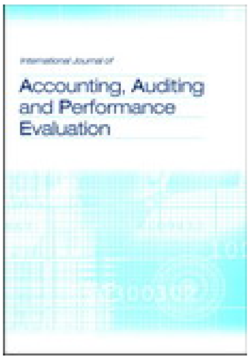

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Financial contagion during the COVID-19 pandemic: the case of African countries

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Abstract: This study investigates pure financial contagion and interdependence as well as the nature of causal relationships between stock markets during the COVID-19 pandemic. We use the daily stock index series of China and African countries namely Tunisia, Egypt, Morocco, Uganda, Kenya, Ivory Coast, Nigeria, South Africa, and Zambia from January 1, 2016 to September 30, 2021.We adopt the cointegration and causality approaches to distinguish cases of pure contagion and interdependence by estimating VAR and VECM models. We find 11 cases of pure contagion, including 7 cases in the short term and four cases in the long term. Moreover, we distinguish 6 cases of financial interdependence including 2 cases in the short term and 4 in the long term. These results provide several implications for investors who seek to diversify their portfolios internationally, and for portfolio managers to predict and minimise market risk. Our findings offer also guidance for regulators and policymakers.

Keywords: Covid-19 pandemic; pure contagion; interdependence; cointegration; causality.

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1 Introduction

Recently, the world has faced many virus outbreaks namely, the Severe Acute Respiratory Syndrome Coronavirus (SARS-COV) in 2003, the Middle East Respiratory Syndrome Coronavirus (MERS-CoV) in 2012 and Ebola in 2014. However, none of these outbreaks had the global impact of COVID-19. The Covid-19 outbreak was announced in December 2019 in Wuhan, China and the World Health Organization declared it as a global pandemic on March 11, 2020. It has since shaken the global financial markets and created a financial contagion between different markets. Contagion has become one of the most debated topics in international finance.

During the last few years, crises have followed one another and multiplied such as, the Asian crisis (1997), Technological crisis (2002), Subprime crisis (2007–2009), Sovereign debt crisis, and currently the COVID-19. Despite the multitude of research on financial contagion during the various crises in the world, there is great ambiguity in the literature regarding the precise definition of contagion. Researchers cannot agree on a theoretical or empirical definition, so the debate over how to define contagion is not only academic, but also has important implications for measuring the concept as well as evaluate policy responses.

Eichengreen et al. (1996) propose the most commonly used definition of contagion: "Contagion is a significant increase in the probability of a crisis in one country, following the occurrence of a crisis in another country". Also, Calvo and Reinhart (1996) define contagion as the transmission of the crisis in a country because of the real and financial interconnection with the countries which are exposed to the risks. The causes of contagion are divided according to Forbes et al. (2002) in two different approaches. The first is called fundamental contagion or interdependence and is essentially based on the effects resulting from the interconnections through the commercial, economic and financial links that exist between countries. Several authors find that this form of co-movement is not a source of contagion, but rather a source of repercussions even if it occurs during the crisis period.

The second approach is when the links between the markets do not exist. In this case, contagion occurs through the behaviours of investors and financial agents. This approach is called psychological contagion or pure contagion.

Many contagion studies focused on the distinction between interdependence and pure contagion. In fact, Masson (1999) and Kaminsky and Reinhart (2000) investigate the cause of the transmission of the crisis, whether because of the fundamentals or it is a pure contagion. They find the existence of 'fundamentals-based contagion' and 'pure contagion' during the sovereign debt crisis. Additionally, Ahmad et al. (2013) examine the impact of Eurozone crisis on emerging markets. They find that Brazil, India, Russia, China and South Africa are strongly hit by contagion shock, while Indonesia and South Korea report only interdependence and not contagion. Shen et al. (2015) also investigate the contagion effect of European debt crisis on China's stock market. They find that the pure contagion effect on investors' psychology is limited, whereas the interdependence on the macroeconomic channel is significant.

The purpose of this study is to investigate pure financial contagion and interdependence between China and African countries during the COVID-19 pandemic. We also try to determine the nature of causal relationships between stock markets.

The contribution of this paper is threefold. First, to our knowledge, the only study that has dealt with the case of African countries during the COVID-19 epidemic is Akhtaruzzaman et al. (2022). The authors study financial risk spillovers from US to developing economies in Africa during the COVID-19 pandemic. Our study tries to consolidate this study by taking China as the country originating from the crisis. Second, we extend the existing literature by distinguishing cases of pure contagion and cases of interconnection and the type of causality during the COVID-19 pandemic, which to our knowledge has not been treated so far.

Finally, unlike studies that have used the cointegration technique in the 1997 Asian crisis context (Tan, 1998; Masih and Masih, 1999; Yang et al., 2005), we adopt cointegration and Granger causality approaches by estimating vector autoregressive (VAR) and vector error correction models (VECM). The Granger causality approach provides information on whether pure contagion and financial interconnection exist in the short and long terms. It also indicates the causality direction between returns from different markets.

The remainder of this paper is structured as follows. Section 2 presents the literature review. Section 3 explains the econometric methodology. Section 4 describes the data. Section 5 presents the study results and discussion. Finally, Section 6 concludes.

2 Literature review

Following the COVID-19 pandemic, the literature on its financial and economic effects is growing. Some researchers have studied the effects of COVID-19 on financial markets, gold, oil markets, and corporate social responsibility (Conlon and McGee, 2020; Baker et al., 2020; Kristoufek, 2020; Corbet et al., 2020; Ramelli and Wagner, 2020; McKibbin and Fernando, 2020; Zhang et al., 2020, Akhtaruzzaman et al., 2021b; Fu et al., 2021; Gunay and Can, 2022).

Zhang et al. (2020) explore COVID–19's impacts on aggregate markets, while Conlon and McGee (2020) investigate whether Bitcoin might be used as a safe haven during the COVID–19 bear market. Akhtaruzzaman et al. (2021b) investigate the role of gold in the COVID–19 crisis. The authors find that gold acts as safe-haven asset during Phase I of the pandemic (31 Dec 2019–16 Mar 2020), while it loses the safe-haven status during Phase II (17 March–24 April 2020).

In the same vein, Corbet et al. (2020) find that Bitcoin does not serve as a hedge or safe haven during the COVID-19 outbreak. Furthermore, Guo et al. (2021) compare the contagion phenomenon of Bitcoin and other financial markets or assets before and during the COVID-19 pandemic, both contemporaneously and non-contemporaneously. They employ the directed acyclic graph (DAG), network topology and spillover index, to provide strong evidence on Bitcoin and other asset directional contagion outcomes. The empirical results show that the COVID-19 crisis strengthens the contagion effect between Bitcoin and developed markets. Baker et al. (2020) and Albulescu (2020) demonstrate that the COVID-19 pandemic deteriorates US market stability and contributes to the recent increase in equity volatility.

According to Al-Awadhi et al. (2020), COVID-19 has a significant negative effect on all Chinese stock returns. From their side, Belhassine and Karamti (2021) examine the impact of the COVID-19 outbreak on the interconnectedness of the Chinese stock market with major financial and commodity markets: silver, gold, WTI, Bitcoin, and Euro STOXX 50. The authors analyse the portfolio design implications. Using daily data from 2018 to 2021, they visualise volatility shifts by applying the wavelet power spectrum (WPS). In addition, to determine the precise COVID-19 outbreak dates for each market, they use the Perron (1997) breakpoint test. Finally, to examine market connectivity, they use the bivariate DCC-GARCH model. The findings show that the COVID-19 pandemic causes volatility shifts of varying intensity in all of the markets studied. Following the COVID-19 outbreak, correlations, hedge ratios, and optimal portfolio weights all changed significantly. There is evidence of spillover effects between the Chinese stock market and the Euro STOXX 50, gold, and silver. Moreover, the authors examine the relationship between the COVID-19 outbreak and major financial markets. Using Wavelet, the analysis reveals perceptual differences between the reactions of short-term and long-term markets to the pandemic waves. They also find that oil, gold and Shanghai Stock Exchange (SSE), are the safest assets.

The literature of financial contagion during this pandemic is increasing. For instance, to analyse the tail risk contagion between international financial markets during the COVID-19 outbreak, Guo et al. (2021) combine the time-varying financial network model and the FARM-selection approach. They investigate tail risk contagion during the epidemic using a sample of 19 international financial markets. The authors show the number increase of contagion channels in the international financial system during the COVID-19 outbreak.

Additionally, Fu et al. (2021) investigate the impact of COVID-19 outbreak on global stock markets. The authors focus on 15 countries from Europe, Asia, North America and Latin America, and use the extremal dependence tests for contagion. The findings indicate that contagion effects are significant in global equity markets across four regions. Latin America and North America are the most sensitive to contagion risks, followed by Europe and Asia. They also reveal that the effects of contagion are higher in countries with more severe outbreaks.

From their side, Akhtaruzzaman et al. (2021a) investigate the occurrence of financial contagion between China and the G7 nations via financial and non-financial enterprises during the COVID–19 outbreak. Using the dynamic conditional correlations approach (DCCs), they find that financial firms are more prominent in transmitting contagion than non-financial firms. They also find that China and Japan transmitted more spillovers than they received during the COVID-19 period.

Furthermore, Gunay and Can (2022) study the stock market's reaction to the COVID-19 outbreak and the subprime crisis 2007–2009, and compare their impact in terms of risk exposures. To investigate financial contagion and volatility spillovers, the authors use the modified Iterative Cumulative Sums of Squares (ICSS) test, the Diebold-Yilmaz connectedness analysis and DCC-GARCH approach. The finding show that although the origin of the outbreak is China, US stock market is the source of financial contagion and volatility spillovers during the COVID-19 outbreak, as it was during the subprime crisis. They find also that the COVID-19 pandemic has a more severe contagious effect than the subprime crisis.

Besides, Memon and Yao (2021) examine the impact of COVID-19 using network dynamics to assess a local stock market. They study 58 global stock market networks using a complex network approach that spans the crisis periods caused by the COVID-19 outbreak. The finding suggests that during the first wave of the COVID-19 pandemic in February and March 2020, the world stock markets will have the highest correlation.

Karamat et al. (2020) study the impact of the COVID-19 pandemic on the stock markets of sixteen different countries. The study's results are estimated using a combination of pooled OLS regression, conventional t-test, and Mann-Whitney test. Moreover, Liu et al. (2021) use realised volatility data from sixteen major stock markets around the world to study the risk contagion among international stock markets during the COVID-19 pandemic. According to empirical evidence based on Diebold and Yilmaz (2012) and Barunk and Kehlk (2018) connectedness methods, they show that the COVID-19 outbreak significantly increases the risk contagion effects in international stock markets.

During the period of April 7, 2020, to May 25, 2020, Kanno (2021) evaluates the contagion effect on Japanese firms as well as the Japanese government's COVID-19 measures. He also investigates the impact of COVID-19 on Japanese businesses using correlation-based network and credit risk analyses. He shows that COVID-19 parameters are almost the only risk factors that affect a firm's credit risk. Banerjee (2021) studies the existence of financial contagion between China and its major trading partners during the COVID-19 outbreak. Using the multivariate ADCC-EGARCH model, the author shows significant financial contagion in the majority of developed and emerging markets with significant trade relationships with China.

More recently, Benkraiem et al. (2022) investigate financial contagion intensity during the COVID-19 pandemic. Using copula approach, they find that all studied markets are affected by the crisis and the existence of financial contagion for all Asian and American countries. The authors find also that contagion is more intense for American countries than Asian ones.

Several studies have used the cointegration theory to detect long-term relationships between time series. For instance, Masih and Masih (1999) use cointegration to detect contagion in four Asian stock indexes. Yang et al. (2005) investigate the short and long-term cointegration relationships between the US, Japan, and ten other Asian markets. Their findings show the existence of strong integration during the Asian crisis, and that this integration was exacerbated afterward. Gómez-Puig and Sosvilla-Rivero (2016) use a dynamic Granger-causality approach to detect contagion and assess the transmission of the European sovereign debt crisis. The authors discover the coexistence of pure and fundamentals-based contagion using a logit model. More recently, Ozparlak (2020) studies the long and short run impact of the Covid-19 crisis on Credit Default Swap (CDS) markets and stock markets using the cointegration methodology. The author discovers a long-term relationship between the total cases of COVID-19 and China, France, UK, Germany, Turkey, and Spain, but none between the total cases of COVID-19 and Italy or the US.

Although, Masih and Masih (1999), Tan (1998), and Yang et al. (2005) use the cointegration technique in the 1997 Asian crisis context, we adopt cointegration and Granger causality approaches by estimating vector autoregressive (VAR) and vector error correction models (VECM) during the COVID-19 pandemic. Additionally, we extend Akhtaruzzaman et al. (2022) who use both value-at-risk (VaR) and conditional VaR (CVaR), and investigate the spillover effects of US financial risks on developing economies in Africa during the COVID-19 pandemic. We attempt to consolidate this study by taking China as the country of origin of the crisis.

3 Econometric methodology

We analyse the presence of pure contagion and interdependance using cointegration procedure. This method is robust to the main econometric problems of the financial time series. We also introduce the approach of causality analysis to examine the relationships between markets and conclude about the existence of interdependence or pure contagion.

The cointegration approach, presented by Granger (1983) and Engel and Granger (1987), is considered one of the most important concepts in econometrics and time series analysis. It makes it possible to detect the long-term relationship between two or more time series. Tests of cointegration identify scenarios where two or more non-stationary time series are integrated together in a way that they cannot deviate from equilibrium in the long term. Indeed, the method selection for data analysis is based on the unit root test results, which determine the stationarity of the variable.

The Engel-Granger and Johansen cointegration techniques require that all the series are integrated into the same order 1. Furthermore, the Johansen cointegration methodology needs large sample sizes for validity which is not allowed under other cointegration approach such as the autoregressive distributed lag (ARDL) developed by Pesaran et al. (2001). The ARDL can be applied regardless of the stationary properties of the variables and has robust results for the cointegration analysis of small and finite sample sizes (Pesaran, 1997).

Before performing any cointegration analysis on time series data, the univariate properties of the stock index data must be examined to determine whether the data series is non-stationary or contains a unit root. The popular test in applied econometrics is used here; the ADF tests (Augmented Dickey-Fuller). Then, the Akaike Information Criterion is used to select the number of lags lengths used in unit root tests (AIC). Our goal is to select the number of parameters that minimises the value of the information criteria.

3.1 Bivariate cointegration test

The Engel Granger method (1987) is carried out in two stages. A first step consists in estimating the following relation, by the ordinary least squares method:

$$Y_t = a + bX_t + e_t$$

Then, we proceed to the unit root tests in order to examine the stationarity of the error terms. If the residuals are stationary, this implies the existence of a cointegrating relation between X_t and Y_t. The second step is to estimate the error correction model (ECM).

Regarding the cointegration test and referring to the work of Engel and Granger (1987), if the linear combination z_t of two non-stationary series x_t and y_t is stationary, the two series are cointegrated. The Engel and Granger method is valid only for cointegrated series of order 1 and they must be integrated of the same order.

The long-term equilibrium relationship between y_t and x_t is given by the following equation:

$$y_t = ax_t + z_t$$

The linear ECM representation is illustrated as follows:

$$\Delta y_t = \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \sum_{i=1}^{q} \lambda_t \Delta x_{t-i} + \delta z_{t-1} + \varepsilon_t$$

With z_{t-1}: The equilibrium error of the long-term relationship.

δ: The speed of adjustment towards long-term equilibrium.

3.2 Multivariate cointegration test using the methodology of Johansen (1988)

The starting point for Johansen's method is the vector autoregressive (VAR) model of order p proposed by:

$$Y_t = A_1 Y_{t-1} + \ldots A_p Y_{t-p} + BX_t + \varepsilon_t$$

Y_t: A vector with K endogenous variables

X_t: A vector with n exogenous variables

$A_1, \ldots, A_p$ and B : are matrices of the coefficients to be estimated.

In order to test the existence of r cointegration relations between the variables and to verify the null hypothesis $H0$: X_t is cointegrated of rank r, Johansen proposes two different tests: the trace and the maximum eigenvalue tests.

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda})$$

$$J_{\max} = -T \ln(1-\hat{\lambda}_{r+1})$$

where

T: Sample size

λ_i: The ith eigenvalue

In order to test the causal links between the different markets, we estimate the VAR and VECM models. We first specify a bivariate VAR model of order p:

$$X_t = \alpha_x + \sum_{i=1}^{p} \beta_{x,i} X_{t-i} + \sum_{i=1}^{p} \tau_{x,i} Y_{t-i} + \varepsilon_{x,t}$$

$$Y_t = \alpha_y + \sum_{i=1}^{p} \beta_{y,i} Y_{t-i} + \sum_{i=1}^{p} \tau_{y,i} X_{t-i} + \varepsilon_{y,t}$$

with

X_t: The price of a country's stock market index at time t

Y_t: The price of another country's stock index at time t.

$\varepsilon_{x,t}$ and $\varepsilon_{y,t}$: the error terms at time t.

In the case where the two series are integrated of order 1, then we consider the following two cases:

- If there is no cointegration, we estimate the VARs using the following equations:

$$\Delta x_t = \alpha_x + \sum_{i=1}^{k} \beta_{x,i} \Delta x_{t-i} + \sum_{i=1}^{k} \tau_{x,i} \Delta y_{t-i} + \varepsilon_{x,t}$$

$$\Delta y_t = \alpha_y + \sum_{i=1}^{k} \beta_{y,i} \Delta y_{t-i} + \sum_{i=1}^{k} \tau_{y,i} \Delta x_{t-i} + \varepsilon_{y,t}$$

- In the presence of cointegration, we integrate an error correction term (ECT) in the VAR in difference, and we estimate the VECM by the following equations:

$$\Delta x_t = \alpha_x + \sum_{i=1}^{k} \beta_{x,i} \Delta x_{t-i} + \sum_{i=1}^{k} \tau_{x,i} \Delta y_{t-i} + \delta_x ECT_{x,(t-1)} + \varepsilon_{x,t}$$

$$\Delta y_t = \alpha_y + \sum_{i=1}^{k} \beta_{y,i} \Delta y_{t-i} + \sum_{i=1}^{k} \tau_{y,i} \Delta x_{t-i} + \delta_y ECT_{y,(t-1)} + \varepsilon_{y,t}$$

4 Data and descriptive statistics

4.1 Sample data

We consider the daily series of stock indexes of the china and African countries. Our sample includes the following countries: China (SSE), Tunisia (tunindex), Egypt (EGX30), Morocco (MASI), Uganda (USE), Kenya (NSE20), Ivory Coast (BRVM), Nigeria (NSE30), South Africa (JSE), and Zambia (LES).

We investigate financial contagion during the COVID-19 outbreak; the sampled period lasts from January 1, 2016 to September 30, 2021. We consider the first date of the pre-COVID-19 period as January 1, 2016 to separate it from the subprime crisis (2007) and sovereign debt crisis (2011–2013).

Our data relates to the closing prices of the stock market in the local currency. For more robustness results, we use also common currency returns (e.g., USD). The same results are found when we use the local currency returns. Indeed, according to Mink (2015), the use of local currency returns is preferable to common currency returns (e.g., USD). Moreover, Akhtaruzzaman and Shamsuddin (2016) and Forbes and Rigobon (2002) find the same results for financial contagion when using local and common currency returns.

We based on daily data (five days of the week). The returns of the daily indices are obtained by taking the difference logarithm of the stock market index multiplied by 100.

$$R_t = 100 * (\log P_t - \log P_{t-1}) \;\; t = 1, 2, 3 \ldots T$$

where P_t represents the last price of the interval t, P_{t-1} represents the last price of the interval t–1.

The entire sample period is divided into two sub-periods: the pre-crisis period is January 1, 2016 to December 30, 2019 (T1 = 994 observations) and the COVID-19 period is December 31, 2019 to September 30, 2021 (T2 = 433 observations). This paper is following the literature by choosing December 31, 2019, when China reported the first case of COVID-19 to the World Health Organization (WHO), as the starting date for the COVID-19.

We finally note that the data are obtained from Yahoo Finance.

4.2 Descriptive statistics

Table 1 shows the characteristics of stock return indexes for various markets during the entire period from January 1, 2016 to September 30, 2021 (1429 observations). We find that the mean of all stock returns indexes is close to zero.

Table 1 Descriptive statistics

Markets	*China*	*Tunisia*	*Egypt*	*Morocco*	*Uganda*	*Kenya*	*Ivory Coast*
Observations	1429	1429	1429	1429	1429	1429	1429
Minimum	–7.305	–4.1858	–9.8078	–15.3554	–18.332	–5.6262	–6.9488
Maximum	7.6491	2.6777	6.4889	8.6348	16.5410	3.3612	5.0522
Mean	0.0049	0.0247	0.0282	0.1351	–0.0122	–0.0477	–0.0495
Variance	1.263	0.2228	1.6108	3.3144	1.9232	0.4977	1.0680
StDev	1.1238	0.4720	1.2691	1.8205	1.3868	0.7054	1.0334
Skewness	–0.6832	–1.2459	–0.66133	–0.6128	–0.3659	–1.1366	–0.0991
Kurtosis	7.0375	12.0267	7.0693	6.6670	49.2128	8.3468	5.8177
J.B	3072.2***	9013***	3091.9***	2747***	144665***	4472.4***	2026.2***
Q(10)	41.297***	125.51***	99.656***	26.592**	72.231***	205.8***	73.601***

Table 1 Descriptive statistics (continued)

Markets	*South Africa*	*Zambia*	*Nigeria*
Observations	1429	1429	1429
Minimum	–10.2268	–9.2138	–5.6982
Maximum	7.2614	4.9702	5.9152
Mean	0.0180	–0.0105	0.0180
Variance	1.3420	0.4686	1.0273
StDev	1.1584	0.6845	1.0135
Skewness	–0.8924	–1.9765	0.4096
Kurtosis	10.2665	40.7332	5.1630
J.B	6488.6***	100021***	1634.3***
Q(10)	48.412***	49.149***	187.92***

J.B: designed the Jarque–Bera test, used to test the return distribution's normality. Q(10): designed the Box–Pierce–Ljung statistic for autocorrelation. *** represent significance at 1% level.

Table 1 also shows that, with the exception of Nigeria, the value of skewness is negative and far from zero for all stock return indexes. As a result, the return distribution has a long tail on the left side. Furthermore, the value of kurtosis is greater than 3, indicating that the return series is non-normal and that extreme values occur. The index return distribution is then leptokurtic. The Jarque-Bera test demonstrates also the non-normality of the return indexes.

Finally, the order 15 of Box-Pierce-Ljung portmanteau test shows that the most index returns are uncorrelated.

5 Results and discussion

To begin, we investigate the stationarity of the series of returns from stock market indices for both sub-periods (stability and COVID-19 crisis periods).

5.1 Unit root test

We propose to test stationarity by applying the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981). For more robustness, we implement the Phillips-Perron test (PP). The application of unit root ADF and PP tests shows that all stock index series in level for the two sub-periods of stability and crisis are non-stationary. Indeed, according to Table 2, the value of the ADF test is higher than the critical value of 5%. We also notice that all the series are integrated into order 1 at the 5% confidence level, and that all the series in first difference are stationary.

Table 2 ADF and Philips Perron Tests during Stability Period (COVID-19 Period)

	ADF test		*PP test*		
Countries	*Level*	*First difference*	*Level*	*First difference*	*I*(*d*)
China	–2.2379	–21.6695	–2.4051	–33.8825	*I*(1)
	(–2.9699)	(–13.6179)	(–1.404)	(–20.1132)	(*I*(1))
Tunisia	–0.6177	–19.8007***	–1.3905	–27.6755***	*I*(1)
	(–2.6845)	(–12.1334)***	(–1.5482)	(–13.3353)	(*I*(1))
Egypt	–1.1185	–18.8399***	–1.8523	–25.326***	*I*(1)
	(–2.8319)	(–13.6337)***	(–2.8358)	(–15.7113)	(*I*(1))
Morocco	–2.9405	–21.8562***	–2.8142	–32.1919***	*I*(1)
	(–2.6332)	(–14.0235)	(–2.0532)	(–20.4226)	(*I*(1))
Uganda	–1.5803	–27.0775***	–1.638	–41.6458***	*I*(1)
	(–2.3117)	(–13.3182)	(–2.684)	(–18.6007)	(*I*(1))
Kenya	–1.4427	–17.0447***	–1.2036	–24.5186***	*I*(1)
	(–2.6225)	(–11.4082)	(–2.3575)	(–14.7176)	(*I*(1))
Ivory Coast	–3.0836	–25.517***	–1.1354	–37.4551***	*I*(1)
	(–2.0728)	(–13.322)	(–2.1174)	(–20.045)	(*I*(1))
Nigeria	–0.8677	–19.433***	–0.9909	–23.3172***	*I*(1)
	–1.6338	(–10.0945)	(–0.4441)	(–16.1713)	(*I*(1))
South Africa	–3.3248	–22.7946***	–2.8493	–30.8443***	*I*(1)
	(–2.4933)	(–14.0105)	(–1.2241)	(–21.6505)	(*I*(1))
Zambia	–1.3592	–20.2025***	–1.3228	–27.2434***	*I*(1)
	(–0.2759)	(–16.6027)	(1.3235)	(–22.9868)	(*I*(1))

***is statistical significance at the 5% level. For the period of stability and crisis in level the critical value is-3.41 and in the first difference, the critical value is –1.95 at the level 5%. The critical values for PP test is –2.86 at the level 5%.

5.2 *Cointegration test*

We begin our analysis with a bivariate cointegration test using the method of Engel and Granger (1987). Then, for more robustness, we test the cointegration using the methodology of Johansen (1988).

Bivariate cointegration test: Engel and Granger (1987)

Table 3 illustrates the results of the Engel and Granger bivariate cointegration tests for the two sub-periods: stability and COVID. It reports the pairwise results of china and countries in the African region. The number of bivariate cointegrating relations is almost the same in the crisis period (December 31, 2019 to September 30, 2021), compared to the stability period (January 1, 2016 to December 30, 2019). Indeed, there are 11 cointegrating relationships during the stability period compared to 10 cointegrating relationships during the crisis period.

Table 3 Bivariate cointegration between countries: stability/Covid-19 crisis periods

Bivariate Cointegration			
Markets	*ADF*	*Critical value 5%*	*Decision*
China-Tunisia	–2.3842	–1.95	Yes
	(–2.1076)	(–1.95)	(Yes)
China-Egypt	–2.3849	–1.95	Yes
	(–1.4825)	(–1.95)	(No)
China-Morocco	–2.2561	–1.95	Yes
	(–2.561)	(–1.95)	(Yes)
China-Uganda	–2.2872	–1.95	Yes
	–1.3348	–1.95	(No)
China-Kenya	–2.3639	–1.95	Yes
	–1.6221	–1.95	(No)
China- Ivory Coast	–2.2651	–1.95	Yes
	–1.2435	–1.95	(No)
China-Nigeria	–2.4762	–1.95	Yes
	–2.7579	–1.95	(Yes)
China-South Africa	–2.4585	–1.95	Yes
	–2.7151	–1.95	(Yes)
China-Zambia	–2.4332	–1.95	Yes
	–1.5574	–1.95	(No)
Tunis-China	–1.2965	–1.95	No
	–2.1639	–1.95	(Yes)
Egypt -China	–2.0306	–1.95	Yes
	–2.9981	–1.95	(Yes)
Morocco- China	–0.5278	–1.95	No
	–3.0268	–1.95	(Yes)
Uganda-China	–1.4979	–1.95	No
	–2.4527	–1.95	(Yes)
Kenya-China	–1.2226	–1.95	No
	–3.2391	–1.95	(Yes)
Ivory Coast-China	–0.9465	–1.95	No
	–1.8084	–1.95	(No)
Nigeria-China	–1.3128	–1.95	No
	–2.347	–1.95	(No)
South Africa-China	–2.9607	–1.95	Yes
	–2.5867	–1.95	(Yes)
Zambia-China	–1.5712	–1.95	No
	0.7097	–1.95	(No)

Cointegration test using Johansen's methodology

We then begin this part by determining the number of delays *p*. By using the SBIC criterion (Schwarz Bayesian Information Criterion), the optimal number of lags retained is equal to 1, both for the period of stability and for the period of crisis. On the other hand, the optimal number of lags for the total period is equal to 2. Subsequently, we proceed to the Johansen multivariate cointegration test between the Chinese stock market and the other markets considered during the two sub-periods, stability and COVID-19 crisis.

In order to test the existence of *r* cointegration relations between the variables, we use the trace test and the Johansen maximum eigenvalue test. The decision rule for this test is to reject the null hypothesis of *r* relation of cointegration when the TR statistic is greater than its critical value.

By analysing Table 4, we note the absence of a cointegration relationship during the two periods studied, between the Chinese stock market and the other markets in the African region using the trace and the maximum eigenvalue tests.

Table 4 Multivariate cointegration test: Stability/COVID-19 periods

Trace test					
H0	*Eigenvalues*	λ_{trace}	*Critical value 10%*	*Critical value 5%*	*Critical value 1%*
$r = 0$	0.070600	231.96	226.34	232.49	246.27
	(0.18422)	(278.46)	(226.34)	(232.49)	(246.27)
$r <= 1$	0.042717	159.25	186.54	192.84	204.79
	(0.11328)	(190.49)	(186.54)	(192.84)	(204.79)
$r <= 2$	0.037122	115.90	151.38	157.11	168.92
	(0.0752)	(138.55)	(151.38)	(157.11)	(168.92)
$r <= 3$	0.02558	78.34	118.99	124.25	136.06
	(0.06231)	(104.77)	(118.99)	(124.25)	(136.06)
$r <= 4$	0.01810	52.60	85.18	90.39	104.20
	(0.05498)	(76.97)	(85.18)	(90.39)	(104.20)
$r <= 5$	0.01177	34.45	66.49	70.60	78.87
	(0.05071)	(52.54)	(66.49)	(70.60)	(78.87)
$r <= 6$	0.01121	22.69	45.23	48.28	55.43
	(0.0344)	(30.05)	(45.23)	(48.28)	(55.43)
$r <= 7$	0.00670	11.49	28.71	31.52	37.22
	(0.02370)	(14.90)	(28.71)	(31.52)	(37.22)
$r <= 8$	0.00391	4.81	15.66	17.95	23.52
	(0.00849)	(4.54)	(15.66)	(17.95)	(23.52)
$r <= 9$	0.00092	0.91	6.50	8.18	11.65
	(0.0019)	(0.85)	(6.50)	(8.18)	(11.65)

Table 4 Multivariate cointegration test: Stability/COVID-19 periods (continued)

Maximum eigenvalue test					
H0	*Eigenvalues*	λ_{max}	*Critical value 10%*	*Critical value 5%*	*Critical value 1%*
$r = 0^{*}$	0.070600	72.70	59.00	62.42	68.61
	(0.18422)	(87.96)	(59.00)	(62.42)	(68.61)
$r <= 1$	0.042717	43.35	54.01	57.00	63.37
	(0.11328)	(51.94)	(54.01)	(57.00)	(63.37)
$r <= 2$	0.037122	37.56	48.43	51.07	57.07
	(0.0752)	(33.78)	(48.43)	(51.07)	57.07
$r <= 3$	0.02558	25.74	42.06	44.91	51.30
	(0.06231)	(27.80)	(42.06)	(44.91)	(51.30)
$r <= 4$	0.01810	18.15	36.25	39.43	44.59
	(0.05498)	(24.43)	(36.25)	(39.43)	(44.59)
$r <= 5$	0.01177	11.76	30.84	33.32	38.78
	(0.05071)	(22.48)	(30.84)	(33.32)	(38.78)
$r <= 6$	0.01121	11.20	24.78	27.14	32.14
	(0.0344)	(15.15)	(24.78)	(27.14)	(32.14)
$r <= 7$	0.00670	6.68	18.90	21.07	25.75
	(0.02370)	(10.36)	(18.90)	(21.07)	(25.75)
$r <= 8$	0.00391	3.89	12.91	14.90	19.19
	(0.00849)	(3.69)	(12.91)	(14.90)	(19.19)
$r <= 9$	0.00092	0.91	6.50	8.18	11.65
	(0.00197)	(0.85)	(6.50)	(8.18)	(11.65)

5.3 *Causality test results*

The next step of our work consists in testing the direction of causality in the Granger sense of the different returns of the stock market indices considered. The results are shown in Table 5. From the Fisher statistics and the *p*-values, we determine the existence or not of this causal relationship. Table 5 shows the causal relationships between China and countries in the African region during the stability and crisis periods. Indeed, there are 4 causal relationships in the stability period of which there are unidirectional causal relationships for example China to Nigeria and Zambia to China. Moreover, there are one-bidimensionnel causal relationships (China and Tunisia). In the COVID-19 period we find, 9 causal relationships of which there is a single bidimensionnel relationship between China and Kenya.

Furthermore, Table 5 gives an idea of the existence or not of causal relationship between the different countries included in our study. However, we must distinguish between the nature of the causal relationship, of short term or long term (Sander and Kleimer, 2003). Indeed, we note that in the absence of cointegration, the causality study loses the long-term aspect.

Table 5 Granger-causality tests between China and other markets during the stability period (COVID-19 period)

	Causality test		
	Fisher	*P-value*	*Decision*
China -Tunisia	9.8582	0.00174**	Yes
	(4.1387)	(0.0425**)	(Yes)
China-Egypt	2.2995	0.1297	No
	(0.4035)	(0.5256)	(No)
China-Morocco	1.9653	0.1613	No
	(0.0011)	(0.9731)	(No)
China-Uganda	2.4969	0.0974*	No
	(4.8643)	(0.0279**)	(Yes)
China-Kenya	1.431	0.2319	No
	(5.0104)	(0.0257**)	(Yes)
China- Ivory Coast	1.316	0.2516	No
	(1.5583)	(0.2126)	(No)
China-Nigeria	4.4759	0.03462**	Yes
	(3.5238)	(0.0611*)	(Yes)
China-South Africa	1.0099	0.3152	No
	(6.1555)	(0.0134**)	(Yes)
China-Zambia	1.7767	0.1829	No
	(6.5643)	(0.0107**)	(Yes)
Tunis-China	2.6404	0.09045	Yes
	(0.069)	(0.793)	(No)
Egypt -China	0.1553	0.6936	No
	(0.9071)	(0.3414)	(No)
Morocco- China	0.0707	0.7904	No
	(8.3778)	(0.0039***)	(Yes)
Uganda-China	2.398	0.1218	No
	(2.3862)	(0.1231)	(No)
Kenya-China	0.1532	0.6956	No
	(3.9043)	(0.0488**)	(Yes)
Ivory Coast-China	2e-04	0.9883	No
	(0.6487)	(0.421)	(No)
Nigeria-China	0.0683	0.7939	No
	(2.3851)	(0.1232)	(No)
South Africa-China	0.2643	0.6073	No
	(2.7657)	(0.097*)	(Yes)
Zambia-China	2.6975	0.088	Yes
	(0.461)	(0.4975)	(No)

*, **, **** are significance levels at 10%, 5% and 1%, respectively.

In order to test the causal links between the different markets, we estimate VAR and VECM models. We distinguish two types of causality: The non-causality in the short-term which is tested by the hypothesis H0: $\tau_{x,i} = 0$. If H0 is rejected, then *y* causes *x* in the short term in the Granger sense.

The non-causality long-term tested by the H0 hypothesis: $\delta_x = 0$. Similarly, if H0 is rejected then *y* causes *x* in the long term in the Granger sense. The hypotheses tested are then:

$$\begin{cases} H_0 : \tau_{j,i} = 0 : \textit{non causality in the short term} \\ H_1 : \tau_{j,i} \neq 0 : \textit{ causality in the short term} \end{cases}$$

$$\begin{cases} H_0 : \delta = 0 : \textit{non causality in the long term} \\ H_1 : \delta \neq 0 : \textit{ causality in the long term} \end{cases}$$

The parameters $\tau_{j,i}$ and δ denote short-term and long-term causality evidence.

Table 6 summarises the causality test results during the stability and the COVID-19 crisis periods for China with the countries of the African region. The analysis of this table shows that the number of causal relationships is significantly greater during the COVID-19 period than during the stable period. Indeed, there are only 2 causal relations in the short term and 10 causal relations in the long term during a period of stability; while the crisis period illustrates nine causal relationships in the short term and eight relationships in the long term.

Table 6 Short and long-term causal results

	Short-term			*Long-term*		
Markets	$\tau_{j,i}$	*t-student*	*Probability*	δ	*t-student*	*Probability*
China-Tunisia	–0.0021	–1.625	0.10450	–0.0117	–2.359	0.0185**
	(0.0017)	(0.263)	(0.793)	(–0.0057)	(–0.863)	(0.389)
China-Egypt	1.361e-04	0.394	0.6936	–0.0088	–2.127	0.0337**
	(–0.0016)	(–0.952)	(0.3414)	–	–	–
China-Morocco	0.00836	0.266	0.7904	–0.0101	–2.188	0.0289*
	(0.21862)	(2.894)	(0.00399***)	(–0.0220)	(–2.943)	(0.0034***)
China-Uganda	–0.0082	–1.549	0.12181	–0.01107	–2.422	0.0156*
	(–0.018)	(–1.545)	(0.1231)	–	–	–
China-Kenya	9.663e-04	0.391	0.6956	–0.0113	–2.242	0.0252**
	(–0.0169)	(–1.976)	(0.04**)	–	–	–
China-Ivory Coast	3.63e-04	0.015	0.9883	–0.0105	–2.185	0.0291**
	(–0.176)	(–0.805)	(0.421)	–	–	–
China-Nigeria	0.0010	0.261	0.794	–0.0105	–2.166	0.0305**
	(0.018)	(1.544)	(0.123)	(–0.024)	(–2.133)	(0.0335 **)
China-South Africa	1.870e-04	0.514	0.607	–0.0014	–0.684	0.4943
	(7.75e-04)	(1.663)	(0.0970*)	(–0.0246)	(–2.057)	(0.0403**)

Table 6 Short and long-term causal results (continued)

	Short-term			*Long-term*		
Markets	$\tau_{j,i}$	*t-student*	*Probability*	δ	*t-student*	*Probability*
China-Zambia	–0.003	–1.642	0.10082	–0.0124	–2.805	0.00514***
	(–0.0041)	(–0.679)	(0.498)	–	–	–
Tunis-China	0.0139	3.140	0.0017***	–	–	–
	(0.0157)	(2.034)	(0.0425**)	(0.0136)	(2.279)	(0.0232**)
Egypt-China	0.03045	1.516	0.13	0.03276	1.851	0.0644*
	(1.69e-02)	(0.635)	(0.526)	(–0.0083)	(–2.889)	(0.0040**)
Morocco-China	–0.0003	–1.402	0.161	–	–	–
	(–3.9e-05)	(–0.034)	(0.973)	(0.00125)	(1.308)	(0.192)
Uganda-China	0.0054	1.580	0.114	–	–	–
	(0.0066)	(2.206)	(0.0279**)	(0.0056)	(3.205)	(0.0014***)
Kenya-China	0.0040	1.196	0.232	–	–	–
	(0.0068)	(2.238)	(0.0257**)	(0.00311)	(3.905)	(0.0001***)
Ivory Coast-China	0.0003	1.147	0.252	–	–	–
	(0.0002)	(1.248)	(0.213)	–	–	–
Nigeria-China	0.0043	2.116	0.0346 **	–	–	–
	(0.0078)	(1.877)	(0.0612*)	–	–	–
South Africa-China	7.180e-02	1.005	0.3152	0.0906	2.858	0.00435 ***
	(0.6598)	(2.481)	(0.0135**)	(0.4327)	(1.720)	(0.0861*)
Zambia-China	0.0067	1.333	0.183	–	–	–
	(0.0126)	(2.562)	(0.0107 **)	–	–	–

*, **, **** are significance levels at 10%, 5% and 1%, respectively.

In order to identify the cases of financial contagion and interdependence between the different markets of our study, we apply the Granger causality approach. Indeed, the existence of short-term or long-term causal relationships between stock markets presents evidence of pure contagion. If this relationship still exists in a period of stability, this indicates that there is a transmission of crisis from one market to another, or it is an interdependence between the country originating from the crisis and the country affected by the crisis.

In Table 7, we note the existence of 11 cases of pure contagion, including seven cases in the short term and four in the long term. Additionally, we distinguish six cases of financial interdependence, including two in the short term and four in the long term.

In terms of portfolio diversification, when equity returns are cointegrated, we note that in the long run, these stocks have high long run correlations and are therefore unnecessary redundant diversifiers in portfolios. Then, from an investment standpoint, there is less potential gain from international portfolio diversification. Furthermore, the existence of a short-term causal relationship between the US and other markets helps investors making investment decisions. These results are consistent with Davidson (2020) who shows that during the global financial crisis, Mexico is contagious due to existing interconnections with the US. However, our results are inconsistent with Dewandaru et al. (2016) who argue that the subprime crisis had fundamentals-based contagion. Instead, they find high co-movements in the long-term and low co-movements in the short-term.

Table 7 Identification of cases of contagion and interdependence

Contagion cases		*Interdependence cases*	
Causal relationships	*Type of causality*	*Causal relationships*	*Type of causality*
China-Morocco	Short term	Tunis-China	short term
China-Kenya	Short term	Nigeria-China	short term
China-South Africa	Short term	China-Morocco	Long term
Uganda-China	Short term	China-Nigeria	Long term
Kenya-China	Short term	Egypt -China	Long term
South Africa-China	Short term	South Africa-China	Long term
Zambia-China	Short term		
Tunis-China	Long term		
Uganda-China	Long term		
Kenya-China	Long term		
China-South Africa	Long term		

6 Conclusion and policy implications

The purpose of our study is to investigate pure financial contagion and interdependence between markets during the COVID-19 outbreak. We also examine the nature of causal relationships between stock markets. We use the daily stock index series of China and African countries, namely Tunisia, Egypt, Morocco, Uganda, Kenya, Ivory Coast, Nigeria, South Africa, and Zambia from January 1, 2016 to September 30, 2021. We adopt the cointegration and causality approaches to distinguish cases of pure contagion and interdependence.

We show the existence of 11 cases of pure contagion including seven cases in the short term and four in the long term. Moreover, we distinguish six cases of financial interdependence including two in the short term and four in the long term. Our finding is consistent with the study of Zorgati and Garfatta (2021). They find the existence of financial contagion between China and geographically distant countries during the COVID-19. Moreover, our findings support the contagious nature of the COVID-19 crisis between China and others countries.

Our research has implications for investors looking to diversify their portfolios globally. When it comes to portfolio diversification, we notice that when equity returns are cointegrated. Our findings have also far-reaching policy implications. Indeed, financial contagion between international stock markets can help decision-makers in developing the existing financial system and making it more resilient to crisis transmission. As future research avenues, we seek to compare the impact of the Subprime and COVID-19 crises on the financial markets.

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