in the US market could be easily transferred to other African markets, as spillovers.

We see from Table 6 that in the presence of the GFC, South Africa experiences the strongest contagion, followed by Tunisia and Egypt, with the coefficient of the dummy variable being significant at the 1%

Table 2
Correlation pre and during crisis.

Country	Pre GFC	GFC	Country	Pre EDC	EDC	Country	Pre Brexit	Brexit	Country	Pre COVID -19	COVID - 19
CIV	−0.050	−0.033	CIV	−0.125	−0.021	CIV	−0.110	−0.015	CIV	−0.047	−0.058
EGY	0.067	0.285	EGY	−0.126	0.100	EGY	0.182	0.130	EGY	0.089	0.308
MAR	0.048	0.126	KEN	−0.101	0.050	GHA	−0.037	0.070	GHA	−0.020	−0.035
MUS	0.036	0.109	MAR	−0.023	0.118	KEN	−0.071	−0.060	KEN	0.030	0.343
NGA	0.022	−0.018	MUS	0.125	0.081	MAR	−0.155	0.057	MAR	−0.202	0.344
TUN	0.044	0.152	NGA	0.191	0.109	MUS	−0.060	0.045	MUS	0.318	0.348
ZAF	0.392	0.559	TUN	0.105	−0.118	NGA	0.137	0.048	NGA	0.084	0.229
			ZAF	0.247	0.382	TUN	0.041	0.055	TUN	0.085	0.344
			ZMB	0.027	−0.074	TZA	0.013	0.021	TZA	−0.034	0.078
						ZAF	0.742	0.581	UGA	0.075	0.145
						ZMB	−0.008	0.011	ZAF	0.537	0.586
									ZMB	−0.312	0.228

This table presents the Pearson correlations of returns between crisis origin and African markets pre and during each crisis. GFC, EDC, Brexit and COVID-19 represent the global financial crisis, European debt crisis, the UK vote to leave the European Union and the coronavirus pandemic crisis, respectively. The pre-crisis period for the GFC is defined as 1st January 2005 to 8th August 2007; the crisis period is defined as 9th August 2007 to 31st December 2009. The pre-crisis period for EDC is defined as 1st January 2010 to 1st May 2010; the crisis period is defined as 2nd May 2010 to 9th June 2013. The pre-crisis period for Brexit is defined as 1st January 2016 to 23rd June 2016; the crisis period is defined as 24th June 2016 to 30th September 2017. The pre-crisis period for COVID-19 is defined as 1st October 2019 to 31st December 2019; the crisis period is defined as 1st January 2020 to 31st March 2020. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020.

level. The two African emerging markets (Egypt and South Africa)[8] are both more contagious in this period and reported to be more integrated to global markets. Consequently, they are more susceptible to contagion effects (Boako & Alagidede, 2017b). In addition, according to WTO statistics, Tunisia relies heavily on international trades in which the foreign trades over GDP are >100%. Thus, it is not surprising that Tunisia suffers from the GFC significantly. Similarly, Morocco's export performance was largely affected by the GFC (Lahrech, Faribi, Al-Malkawi, & Sylwester, 2019). During the GFC crisis period, there is a considerable fall in aggregate demand from Morocco's major trading patterners, in particular European countries, resulting in a large fall in the exports.

The EDC is also a multi-year crisis and the results in Table 6 show contagion effect on the individual markets of Egypt, Morocco, and South Africa out of the nine African markets. However, averaging across the African markets, we do not find significant evidence of contagion effects at the regional level. The financial contagion of African markets from the EDC is likely to be a result of trade relationships, liquidity squeezes, and sovereign risks (Ahmad, Sehgal, & Bhanumurthy, 2013; Beirne & Fratzscher, 2013). For Egypt and South Africa, our results are consistent with Kablan and Kaabia (2018), who find these markets to be among the most exposed African stock markets to the Euro sovereign debt crisis. They find that South Africa responded to the crisis immediately and significantly. This should not come as a surprise as both Egypt and South Africa are considered the region's most established and liquid markets (Allen et al., 2011). Therefore, it is expected that they are more linked to global markets through trades, banks or other financial channels.

The downside of these linkages is an increased exposure to global crisis and contagion effects, as evidenced in this case. Indeed, the high net credit exposure of South African banks to European countries is reported by Ahmad et al. (2013) as a possible explanation of contagion during the Eurozone crisis. Furthermore, South Africa is the EU's largest trading partner in Southern Africa, exhibiting a strong trade relationship with the EU through Germany and the United Kingdom. According to the data from World Integrated Trade Solution (WITS), Germany and the United Kingdom were among the top five trading partners of South Africa in 2009. From 2009 to 2018, Germany was the second-most country South Africa imported from, accounting for 11.66% of South Africa's total imports in 2009. This declined to 9.82% in 2012, a period that corresponds with the European debt crisis. We also attribute the EDC contagion in Morocco to intense reliance on trade and strong trade linkages between Morocco and the EU. Data from WITS show that trade is the biggest contributor to Morocco's GDP, contributing 75.25%, 83.43%, 85.12%, and 80.02% from 2010 to 2013. France, Spain, Italy, and Germany are among the top five trading partners of Morocco. In particular, France and Spain were the top two trading partners of Morocco from 2009 to 2018. According to the European Commission, the EU remained Morocco's biggest trading partner in 2019, accounting for 64% of Morocco's exports and 51% of its imports.

Regarding Brexit, individual market contagion effects are evident in Côte d'Ivoire, Ghana, Morocco, and Zambia, while we observe the effects on the stock markets of Côte d'Ivoire, Kenya, and Nigeria during COVID-19. In general, stock market performance in Africa has significantly reduced during and after the occurrence of COVID-19, usually between −2.7% and − 20% (Takyi & Bentum-Ennin, 2021). Brexit came with political and economic uncertainties surrounding trade to European and non-European countries. For Africa, it is feared that Brexit will cause a recession in the UK that could lead to a reduction in foreign aid and a decrease in FDI (Norton Rose Fulbright, 2017). However, the world was plunged into a pandemic right in the middle of Brexit negotiations. This muddies the water as the UK is now exposed to the combined effects of economic and health crises. Indeed, a temporary reduction in UK foreign aid from 0.7% to 0.5% was announced by the Chancellor of the Exchequer in November 2020.[9] Although, the announcement came after our Brexit data period, we argue that anticipation of such macroeconomic adjustments could have led to the Brexit contagion found in Ghana and Zambia. According to the International Monetary Fund's (IMF) Coordinated Direct Investment Survey, the UK was among the top five economies providing inward direct investment to Zambia from 2010 through 2019, excepting 2013 and 2016. In the case of Ghana, the UK was the highest provider of inward direct investment in 2017 and 2018. There is also the issue of trade where the UK was among the top five countries that Ghana imported from in 2016 and 2017.

We attribute the Brexit contagion found in the French-speaking African countries of Morocco and Côte d'Ivoire to the presence of foreign banks or a reflection of portfolio rebalancing by foreign investors. The finding is consistent with Kodres and Pritsker (2002), who argue that

[8] Classification of African markets is obtained from MSCI, where Egypt and South Africa are classified as emerging markets. Kenya, Mauritius, Morocco, Nigeria, and Tunisia are classified as frontier markets. Other African markets in our sample are not classified by MSCI. See https://www.msci.com/market-classification, for more details.

[9] The data are obtained from the UK government website: Changes to the UK's aid budget in the Spending Review - GOV.UK (www.gov.uk)

Table 3
Granger Causality tests.

DoC	Pre GFC	GFC	DoC	Pre EDC	EDC	DoC	Pre Brexit	Brexit	DoC	Pre COVID-19	COVID-19
	F-Statistics	F-Statistics		F-Statistics	F-Statistics		F-Statistics	F-Statistics		F-Statistics	F-Statistics
CIV → USA	0.697	0.062	CIV → GRC	0.427	0.398	CIV → GBR	0.587	0.353	CIV → CHN	1.530	0.616
USA → CIV	1.028	0.214	GRC → CIV	0.011	0.155	GBR → CIV	0.407	0.210	CHN → CIV	0.130	0.598
EGY → USA	3.387**	0.352	EGY → GRC	0.043	0.532	EGY → GBR	0.812	0.384	EGY → CHN	0.567	0.031
USA → EGY	2.505*	0.165	GRC → EGY	0.585	4.478**	GBR → EGY	0.037	0.265	CHN → EGY	8.320*	0.099
MAR → USA	7.054***	2.580*	KEN → GRC	3.824**	1.345	GHA → GBR	2.048	0.227	GHA → CHN	0.035	0.077
USA → MAR	1.425	0.101	GRC → KEN	0.745	0.098	GBR → GHA	1.987	0.728	CHN → GHA	0.070	0.111
MUS → USA	6.058***	0.386	MAR → GRC	3.735**	0.034	KEN → GBR	1.867	1.095	KEN → CHN	0.212	0.031
USA → MUS	0.865	0.059	GRC → MAR	5.796***	1.913	GBR → KEN	0.957	3.386**	CHN → KEN	2.053	0.082
NGA → USA	5.207***	0.435	MUS → GRC	3.290**	0.206	MAR → GBR	0.010	0.036	MAR → CHN	1.372	0.368
USA → NGA	0.946	0.749	GRC → MUS	2.044	17.909***	GBR → MAR	0.166	0.646	CHN → MAR	1.137	0.000
TUN → USA	0.880	1.230	NGA → GRC	3.763**	2.319*	MUS → GBR	0.876	1.541	MUS → CHN	1.183	0.049
USA → TUN	1.780	1.668	GRC → NGA	0.356	2.335*	GBR → MUS	0.306	0.170	CHN → MUS	3.146***	0.631
ZAF → USA	8.995***	1.300	TUN → GRC	0.575	0.502	NGA → GBR	2.120	2.633***	NGA → CHN	1.511	0.014
USA → ZAF	5.388***	0.174	GRC → TUN	0.025	0.034	GBR → NGA	0.333	1.177	CHN → NGA	0.676	0.003
			ZAF → GRC	2.480*	0.283	TUN → GBR	0.459	0.024	TUN → CHN	0.205	0.105
			GRC → ZAF	2.480*	1.521	GBR → TUN	1.160	2.123	CHN → TUN	0.896	0.052
			ZAM → GRC	0.528	0.213	TZA → GBR	0.738	0.330	TZA → CHN	0.199	0.077
			GRC → ZAM	1.908	0.181	GBR → TZA	0.328	0.305	CHN → TZA	1.565	1.526
						ZAF → GBR	0.637	2.672***	ZAF → CHN	0.920	0.105
						GBR → ZAF	0.264	0.249	CHN → ZAF	4.061**	0.221
						ZMB → GBR	0.061	0.044	ZMB → CHN	0.770	1.264
						GBR → ZMB	0.072	0.080	CHN → ZMB	0.120	0.095

This table reports the Granger causality test between crisis origin and African markets before and during the GFC, EDC, Brexit, and COVID-19 crises. The pre-crisis period for the GFC is defined as 1st January 2005 to 8th August 2007; the crisis period is defined as 9th August 2007 to 31st December 2009. The pre-crisis period for EDC is defined as 1st January 2010 to 1st May 2010; the crisis period is defined as 2nd May 2010 to 9th June 2013. The pre-crisis period for Brexit is defined as 1st January 2016 to 23rd June 2016; the crisis period is defined as 24th June 2016 to 30th September 2017. The pre-crisis period for COVID-19 is defined as 1st October 2019 to 31st December 2019; the crisis period is defined as 1st January 2020 to 31st March 2020. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. DoC represents Direction of Causality. The symbol → implies direction of causality between markets. *, **, and *** represent p-values <0.10, <0.05, and < 0.01.

cross-market rebalancing could explain contagion between Asia and Latin America during the crises of the 1990s even though the macroeconomies of the two regions are weakly linked. Most foreign banks in Africa have their headquarters in the UK, France, and Portugal. If they reduce their exposure in Africa, it could result in severe consequences such as financial contagion. The most vulnerable African countries to be affected through this channel include but are not limited to Botswana, Côte d'Ivoire, and Zambia (United Nations & African Union Commission, 2009).

Financial contagion from COVID-19 is found in Côte d'Ivoire, Kenya, and Nigeria, which have strong trade relationships with China. According to IMF data, Côte d'Ivoire is ranked among the top import partner which is around $1.96 billion in 2019 followed by Nigeria ($1.42 billion) and France ($1.23 billion). Kenya and Nigeria are among the largest trade partners with China in which their imports made up more than half of all imports of Chinese good in 2020. Therefore, it is not surprising that financial contagion from the COVID-19 occurs in those markets due to the strong relationships between those markets and China.

We argue that the contagion effect found during the COVID-19 period is a result of trade relationships between China and these countries as the Chinese market is dominated by export-oriented manufacturing companies. In 2015, the Financial Times reported that China accounts for 20% of imports and 15% of exports in Sub-Saharan Africa.[10] Therefore, it should be expected that changes in trading patterns associated with the crisis, such as border closures, would have an impact on the share prices of exporting companies and on the market. Evidence of financial market contagion in this period gains support from Ahmed and Huo (2018), who report that the Chinese stock market plays an important role in Africa with investments in 46 out of 54 countries. They show spillover effects from China to African markets, indicating that the shocks can be propagated from China to Africa most likely through the trading channel of transmission.

Africa's emerging markets, Egypt and South Africa are not contaminated during the Brexit and COVID-19 periods. Except for Nigeria, the rest of the markets where contagion is observed are small and much less

[10] The data are from Financial Times: https://www.ft.com/content/c53e7f68-9844-11e5-9228-87e603d47bdc

Table 4
Estimation of Results from the GJR – GARCH (1,1) Model.

Panel A: GFC					Panel B: EDC				
Country	Variance Equation				Country	Variance Equation			
	α	β	g	P		α	β	g	P
CIV	0.258 (3.179)***	0.747 (9.947)***	−0.113 (−1.523)	0.949	CIV	0.173 (1.721)*	0.217 (1.895)*	0.119 (1.057)	0.450
USA	−0.006 (−0.491)	0.912 (58.020)***	0.172 (6.079)***	0.992	GRC	0.053 (2.599)***	0.879 (32.310)***	0.034 (0.989)	0.949
EGY	0.055 (3.218)***	0.932 (69.340)***	0.021 (0.950)	0.998	EGY	0.048 (1.686)*	0.807 (20.030)***	0.142 (2.464)**	0.926
USA	0.003 (0.296)	0.914 (60.470)***	0.143 (4.967)***	0.989	GRC	0.050 (2.299)**	0.880 (34.420)***	0.041 (1.120)	0.951
MAR	0.202 (3.987)***	0.752 (13.300)***	0.008 (0.173)	0.958	KEN	0.197 (3.402)***	0.736 (8.286)***	−0.072 (−1.474)	0.897
USA	−0.013 (−1.263)	0.911 (60.700)***	0.178 (5.589)***	0.987	GRC	0.047 (2.512)**	0.887 (39.490)***	0.038 (1.161)	0.953
MUS	0.623 (3.477)***	0.613 (6.540)***	−0.217 (−1.271)	1.128	MAR	0.116 (2.337)**	0.685 (5.443)***	0.101 (1.660)*	0.852
USA	−0.012 (−1.080)	0.918 (66.220)***	0.166 (6.244)***	0.989	GRC	0.057 (2.362)**	0.865 (22.660)***	0.028 (0.778)	0.936
NGA	0.179 (2.812)***	0.796 (15.960)***	0.019 (0.305)	0.985	MUS	0.269 (2.319)**	0.531 (4.021)***	0.051 (0.562)	0.826
USA	−0.022 (−1.912)*	0.921 (65.150)***	0.176 (6.386)***	0.987	GRC	0.048 (2.367)**	0.879 (33.850)***	0.042 (1.208)	0.948
TUN	0.143 (3.833)***	0.770 (12.630)***	0.029 (0.582)	0.928	NGA	0.268 (2.711)***	0.555 (2.185)**	0.070 (0.268)	0.858
USA	0.006 (0.518)	0.910 (57.490)***	0.151 (4.936)***	0.992	GRC	0.042 (2.173)**	0.898 (40.200)***	0.033 (1.050)	0.957
ZAF	0.051 (2.907)***	0.895 (52.850)***	0.077 (2.845)***	0.985	TUN	0.200 (2.508)**	0.531 (5.906)***	0.354 (1.992)**	0.908
USA	−0.013 (−1.232)	0.921 (64.230)***	0.164 (5.989)***	0.990	GRC	0.043 (2.278)**	0.890 (40.910)***	0.045 (1.337)	0.956
					ZAF	−0.010 (−0.653)	0.912 (36.220)***	0.142 (3.758)***	0.973
					GRC	0.047 (2.396)**	0.880 (33.910)***	0.044 (1.231)	0.949
					ZMB	0.248 (4.250)***	0.804 (19.630)***	−0.208 (−3.668)***	0.948
					GRC	0.060 (2.729)**	0.873 (33.630)***	0.039 (1.061)	0.953

Panel C: Brexit					Panel D: COVID-19				
Country	Variance Equation				Country	Variance Equation			
	α	β	g	P		α	β	g	P
CIV	0.148 (4.312)***	0.771 (13.670)***	−0.060 (−0.968)	0.889	CIV	0.203 (2.501)**	0.862 (16.290)***	−0.256 (−2.737)**	0.937
GBR	−0.004 (−0.136)	0.867 (19.520)***	0.188 (3.056)***	0.957	CHN	−0.136 (−2.445)**	0.668 (6.486)***	0.686 (2.193)**	0.875
EGY	0.061 (0.674)	0.932 (14.660)***	0.004 (0.958)***	0.995	EGY	−0.187 (−2.117)**	0.841 (8.510)***	0.532 (2.725)***	0.920
GBR	−0.002 (−0.073)	0.880 (25.900)***	0.157 (3.064)**	0.957	CHN	−0.017 (−0.232)	0.684 (4.991)***	0.520 (1.173)	0.927
GHA	0.357 (1.450)	0.704 (4.042)***	−0.232 (−0.945)	0.945	GHA	0.576 (1.816)*	0.418 (1.299)	0.020 (0.049)	1.004
GBR	0.008 (0.269)	0.883 (18.610)***	0.148 (2.752)***	0.965	CHN	−0.024 (−0.441)	0.711 (4.169)***	0.605 (1.309)	0.990
KEN	0.332 (2.685)***	0.767 (14.660)***	−0.223 (−1.921)*	0.988	KEN	0.253 (1.542)	0.758 (10.500)***	−0.076 (−0.328)	0.973
GBR	−0.012 (−3.487)	0.884 (20.840)***	0.175 (3.536)***	0.960	CHN	0.005 (0.057)	0.750 (2.268)**	0.419 (0.616)	0.965
MAR	0.171 (1.252)	0.824 (4.798)***	−0.091 (−1.006)	0.950	MAR	0.034 (0.929)	0.688 (9.344)***	0.653 (2.685)***	1.049
GBR	−0.004 (−0.098)	0.889 (17.480)***	0.154 (3.253)***	0.962	CHN	−0.055 (−0.518)	0.745 (3.370)***	0.474 (0.865)	0.927
MUS	0.213 (2.970)**	0.798 (16.090)***	−0.240 (−2.833)***	0.891	MUS	0.158 (1.051)	0.840 (17.720)***	0.245 (0.926)	1.121
GBR	−0.001 (−0.037)	0.895 (22.950)***	0.146 (3.149)***	0.967	CHN	−0.061 (−0.724)	0.663 (3.846)***	0.645 (1.114)	0.925
NGA	0.204 (2.147)**	0.775 (6.326)***	−0.126 (−2.037)**	0.916	NGA	0.383 (2.154)**	0.643 (4.778)***	−0.038 (−0.148)	1.007
GBR	−0.021 (−0.7655)	0.906 (30.740)***	0.170 (3.351)***	0.970	CHN	−0.126 (−3.868)***	0.617 (5.454)***	0.621 (2.295)**	0.802
TUN	0.066 (2.690)***	0.937 (46.700)***	−0.045 (−1.306)	0.981	TUN	0.367 (1.704)*	0.585 (6.355)***	0.154 (0.679)	1.029
GBR	0.028 (0.671)	0.840 (18.460)***	0.150 (2.400)**	0.943	CHN	−0.099 (−1.370)	0.657 (3.994)***	0.659 (1.336)	0.888
TZA	0.060 (0.511)	0.345 (1.702)*	0.201 (1.111)	0.506	TZA	4.184 (1.441)	0.024 (1.200)	−3.998 (−1.369)	2.209
GBR	−0.017 (−0.567)	0.883 (24.700)***	0.193 (3.854)***	0.963	CHN	−0.075 (−0.945)	0.666 (3.423)***	0.629 (0.217)	0.906
ZAF	0.024 (0.784)	0.910 (24.350)***	0.887 (2.080)**	1.378	ZAF	−0.053 (−0.500)	0.795 (6.424)***	0.487 (2.101)**	0.986
GBR	0.011 (0.333)	0.858 (20.160)***	0.164 (2.718)***	0.951	CHN	−0.034 (−0.388)	0.843 (7.931)***	0.323 (1.276)	0.971
ZMB	0.107 (2.108)**	0.865 (10.984)***	0.262 (3.110)***	1.013	ZMB	−0.067 (−2.568)**	0.306 (0.589)	1.745 (0.902)*	1.112
GBR	0.024 (0.585)	0.858 (16.290)***	0.161 (2.484)**	0.962	CHN	−0.115 (−0.893)	0.728 (3.814)***	0.654 (1.298)	0.940

This table reports the average variance estimated from Eq. 5 of GJR–GARCH (1,1) model. Panels A, B, C, and D report results for the crises of GFC, EDC, Brexit, and COVID-19, respectively. The country represents African and crisis-origin markets. The full sample period for each crisis is defined as 1st January 2005 to 31st December 2009 for the GFC, 1st January 2010 to 9th June 2013 for the EDC, 1st January 2016 to 30th September 2017 for Brexit, and 1st October 2019 to 31st March 2020 for COVID-19. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. Alpha (α) and beta (β) are the ARCH and GARCH parameters while gamma (g) is asymmetric volatility effect. The t-statistics are in parentheses. *, ** and *** represent the p-values <0.10, <0.05, and < 0.01. P represents persistence.

developed. African markets are mostly illiquid and have a relatively small number of listed companies. The concentration of trade in a few stocks and the dominance of few firms on stock exchanges are also reported as characteristics of African markets (Alagidede, 2009; Allen et al., 2011). There is also the perspective that Brexit might expand trading opportunities for African markets through, for example, the creation of new export opportunities (Mold, 2018). This might be the reason why Africa's largest economies, South Africa, and Nigeria, did not exhibit contagion during Brexit.

For COVID-19, China is selected as the origin of crisis. However, the pandemic outbreak in China in December 2019 did not trigger a drastic fall in global stock markets until March 2020. The effect was apparent on the Dow Jones Industrial Average, dropping around 26% in four trading days – 9th, 12th, 16th, and 23rd March (Mazur, Dang, & Vega, 2021). Although, these dates are incorporated in our data, we did not find the regional contagion effect in Africa as shown in Table 6.

As evident in the regional analysis in Table 6 and Fig. 1, the African markets only experience significant financial contagion during the GFC but not the rest of the crises. The finding is consistent with the nature of those crises. In particular, the GFC is a global crisis that is more likely to affect most markets, especially the more developed markets, such as South Africa and Egypt. As expected, those markets which are relatively less developed are not significantly impacted by the GFC.

However, the EDC and Brexit are regional crises which tend to affect the markets who have strong trade relationships and financial linkages with the crisis origin countries (Greece and the UK in this case). In addition, we do not find any financial contagion at the regional level during COVID-19 since the COVID-19 crisis is still ongoing, we may not

Table 5
Conditional Correlation Results from the DCC–GJR–GARCH (1,1) Model.

Panel A: GFC				Panel B: EDC			
Country	α	β	DCC coefficient	Country	α	β	DCC coefficient
USA CIV	0.014	0.613	−0.017	GRC CIV	0.009	0.947	−0.010
	(0.520)	(1.682)*	(−0.577)		(0.935)	(47.290)***	(−0.245)
USA EGY	0.014	0.946	0.076	GRC EGY	0.03	0.936	0.077
	(0.131)	(26.520)***	(1.887)*		(2.969)***	(46.820)***	(1.067)
USA MAR	0.017	0.955	0.697	GRC KEN	0.028	0.837	0.004
	(2.496)**	(67.340)***	(0.389)		(0.196)	(5.343)***	(0.106)
USA MUS	0.000	0.806	0.065	GRC MAR	0.000	0.831	0.050
	(0.115)	(0.958)	(2.397)**		(0.279)	(1.704)*	(1.455)
USA NGA	0.017	0.833	0.009	GRC MUS	0.016	0.964	0.063
	(0.870)	(11.210)***	(0.255)		(1.977)**	(77.470)***	(1.137)
USA TUN	0.006	0.978	0.011	GRC NGA	0.008	0.691	0.045
	(0.794)	(34.180)***	(0.296)		(0.275)	(3.114)***	(1.130)
USA ZAF	0.019	0.965	0.388	GRC TUN	0.000	0.838	−0.086
	(2.728)***	(70.960)***	(7.440)***		(0.001)	(0.102)	(−2.237)**
				GRC ZAF	0.024	0.936	0.316
					(1.310)	(21.440)***	(6.587)***
				GRC ZMB	0.010	0.965	−0.066
					(1.078)	(30.840)***	(−1.171)
Panel C: Brexit				Panel D: COVID-19			
Country	α	β	DCC coefficient	Country	α	β	DCC coefficient
GBR CIV	0.000	0.837	−0.035	CHN CIV	0.000	0.637	0.134
	(0.446)	(4.729)***	(−0.734)		(0.000)	(0.326)	(1.024)
GBR EGY	0.000	0.775	0.105	CHN EGY	0.144	0.331	0.127
	(0.019)	(1.811)*	(1.933)*		(1.154)	(2.802)***	(1.028)
GBR GHA	0.000	0.863	0.047	CHN GHA	0.000	0.787	−0.018
	(0.596)	(3.132)***	(1.070)		(0.994)	(4.740)***	(−0.164)
GBR KEN	0.034	0.769	−0.041	CHN KEN	0.197	0.624	0.295
	(1.063)	(11.330)***	(−0.669)		(2.074)**	(3.806)***	(2.190)**
GBR MAR	0.009	0.962	−0.055	CHN MAR	0.218	0.452	0.301
	(0.602)	(51.52)***	(−0.811)		(2.349)**	(5.020)***	(2.319)**
GBR MUS	0.000	0.847	0.071	CHN MUS	0.084	0.901	0.767
	(0.000)	(2.251)**	(1.676)*		(1.893)*	(15.000)***	(6.519)***
GBR NGA	0.088	0.000	0.011	CHN NGA	0.000	0.737	0.230
	(0.412)	(0.000)	(0.196)		(0.211)	(2.8891)***	(2.113)**
GBR TUN	0.000	0.824	0.035	CHN TUN	0.005	0.886	0.108
	(0.008)	(3.125)***	(0.770)		(0.145)	(4.116)***	(1.387)
GBR TZA	0.014	0.794	0.039	CHN TZA	0.027	0.954	0.151
	(0.424)	(1.689)*	(0.645)		(1.544)	(4.826)***	(0.180)
GBR ZAF	0.071	0.757	0.562	CHN ZAF	0.016	0.892	0.558
	(2.222)**	(7.931)***	(14.660)***		(0.482)	(32.120)***	(6.722)***
GBR ZMB	0.013	0.947	0.030	CHN ZMB	0.000	0.837	−0.114
	(0.860)	(39.590)***	(0.471)		(0.001)	(1.577)	(−1.106)

This table reports the average conditional correlation results estimated from Eqs. 9 and 10 of the DCC–GJR–GARCH (1,1) model. Panels A, B, C, and D report results for the crises of GFC, EDC, Brexit, and COVID-19, respectively. The country represents the crisis-origin country against an African country. The full sample period for each crisis is defined as 1st January 2005 to 31st December 2009 for the GFC, 1st January 2010 to 9th June 2013 for the EDC, 1st January 2016 to 30th September 2017 for Brexit, and 1st October 2019 to 31st March 2020 for COVID-19. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. The DCC coefficient is the average conditional correlation estimated from Eq. 10. The *t*-statistics are in the parentheses. *, ** and *** represent the *p*-values <0.10, <0.05, and < 0.01.

capture the full effect of the crisis based on our data. An initial market fall at the beginning of the COVID-19 crisis is not unexpected as investors are fearful of a systemic collapse, and therefore, develop a panic-driven sell. Furthermore, the uniqueness of the COVID-19 crisis is its prolonged nature with a series of global measures from both developed and developing countries which all have the potential of experiencing global impacts. In fact, the crisis metamorphoses rapidly into a capitulation-type event, that leads to a fear of the global financial system risking systemic failure.

4.2. Regression analysis

To further examine financial contagion in African stock markets during major crises periods, we investigate financial contagion in a multivariate regression setting, taking account of a battery of macro-economic variables and country characteristics. Dynamic conditional correlations are regressed on the dummies of major crisis variables, the lag of the conditional correlations and other control variables, as shown in the following model:

$$\rho_{ij,t} = \theta_1 + \theta_2 GFC + \theta_3 EDC + \theta_4 BREXIT + \theta_5 COVID + \theta_6 \rho_{ij,t-1} + \theta_7 Risk + \theta_8 Financial\_Claim + \theta_9 Market\_Cap + \theta_{10} Corruption + \theta_{11} FDI + \theta_{12} Export\_GDP + \pi_{ij,t} \quad (14)$$

where $\rho_{ij,\,t}$ is the daily conditional correlation from Eq. 10. *GFC*, *EDC*, *Brexit* and *COVID-19* equal to 1 in the presence of *GFC*, *EDC*, *Brexit* and *COVID-19* crises, respectively and 0 otherwise. *Risk* is the difference in the country risk score at year *t* between country *i* and the crisis country, *Financial_Claim* is the difference in financial claim at year *t* between country *i* and the crisis country, *Market_Cap* is the difference in market capitalizations in US dollars at year *t* between country *i* and the crisis country, *Corruption* is the difference in corruption index score at year *t* between country *i* and the crisis country, *FDI* is the foreign investment at year *t* and *Export_GDP* is the ratio of export to GDP. The data for control variables are obtained from Bloomberg. We transform all control

Table 6
Contagion Tests on Dynamic Conditional Correlations Estimated from the DCC–GJR–GARCH (1,1) Model.

Panel A: GFC			Panel B: EDC		
Country	Constant	Dummy	Country	Constant	Dummy
USA CIV	−0.016	−0.002	GRC CIV	0.001	−0.013
	(−23.900)***	(−2.530)**		(0.434)	(−3.600)***
USA EGY	0.066	0.017	GRC EGY	0.012	0.061
	(33.600)***	(6.160)***		(0.867)	(4.240)***
USA MAR	0.009	0.014	GRC KEN	0.015	−0.011
	(3.630)***	(3.870)***		(2.530)**	(−1.880)*
USA MUS	0.065	−4.60809e-08	GRC MAR	0.050	0.000
	(2.094e+06)***	(−1.030)		(5.422e+04)***	(2.590)**
USA NGA	0.008	0.002	GRC MUS	0.088	−0.027
	(5.930)***	(1.350)		(10.300)***	(−3.000)***
USA TUN	−0.003	0.030	GRC NGA	0.046	−0.001
	(−2.680)**	(17.800) ***		(35.500)***	(−0.979)
USA ZAF	0.333	0.079	GRC TUN	0.000	−0.086
	(106.000)***	(17.500)***		(−1.600)	(−7.627e+04)***
RAVERAGE	0.067	0.019	GRC ZAF	0.280	0.036
	(76.307)***	(15.119)***		(35.100)***	(4.360)***
			GRC ZMB	−0.032	−0.037
				(−5.970)***	(−6.660)***
			RAVERAGE	0.042	0.001
				(17.745)***	(0.284)

Panel D: Brexit			Panel D: COVID-19		
Country	Constant	Dummy	Country	Constant	Dummy
GBR CIV	−0.035	3.62995e-08	CHN CIV	0.134	6.18783e-14
	(−3.146e+06)***	(2.820)**		(5.668e+12)***	(1.880)*
GBR EGY	0.105	−6.91464e-09	CHN EGY	0.110	0.005
	(5.748e+07)***	(−3.250)***		(7.870)***	(0.243)
GBR GHA	0.047	1.55176e-06	CHN GHA	−0.018	−1.04194e-08
	(1.215e+05)***	(3.450)***		(−1.465e+06)***	(−0.602)
GBR KEN	−0.036	−0.009	CHN KEN	0.219	0.096
	(−6.790)***	(−1.460)		(7.970)***	(2.520)**
GBR MAR	−0.086	0.043	CHN MAR	0.259	0.012
	(−24.600)***	(10.600)***		(9.420)***	(0.324)
GBR MUS	0.071	−5.48367e-15	CHN MUS	0.533	−0.375
	(3.077e+12)***	(−0.204)		(24.500)***	(−12.000)***
GBR NGA	0.006	0.008	CHN NGA	0.231	1.64920e-08
	(0.867)	(0.938)		(2.831e+07)***	(1.460)*
GBR TUN	0.035	−5.04718e-11	CHN TUN	0.108	−0.001
	(2.135e+09)***	(−2.640)**		(95.600)***	(−0.522)
GBR TZA	0.038	0.001	CHN TZA	0.227	−0.136
	(16.300)***	(0.385)		(25.100)***	(−10.900)***
GBR ZAF	0.596	−0.052	CHN ZAF	0.549	0.003
	(85.500)***	(−6.410)***		(174.000)***	(0.795)
GBR ZMB	0.022	0.010	CHN ZMB	−0.114	−5.66037e-11
	(5.470) ***	(2.160)**		(−8.401e+08)***	(−0.313)
RAVERAGE	0.070	0.001	RAVERAGE	0.213	−0.037
	(53.372)***	(0.483)		(34.914)***	(−4.330)***

This table reports the estimation results of regression Eq. 11 based on the DCC–GJR–GARCH (1,1) model. Panels A, B, C, and D report results for the crises of GFC, EDC, Brexit and COVID-19, respectively. The country represents a crisis-origin country against an African country. The full sample period for each crisis is defined as 1st January 2005 to 31st December 2009 for the GFC, 1st January 2010 to 9th June 2013 for the EDC, 1st January 2016 to 30th September 2017 for Brexit, and 1st October 2019 to 31st March 2020 for COVID-19. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. Dummy is the dummy variable of each crisis, which equals 1 during the crisis periods and 0 otherwise. RAVERAGE represents the regional average across African stock markets. The *t*-statistics are in parentheses. *, ** and *** represent the *p*-values <0.10, <0.05, and < 0.01.

variables to daily frequency using the last available value. In addition, the fixed-effect panel regression method is employed at both country and year levels.

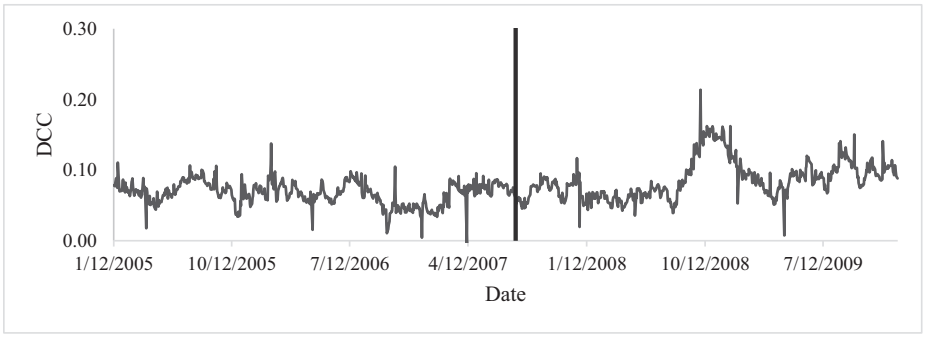
The results using GJR–GARCH (1,1) model are reported in Table 7.[11] As Egypt and South African markets are developing markets that are documented to be more connected to the rest of world, financial contagion is expected to be more pronounced in those two markets than the rest of the markets in Africa. Models 1 and 2 report the results for all African markets; Models 3 and 4 Egypt and South Africa; and Models 5 and 6 all African markets except for Egypt and South Africa. Models 1, 3 and 5 (2, 4 and 6) report the results without (with) controlling for other variables.

We find that the coefficients of dummy variables are either insignificant or significantly negative, suggesting that no significant financial contagion occurs at the regional level as shown in Models 1 and 2. The findings support the results of portfolio analysis except for the significant financial contagion from the GFC crisis. After controlling for the conditional correlation for the previous day, the GFC financial contagion largely disappears. In relation to Egypt and South Africa, we find significant financial contagion from the EDC crisis even after controlling for other variables. The finding is consistent with Kablan and Kaabia (2018) – that those two markets are among the most exposed African stock markets to the EDC.

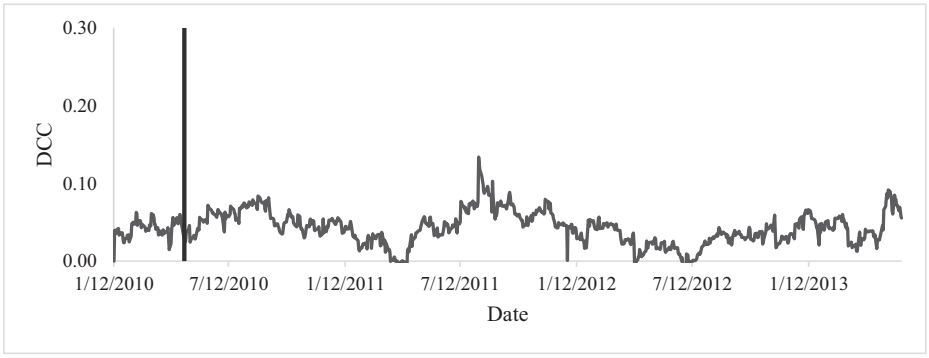
As far as control variables are concerned in Model 2, the dynamic condition correlation significantly increases in country-level risk, market capitalization, and the export to GDP and decreases in corruption.

[11] The results using GARCH (1,1) model which are reported in Table B4 are qualitatively similar to those using GJR GARCH (1,1) model.

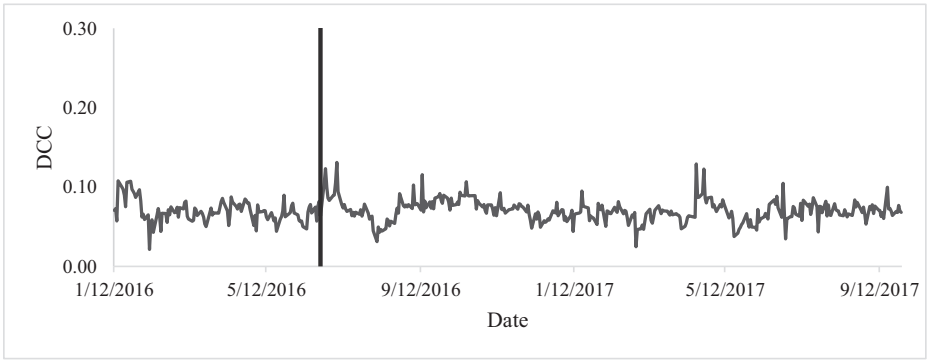
Panel A. GFC



Panel B. EDC



Panel C. Brexit



Panel D. COVID-19

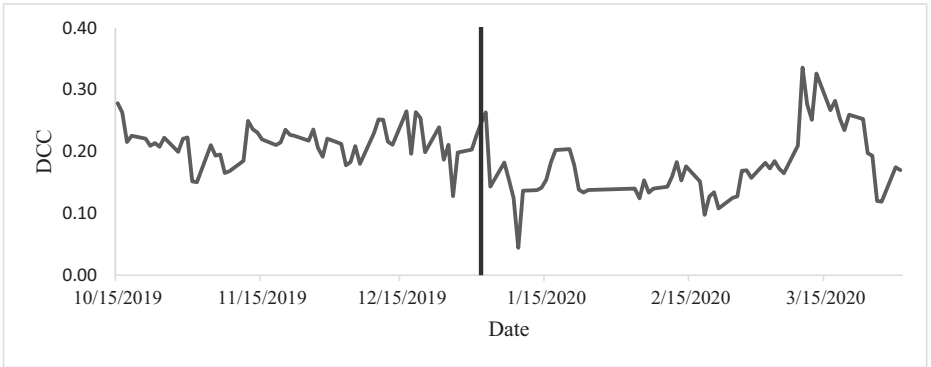


Fig. 1. Dynamic Conditional Correlations (DCC) for Each Crisis. This figure depicts the time-varying conditional correlation estimates by using the GJR–GARCH (1,1) model for the African market at a regional level. Panels A, B, C, and D report results for the crises of GFC, EDC, Brexit, and COVID-19, respectively. The black bar represents the occurrence of the financial crisis.

Table 7
Fixed-Effect Panel Regression Results Based on the DCC–GJR–GARCH (1,1) Model.

	All African markets		Egypt and South Africa only		All markets except Egypt and South Africa	
	(1)	(2)	(3)	(4)	(5)	(6)
GFC	0.000	0.000	0.001	−0.000	0.000	0.001
	(0.070)	(0.270)	(−0.230)	(−0.930)	(0.260)	(7.600)***
EDC	0.002	0.000	0.013	0.009	−0.002	−0.000
	(1.330)	(1.190)	(3.650)***	(3.690) ***	(−1.180)	(−0.360)
Brexit	0.001	0.000	−0.004	−0.001	0.001	0.000
	(−0.090)	(0.170)	(−1.320)	(−0.630)	(0.910)	(−0.390)
COVID-19	−0.004		0.000		−0.006	
	(−2.180)		(−0.080)		(−2.900)	
	**				***	
Coef_1	0.898	0.996	0.908	0.918	0.871	0.922
	(303.980)	(204.170)	(159.580)	(202.360)	(230.090)	(173.000)
	***	***	***	***	***	***
Risk		0.025		0.007		0.021
		(5.280) ***		(0.440)		(4.650) ***
Financial Claim		−0.000		0.000		0.000
		(−0.810)		(−0.880)		(0.580)
Market Capitalization		0.000		0.000		0.000
		(6.470) ***		(0.390)		(−0.740)
Corruption		−0.008		0.001		−0.017
		(−1.990) **		(0.390)		(−8.510) ***
FDI		0.000		−0.001		−0.001
		(0.880)		(−1.680)*		(−1.880)*
Export to GDP		0.001		0.000		0.001
		(3.360) ***		(0.890)		(1.710)*
R-square	0.754	0.818	0.764	0.825	0.749	0.829
Country Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22,692	12,619	5358	2971	17,334	9648

Table 7 reports regression results using Eq. 10 and the conditional correlation is estimated using the DCC–GJR–GARCH (1,1) model. Models 1 and 2 report the results for all African markets, Models 3 and 4 Egypt and South Africa, and Models 5 and 6 all African markets except for Egypt and South Africa. The full sample period for each crisis is defined as 1st January 2005 to 31st December 2009 for the GFC, 1st January 2010 to 9th June 2013 for the EDC, 1st January 2016 to 30th September 2017 for Brexit, and 1st October 2019 to 31st March 2020 for COVID-19. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. *GFC, EDC, Brexit* and *COVID-19* equal to 1 in the presence of GFC, EDC, Brexit and COVID-19 crises, respectively and 0 otherwise. *Coef_1* is the conditional correlation with a lag. *Risk* is the difference in the country risk score at year *t* between country *i* and a crisis country and its coefficient is reported as percentage, *Financial_Claim* is the difference in financial claim at year *t* between country *i* and a crisis country, *Market_Cap* is the difference in market capitalizations in US dollars at year *t* between country *i* and a crisis country, Corruption is the difference in the corruption index score at year *t* between country *i* and a crisis country. FDI is the foreign investment at year t and Export_GDP is the ratio of export to GDP. The data for control variables is obtained from Bloomberg. *, ** and *** represent the *p*-values <0.10, <0.05, and < 0.01.

This suggests that financial contagion is more likely to occur in countries with a higher level of risk, larger stock markets, and more dependence on exports. This also suggests the correlation between African and crisis markets is more pronounced for countries that are comparably more developed and have stronger trade relationships. However, in Models 3 and 4, we find no such evidence in two subsamples of Egypt and South Africa and the rest of the markets in Africa. This is likely to be due to lack of variations of those control variables in these subsamples.

5. Conclusion

This paper investigates the financial contagion effect of major crises, including the GFC, EDC, Brexit, and COVID-19, in African stock markets over the period of 2005 to 2020. We examine the impact of these different crises on individual African markets and from a regional perspective. We find evidence of contagion in some individual markets during the different crises examined. Contagion is found in Egypt, Morocco, Tunisia, and South Africa for the GFC period. In case of the EDC, the shock from Greece is contagious in Egypt, Morocco, and South Africa. For the Brexit period, Côte d'Ivoire, Ghana, Morocco, and Zambia are significantly affected, while for the COVID-19 period, contagion is found in Côte d'Ivoire, Kenya, and Nigeria. Overall, on an individual market basis, we find that the crises affected the African markets differently. These differences could be a result of the nature and origin of the crisis, heavy dependency on advanced economies through international trade, foreign direct investments, and growing market integration. At the regional level, we find evidence of financial contagion only during the GFC, although after accounting for the return autocorrelation of the regression analysis, the contagion effect during the GFC largely disappears.

In addition, we provide a unique perspective on the nature of the crises and their impacts on African markets. Our findings are particularly relevant to domestic and international portfolio investors, fund managers, and other practitioners who seek investments and predictable returns from African stock markets. We also argue that the contagion effect of each crisis to African markets differs according to the nature and origin of each financial crisis. The findings suggest that international investors can gain diversification benefits from some African markets.

Our study is related to the broad literature on financial market structures, co-movements and portfolio diversification. The central element of the debate is the behaviour of financial markets during crisis. Many studies argue that increasing globalization of financial markets has made them susceptible to contagion events, suggesting that financial contagion is unlikely to be eliminated. The challenge therefore is for countries to take steps to minimize their vulnerability to international financial contagion. However, financial contagion is still evolving as shown by the nature of crises, 1) those that occur slowly over years and are anticipated such as in the GFC and EDC; 2) those from political perspective as Brexit; and 3) sudden crises such as COVID- 19. An extension of this analysis would be to expand the investigation of financial contagion in African stock markets within sectors to assess the

empirical relevance of the sectors to contagion events and subsequently to provide a guiding framework for designing policies aimed at reducing vulnerability to international contagion events through sectors.

CRediT authorship contribution statement

Jaliyyah Bello: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Jiaqi Guo:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Mohammad Khaleq Newaz:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing.

Appendix A. African stock markets under study

Countries	World Bank alphabetic country codes	Stock market indices	Year established
Côte d'Ivoire	CIV	ICXCOMP	1998
Egypt	EGY	EGX30	1883
Ghana	GHA	GGSECI	1989
Kenya	KEN	NSEASI	1954
Mauritius	MUS	SEMDEX Index	1989
Morocco	MAR	MOSENEW INDEX	1929
Nigeria	NGA	NGSEINDX Index	1960
Tanzania	TZA	DARSDSEI Index	1998
Tunisia	TUN	TUSISE Index	1998
South Africa	ZAF	JALSH INDEX	1887
Zambia	ZMB	LUSEIDX	1993

Sources: World Bank WITS; Bloomberg.

Appendix B. Tables

Table B1
Estimation of Results from the GARCH (1,1) Model

Panel A: GFC				Panel B: EDC			
Country	α	β	Persistence	Country	α	β	Persistence
CIV	0.210 (3.564)***	0.743 (10.780)***	0.953	CIV	0.232 (2.752)***	0.270 (1.823)***	0.502
USA	0.997 (6.576)***	0.895 (62.820)***	1.892	GRC	0.682 (4.500)***	0.881 (33.200)***	1.563
EGY	0.068 (3.957)***	0.931 (65.980)***	0.999	EGY	0.139 (3.788)***	0.796 (20.120)***	0.935
USA	0.091 (5.969)***	0.900 (61.980)***	0.991	GRC	0.068 (4.269)***	0.881 (35.570)***	0.949
MAR	0.206 (4.259)***	0.752 (13.510)***	0.958	KEN	0.163 (3.500)***	0.731 (7.452)***	0.894
USA	0.097 (6.161)***	0.896 (58.990)***	0.993	GRC	0.064 (4.741)***	0.889 (47.730)***	0.953
MUS	0.508 (3.272)***	0.618 (5.040)***	1.126	MAR	0.185 (3.510)***	0.642 (5.492)***	0.827
USA	0.095 (6.111)***	0.895 (58.900)***	1.126	GRC	0.069 (3.858)***	0.866 (22.800)***	0.935
NGA	0.190 (4.673)***	0.795 (16.760)***	0.985	MUS	0.307 (3.593)***	0.514 (4.222)***	0.821
USA	0.090 (6.035)***	0.900 (59.720)***	0.990	GRC	0.066 (4.647)***	0.881 (36.270)***	0.947
TUN	0.157 (4.033)***	0.773 (12.890)***	0.930	NGA	0.284 (2.116)***	0.591 (4.393)***	0.875
USA	0.093 (5.540)***	0.903 (56.550)***	0.996	GRC	0.058 (4.094)***	0.898 (42.140)***	0.956
ZAF	0.100 (6.422)***	0.890 (57.080)***	0.990	TUN	0.389 (4.536)***	0.531 (6.616)***	0.920
USA	0.095 (6.315)***	0.897 (60.270)***	0.992	GRC	0.063 (4.414)***	0.891 (43.660)***	0.954
				ZAF	0.083 (3.582)***	0.892 (29.840)***	0.975
				GRC	0.066 (4.588)***	0.883 (35.880)***	0.949
				ZMB	0.164 (3.967)***	0.771 (13.860)***	0.935
				GRC	0.077 (4.779)***	0.876 (35.090)***	0.953

Panel C: Brexit				Panel D: COVID-19			
Country	α	β	Persistence	Country	α	β	Persistence
CIV	0.125 (4.011)***	0.753 (14.850)***	0.878	CIV	0.168 (1.242)	0.647 (2.194)**	0.815
GBR	0.111 (2.677)***	0.831 (12.810)***	0.942	CHN	0.207 (1.076)	0.789 (4.125)***	0.996
EGY	0.064 (1.102)	0.932 (17.180)***	0.996	EGY	0.239 (1.200)	0.750 (4.647)***	0.989
GBR	0.104 (2.794)***	0.845 (13.580)***	0.949	CHN	0.239 (1.200)	0.750 (4.647)***	0.989
GHA	0.244 (1.086)**	0.729 (5.662)***	0.973	GHA	0.582 (1.670)*	0.422 (1.286)	1.004
GBR	0.110 (2.459)***	0.838 (12.230)***	0.948	CHN	0.214 (1.329)	0.810 (8.025)***	1.024
KEN	0.275 (2.560)***	0.707 (15.490)***	0.982	KEN	0.220 (1.960)**	0.747 (9.732)***	0.967
GBR	0.111 (2.941)***	0.832 (14.460)***	0.943	CHN	0.270 (1.219)	0.741 (5.342)***	1.011

(*continued on next page*)

Table B1 (*continued*)

Panel C: Brexit				Panel D: COVID-19			
Country	α	*β*	Persistence	Country	α	*β*	Persistence
MAR	0.133 (1.283)	0.817 (4.337)***	0.950	MAR	0.317 (3.455)***	0.754 (7.347)***	1.071
GBR	0.109 (3.091)***	0.834 (16.270)***	0.943	CHN	0.240 (1.086)	0.765 (3.661)***	1.005
MUS	0.130 (2.631)***	0.780 (20.750)***	0.910	MUS	0.375 (1.618)	0.773 (5.383)***	1.148
GBR	0.108 (2.455)***	0.846 (12.640)***	0.954	CHN	0.266 (1.024)	0.738 (4.132)***	1.004
NGA	0.159 (1.583)	0.738 (3.816)***	0.897	NGA	0.370 (2.246)**	0.634 (5.522)***	1.004
GBR	0.088 (2.836)***	0.875 (18.620)***	0.963	CHN	0.189 (1.130)	0.806 (6.141)***	0.995
TUN	0.049 (2.679)***	0.931 (42.830)***	0.980	TUN	0.464 (2.835)**	0.572 (6.559)***	1.036
GBR	0.123 (3.005)***	0.813 (13.760)***	0.936	CHN	0.238 (0.970)	0.758 (3.839)***	0.996
TZA	0.228 (2.145)***	0.106 (0.406)***	0.334	TZA	3.049 (1.628)*	0.097 (1.198)	3.146
GBR	0.114 (3.136)***	0.831 (15.930)***	0.945	CHN	0.241 (1.144)	0.766 (4.449)***	1.007
ZAF	0.077 (2.650)***	0.887 (23.850)***	0.964	ZAF	0.211 (3.986)***	0.833 (14.080)***	1.044
GBR	0.115 (2.685)***	0.835 (14.010)***	0.950	CHN	0.234 (1.067)	0.768 (3.956)***	1.002
ZMB	0.107 (3.108)***	0.365 (1.984)**	0.472	ZMB	0.107 (3.108)***	0.365 (1.984)**	0.472
GBR	0.130 (2.485)**	0.813 (10.140)***	0.943	CHN	0.253 (1.139)	0.685 (2.845)**	0.938

This table reports the average variance estimated from Eq. 4 of the GARCH (1,1) model. Panels A, B, C, and D report results for the crises of the GFC, EDC, Brexit, and COVID-19, respectively. The country represents African and crisis-origin markets. The full sample period for each crisis is defined as 1st January 2005 to 31st December 2009 for the GFC, 1st January 2010 to 9th June 2013 for the EDC, 1st January 2016 to 30th September 2017 for Brexit, and 1st October 2019 to 31st March 2020 for COVID-19. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. α and beta (*β*) are the ARCH and GARCH parameters in Eq. 4. The *t*-statistics are in parentheses. *, ** and *** represent the *p*-values <0.10, <0.05, and < 0.01.

Table B2
Estimation of Results from the DCC–GARCH (1,1) Model.

Panel A: GFC				Panel B: EDC			
Country	α	*β*	DCC coefficient	Country	α	*β*	DCC coefficient
USA CIV	0.019 (0.605)	0.549 (0.962)	−0.022 (−0.756)	GRC CIV	0.009 (0.922)	0.947 (46.700)***	−0.010 (−0.245)
USA EGY	0.015 (1.407)	0.941 (35.630)**	0.071 (1.714)*	GRC EGY	0.031 (3.098) ***	0.939 (46.430)***	0.079 (1.062)
USA MAR	0.018 (2.632)***	0.952 (62.890)***	0.010 (0.250)	GRC KEN	0.030 (1.256)	0.817 (4.491)***	0.005 (0.119)
USA MUS	0.000 (0.227)	0.795 (0.563)	0.064 (2.328)**	GRC MAR	0.000 (0.191)	0.829 (1.401)	0.050 (1.465)
USA NGA	0.016 (0.834)	0.833 (10.400)***	0.004 (0.120)	GRC MUS	0.015 (1.933) *	0.964 (76.880)***	0.062 (1.131)
USA TUN	0.005 (0.706)	0.978 (36.850)***	0.010 (0.262)	GRC NGA	0.009 (0.304)	0.690 (3.157)***	0.044 (1.088)
USA ZAF	0.019 (2.190)**	0.962 (48.740)***	0.381 (8.003)***	GRC TUN	0.000 (0.066)	0.835 (0.488)	−0.082 (−2.169)**
				GRC ZAF	0.025 (1.480)	0.942 (23.000)***	0.319 (6.226)***
				GRC ZMB	0.009 (0.990)	0.965 (27.810)***	−0.067 (−1.197)

Panel C: Brexit				Panel D: COVID-19			
Country	α	*β*	DCC coefficient	Country	α	*β*	DCC coefficient
GBR CIV	0.000 (1.402)	0.837 (4.803)***	−0.030 (−0.644)	CHN CIV	0.000 (0.036)	0.656 (0.905)	0.142 (1.008)
GBR EGY	0.000 (1.756)*	0.742 (2.381)**	0.109 (1.999)**	CHN EGY	0.320 (2.230)**	0.272 (2.957) **	0.204 (1.438)
GBR GHA	0.000 (0.001)	0.863 (2.385)**	0.038 (0.841)	CHN GHA	0.000 (0.001)	0.787 (3.533)***	−0.050 (−0.486)
GBR KEN	0.048 (1.409)	0.764 (13.810)***	−0.039 (−0.623)	CHN KEN	0.207 (2.440)**	0.605 (4.908)***	0.289 (2.247)**
GBR MAR	0.012	0.958	−0.049	CHN MAR	0.216	0.470	0.308

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Table B2 (*continued*)

Panel A: GFC				Panel B: EDC			
Country	α	*β*	DCC coefficient	Country	α	*β*	DCC coefficient
	(0.770)	(41.570)***	(−0.711)		(2.441)**	(4.484)***	(2.487)**
GBR MUS	0.000	0.840	0.081	CHN MUS	0.088	0.898	0.725
	(0.104)	(2.370)**	(1.900)*		(1.651)*	(12.820)***	(4.622)***
GBR NGA	0.106	0.000	0.012	CHN NGA	0.000	0.782	0.243
	(0.689)	(0.000)	(0.196)		(0.000)	(2.238)**	(2.179)**
GBR TUN	0.000	0.829	0.033	CHN TUN	0.000	0.863	0.090
	(0.011)	(3.135)***	(0.727)		(0.419)	(1.071)	(1.236)
GBR TZA	0.009	0.838	0.045	CHN TZA	0.014	0.862	0.119
	(0.732)	(2.757)**	(0.732)		(0.399)	(4.222)***	(1.060)
GBR ZAF	0.077	0.741	0.568	CHN ZAF	0.010	0.888	0.552
	(2.472)**	(8.079)***	(15.210)***		(0.272)	(29.680)***	(5.891)***
GBR ZMB	0.013	0.929	0.028	CHN ZMB	0.000	0.838	−0.082
	(0.616)	(26.090)***	(0.494)		(+.Inf)***	(0.868)	(−0.922)

This table reports the average conditional correlation results estimated from Eqs. 9 and 10 of the DCC–GARCH (1,1) model. Panels A, B, C, and D report results for the crises of the GFC, EDC, Brexit, and COVID-19, respectively. The country represents the crisis-origin country against an African country. The full sample period for each crisis is defined as 1st January 2005 to 31st December 2009 for the GFC, 1st January 2010 to 9th June 2013 for the EDC, 1st January 2016 to 30th September 2017 for Brexit, and 1st October 2019 to 31st March 2020 for COVID-19. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. The DCC coefficient is the average conditional correlation estimated from Eq. 10. The *t*-statistics are in parentheses. *, ** and *** represent the *p*-values <0.10, <0.05, and < 0.01.

Table B3
Contagion Tests on Dynamic Conditional Correlations Estimated from the DCC-GARCH (1,1) Model

Panel A: GFC			Panel B: EDC		
Country	Constant	Dummy	Country	Constant	Dummy
USA CIV	−0.020	−0.003	GRC CIV	0.002	−0.013
	(−25.400)***	(−2.290)**		(0.579)	(−3.810)**
USA EGY	0.063	0.014	GRC EGY	0.009	0.063
	(30.500)***	(4.650)***		(0.636)	(4.340)***
USA MAR	0.006	0.011	GRC KEN	0.016	−0.011
	(2.180)**	(3.000)***		(2.670)***	(−1.950)*
USA MUS	0.064	−1.84755e-07	GRC MAR	0.050	2.01263e-06
	(548e+05)***	(−1.120)		(6.295e+04)***	(2.400)**
USA NGA	0.003	0.002	GRC MUS	0.087	−0.026
	(2.750)***	(1.210)		(10.300)***	(−3.030)***
USA TUN	−0.002	0.023	GRC NGA	0.046	−0.001
	(−1.520)	(16.000)***		(31.200)***	(−1.120)
USA ZAF	0.335	0.069	GRC TUN	−0.082	−4.03584e-07
	(113.000)***	(16.100)***		(−3.038e+05)***	(−1.420)
RAVERAGE	0.065	0.016	GRC ZAF	0.282	0.037
	(74.935)***	(12.452)***		(31.200)***	(3.850)***
			GRC ZMB	−0.031	−0.038
				(−6.390)***	(−7.490)***
			RAVERAGE	0.042	0.001
				(17.290)	(0.263)
Panel D: Brexit			Panel D: COVID-19		
Country	Constant	Dummy	Country	Constant	Dummy
GBR CIV	−0.030	5.53576e-08	CHN CIV	0.142	1.43552e-08
	(−1.415e+06)***	(2.220)**		(2.770e+07)***	(2.010)**
GBR EGY	0.109	−9.62022e-07	CHN EGY	0.143	0.018
	(3.533e+05)***	(−2.680)**		(5.660)***	(0.514)
GBR GHA	0.038	7.01502e-10	CHN GHA	−0.050	−5.74353e-12
	(2.264e+08)***	(3.590)***		(−1.649e+10)***	(−1.360)
GBR KEN	−0.034	−0.012	CHN KEN	0.221	0.085
	(−4.790)***	(−1.520)		(8.320)***	(2.310)**
GBR MAR	−0.088	0.053	CHN MAR	0.263	0.011
	(−21.300)***	(11.200)***		(10.100)***	(0.312)
GBR MUS	0.081	−3.98197e-12	CHN MUS	0.491	−0.335
	(3.899e+08)***	(−0.016)		(24.300)***	(−11.500)***
GBR NGA	0.004	0.011	CHN NGA	0.243	1.33474e-12
	(0.506)	(1.160)		(6.756e+11)***	(2.680)**
GBR TUN	0.033	−2.22986e-10	CHN TUN	0.090	−2.06561e-05
	(5.371e+08)***	(−3.080)**		(6374.00)***	(−1.050)
GBR TZA	0.045	8.12229e-06	CHN TZA	0.135	−0.026
	(26.200)***	(0.004)		(44.600)***	(−6.340)***
GBR ZAF	0.604	−0.055	CHN ZAF	0.547	0.002
	(85.100)***	(−6.670)***		(293.000)***	(0.725)
GBR ZMB	0.021	0.011	CHN ZMB	−0.082	−1.50840e-14
	(6.350)***	(2.980)**		(−2.530e+12)	(−0.347)
RAVERAGE	0.071	0.002	RAVERAGE	0.204	−0.023
	(44.118)	(0.844)		(32.631)	(−2.607)

This table reports the estimation results of regression Eq. 9 based on the DCC–GARCH (1,1) model. Panels A, B, C, and D report results for the crises of the GFC, EDC, Brexit, and COVID-19, respectively. The country represents a crisis-origin country against an African country. The full sample period for each crisis is defined as 1st January 2005 to 31st December 2009 for the GFC, 1st January 2010 to 9th June 2013 for the EDC, 1st January 2016 to 30th September 2017 for Brexit, and 1st October 2019 to 31st March 2020 for COVID-19. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. Dummy is the dummy variable of each crisis which equals 1 during the crisis periods and 0 otherwise. RAVERAGE represents the regional average across African stock markets. The *t*-statistics are in parentheses. *, ** and *** represent the *p*-values <0.10, <0.05, and < 0.01.

Table B4
Fixed-Effect Panel Regression Results Based on the DCC-GARCH (1,1) Model

	All African markets		Egypt and South Africa only		All markets except Egypt and South Africa	
	(1)	(2)	(3)	(4)	(5)	(6)
GFC	0.000	0.002	0.000	−0.012	0.001	0.002
	(0.270)	(0.510)	(0.160)	(0.810)	(0.420)	(1.190)
EDC	0.002	0.002	0.009	0.009	−0.002	−0.001
	(1.190)	(1.320)	(3.180) ***	(3.290) ***	(−1.040)	(−0.570)
Brexit	0.000	0.001	−0.003	−0.002	0.001	0.001
	(0.070)	(0.480)	(−1.300)	(−0.840)	(0.830)	(0.690)
COVID-19	−0.005		0.000		−0.007	
	(−3.020) ***		(−0.040)		(−4.060) ***	
Coef_1	0.917	0.892	0.941	0.938	0.887	0.775
	(346.070) ***	(194.430) ***	(−204.640) ***	(151.120) ***	(252.910) ***	(100.000) ***
Risk		0.019		0.004		0.018
		(5.670) ***		(0.250)		(6.220) ***
Financial Claim		0.037		0.061		0.040
		(1.120)		(0.510)		(0.580)
Market Capitalization		0.000		0.000		0.000
		(5.400) ***		(0.060)		(0.390)
Corruption		−0.012		0.004		−0.054
		(−2.690)		(0.420)		(9.190) ***
FDI		0.000		−0.002		−0.001
		(0.220)		(−2.250)**		(2.370) **
Export to GDP		0.001		0.001		0.000
		(3.730) ***		(1.140)		(0.790)
R-square	0.762	0.817	0.780	0.821	0.730	0.837
Country Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22,692	12,619	5358	2971	17,334	9648

This Table reports regression results using Eq. 10 and the conditional correlation is estimated using the DCC–GARCH (1,1) model. Models 1 and 2 report the results for the whole African markets, Models 3 and 4 Egypt and South Africa, and Models 5 and 6 all African markets except for Egypt and South Africa. The full sample period for each crisis is defined as 1st January 2005 to 31st December 2009 for the GFC, 1st January 2010 to 9th June 2013 for the EDC, 1st January 2016 to 30th September 2017 for Brexit, and 1st October 2019 to 31st March 2020 for COVID-19. The full sample period of the paper incorporating all testing periods is from 1st January 2005 to 31st March 2020. *GFC, EDC, Brexit* and *COVID-19* equal to 1 in the presence of the GFC, EDC, Brexit and COVID-19 crises, respectively and 0 otherwise. *Coef_1* is the conditional correlation with a lag. *Risk* is the difference in the country risk score at year *t* between country *i* and a crisis country and its coefficient is reported as percentage, *Financial_Claim* is the difference in financial claim at year *t* between country *i* and a crisis country, *Market_Cap* is the difference in market capitalizations in US dollars at year *t* between country *i* and a crisis country, *Corruption* is the difference in corruption index score at year *t* between country *i* and a crisis country. *FDI* is the foreign investment at year t and Export_GDP is the ratio of export to GDP. The data for control variables is obtained from Bloomberg. *, ** and *** represent the *p*-values <0.10, <0.05, and < 0.01.

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