Risk spillovers between China and other BRICS countries during COVID-19 pandemic: A CoVaR-copula approach

Yangnan Cheng1,4, Jianxu Liu2,3 and Songsak Sriboonchitta1,3
1Chiang Mai University, Faculty of Economics, Chiang Mai 50200, Thailand
2Shandong University of Finance and Economics, Faculty of Economics, Jinan 250000, China
3Puey Ungphakorn Center of Excellence in Economics, Chiang Mai University, Chiang Mai 50200, Thailand
4Corresponding author’s e-mail: 706502056@qq.com

Abstract. This paper aims to assess risk spillover effect between China and other BRICS countries by CoVaR-copula method. We analyse the result of ∆CoVaR in two sub-periods—year 2019 and COVID-19 period. Data for stock prices of major stock market in each country are used. Our results show that risk spillover effect from China to other BRICS countries increased during the epidemic. Meanwhile, COVID-19 pandemic enhanced the co-movement between China and other four countries. Under the shock from other countries, stock market in China stayed strong. By contrast, stock markets in Brazil, India and South Africa are vulnerable. The results show the accuracy of CoVaR-copula approach for risk spillover effect measurement.

1. Introduction
Global stock markets are being highly interdependent with each other, making risk spillover across global financial markets an inevitable issue for financial risk management. It is very likely that financial risk or crisis spread from one market to another in a short time, especially for closely related countries. For example, The Global Financial Crisis (GFC) in 2008 originated in the United States quickly spread to major international stock markets and led to a subsequent international recession [1]. Thus, understanding and measuring risk spillovers across countries are important for financial risk management to prevent financial crisis exacerbation.

In 2020, COVID-19 pandemic began in China caused the most severe crisis after the GFC. The spread of COVID-19 has aroused concern about the global economic outlook and caused a freeze of most economic activities. As a result, the financial markets suffered destabilization and drastic plunges. Several stock markets in Asia, Europe, and North America saw their steepest one-day decline in history as well as daily price rebounds that reflect their skyrocketing volatility [2]. Brazil, India, Russia and South Africa have been the most severely affected countries for a long time. In May 2021, India and Brazil are still in the top five most affected countries. China, as the starting place and largest economy among five countries, played an essential role in the group during the COVID-19 pandemic. It seems that the COVID-19 pandemic may last for years, so there exists huge uncertainty in global financial markets. Therefore, analyzing risk spillovers between China and other BRICS countries based on past information will help authorities to understand contagion degree and linkage of stock
markets for five countries, thus timely and effective measures could be taken to meet the challenge of future risk caused by the epidemic.

Some studies in the literature examined the risk spillovers between BRICS countries and other countries or markets (e.g., Jiang et al., 2019 [3]; McIver and Kang, 2020 [4]). Few studies focus on the within-group risk spillovers. Kielmann et al. [5] investigated the risk spillover effects between BRICS stock returns by CoVaR model and found that considerable interdependencies between the BRICS stock markets lead to considerable risk spillovers. Shi [6] studied the spillovers of Stock Markets among the BRICS before the COVID-19. He concluded that dynamics of spillovers were influenced by crucial systematic risk events and China’s stock market and Russia’s stock market were probably influential spillover sources for return linkage and volatility connectedness among the BRICS markets, respectively. No study to date has focused on the financial risk spillover between China and other BRICS countries in COVID-19 period.

Methodologically, numerous studies in the finance literature examine contagion or spillover among financial markets and tend to compare results before and after turbulent periods (e.g., Lien et al., 2018 [7]; Kang et al., 2019 [8]). Popular methods for systemic risk and risk contagion measurement include but are not limited to SRISK [9], Marginal Expected Shortfall (MES) [10] and conditional value-at-risk (CoVaR). However, drawbacks of these methods have gradually been uncovered. For example, MES does not take into account the level of the firm’s characteristics, such as size and leverage. The SRISK is constrained to assume that the liabilities of the firm is constant over the period of crisis, as it combines high frequency market data (daily stock prices and market capitalization) and low frequency balance sheet data (leverage).

With the development of the statistical methods, it is found that most of the linear correlations are not time-varying and it is difficult to investigate the asymmetric dependence of different markets. To deal with these drawbacks, Copula methods have been developed to describe the dynamic and asymmetric dependence structures. As Copula isolates the dependence pattern from the marginal distributions, it is easy to acquire the different dependence structure and contagion effects (Chollete et al., 2009 [11]; Das and Uppal, 2004 [12]). Recent researches illustrated the importance of considering tail (extreme) risk when analyzing spillover effects between financial markets or institutions (e.g., Fang et al., 2018 [13]; Shahzad et al., 2018 [14]).

Considering the highly correlated feature of financial markets, we measured, for the first time, the risk spillovers between China and other BRICS countries during the COVID-19 period. We compute delta CoVaR (ΔCoVaR) through bivariate copulas to emphasize the role of COVID-19 on risk spillover between China and other BRICS countries. Computationally, this approach is more tractable than other parametric approaches. Copulas can measure average dependence and upper and lower tail dependence, making this method more flexible as it takes into account dependence structure of random variables in risk measurement. Through CoVaR-copula approach, we examine whether stock market contagion effects increase under these unprecedentedly severe stock market conditions.

The rest of this paper is organized as follows. Section 2 shows how we deal with the data and methodology is detailed in Section 3. Empirical results are displayed in Section 4. Conclusions are made in section 5.

2. Methodology

In this paper, we first use ARMA-GJR-GARCH (1,1) to obtain the Cumulative Distribution Function (CDF) of each stock. These CDFs are treated as marginal distributions in copula functions. Then, we apply CoVaR-copula approach to measure the spillover effect between China and other BRICS countries.

2.1. ARMA-GJR-GARCH (1,1)

This model contains ARMA (Auto Regressive Moving Average) and GJR-GARCH [15] (the Glosten-Jagannathan-Runkle Generalized Auto Regressive Conditional Heteroskedasticity). ARMA model attempts to capture both mean reversion effects and shock effects, but not volatility clustering.
GARCH model is applied to exhibit time-varying volatility and volatility clustering. Among all types of GARCH models, GJR-GARCH performs better than the original GARCH model does in terms of its ability to increase the leverage of negative impact from time \( t-1 \) to the variance of time \( t \). In finance, negative impact from the past is usually greater than positive impact.

The ARMA-GJR-GARCH (1,1) model is expressed as

\[
\rho_t = c + \varphi \rho_{t-1} + \theta \varepsilon_{t-1} + \varepsilon_t \tag{1}
\]

with

\[
\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma \|_{t-1} \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2}
\]

where \( \rho_t \) is the stock return at time \( t \); \( \varepsilon_t \) is the return residual; \( \sigma_t^2 \) is the variance of \( \varepsilon_t \); \( \gamma \) is the leverage effect and

\[
\|_{t-1} = \begin{cases} 0 & \text{if } \varepsilon_{t-1} \geq 0, \\ 1 & \text{if } \varepsilon_{t-1} < 0. \end{cases} \tag{3}
\]

Note that \( \varepsilon_t = z_t \sigma_t \) where \( z_t \) are i.i.d variables of standard innovation.

To make sure that marginal distributions are uniform \([0,1]\), we filter the error terms by

\[
\hat{\varepsilon}_t = \frac{\varepsilon_t}{\sigma_t}. \tag{4}
\]

### 2.2. CoVaR-copula approach

CoVaR was proposed by Adrian and Brunnermeier [16] to measure systemic risk. “Co” stands for conditional, contagion, or co-movement and “VaR” is value-at-risk. \( \Delta \text{CoVaR} \), the difference between the CoVaR conditional on the distress of an institution and the CoVaR conditional on the “normal” state of the institution, can be used to measure spillover effect.

In this paper, we follow Reboredo and Ugolini [17] by combining CoVaR with copulas. In probability theory and statistics, a copula is a multivariate cumulative distribution function for which the marginal probability distribution of each variable is uniform on the interval \([0,1]\). Copula models are useful when describing the dependence between random variables. The CoVaR-copula model is more flexible since it can measure systemic risk while fully describing the dependence structure of random variables.

Let \( r_{it} \) be the return for country \( i \) and \( r_{jt} \) be the return for country \( j \) at time \( t \). The CoVaR, defined as the \( \beta \)-quantile of the conditional distribution of \( r_{it} \) is as follows:

\[
\text{Pr} \left( r_{jt} \leq \text{CoVaR}_{\beta,t}^{ij}, r_{it} \leq \text{VaR}_{\alpha,t}^i \right) = \beta \tag{5}
\]

where \( \text{VaR}_{\alpha,t}^i \) is the VaR for country \( i \), measuring the maximum loss that country \( i \) may experience for a confidence level \( 1-\alpha \) in a specific time horizon, that is

\[
\text{Pr} \left( r_{it} \leq \text{VaR}_{\alpha,t}^i \right) = \alpha. \tag{6}
\]

Therefore, equation (5) can be expressed as

\[
\frac{\text{Pr} \left( r_{jt} \leq \text{CoVaR}_{\beta,t}^{ij}, r_{it} \leq \text{VaR}_{\alpha,t}^i \right)}{\text{Pr} \left( r_{it} \leq \text{VaR}_{\alpha,t}^i \right)} = \beta. \tag{7}
\]

Thus,

\[
\text{Pr} \left( r_{jt} \leq \text{CoVaR}_{\beta,t}^{ij}, r_{it} \leq \text{VaR}_{\alpha,t}^i \right) = \alpha \beta. \tag{8}
\]

Equation (7) can be expressed in terms of the joint distribution function of \( r_{jt} \) and \( r_{it} \), \( F_{r_{jt},r_{it}} \):

\[
F_{r_{jt},r_{it}} \left( \text{CoVaR}_{\beta,t}^{ij}, \text{VaR}_{\alpha,t}^i \right) = \alpha \beta. \tag{9}
\]

According to Sklar’s [18] theorem, the joint distribution function of two continuous variables can be expressed in terms of a copula function. Hence, equation (9) can be written as

\[
C(u,v) = \alpha \beta \tag{10}
\]
where $C(\cdot, \cdot)$ is a copula function, $u = F_{r_{jt}}(CoVaR_{\beta,t}^{j|\beta})$ and $v = F_{r_{it}}(VaR_{\alpha,t}^{i}) = \alpha$. $F_{r_{jt}}$ and $F_{r_{it}}$ are the marginal distribution functions of $r_{jt}$ and $r_{it}$ respectively. Given the form of copula function $C(\cdot, \cdot)$, the CoVaR can be computed from that equation through copulas in a two-step procedure:

1. Since $\alpha, \beta$ and $v$ are given, we can use $C(u, v) = \alpha \beta$ to get the value of $u$;

2. CoVaR can be obtained by inverting the marginal distribution function of $r_{jt}$: $CoVaR_{\beta,t}^{j|\beta} = F_{r_{jt}}^{-1}(u)$.

The spillover effect from country $i$ to $j$ is thus defined as:

$$\Delta CoVaR_{\beta,t}^{j|i} = \frac{CoVaR_{\beta,t}^{j|\beta} - CoVaR_{\beta,t}^{j|\beta,\alpha=0.5}}{CoVaR_{\beta,t}^{j|\beta,\alpha=0.5}}.$$  \hspace{1cm} (11)

In this study, we define $\alpha = \beta = 0.01$. Note that there is no reason why $\Delta CoVaR_{\beta,t}^{j|i}$ should equal $\Delta CoVaR_{\beta,t}^{i|j}$. It is possible that country $i$‘s distress causes a large risk increase in country $j$, while country $j$ causes almost no risk spillovers onto country $i$.

3. Empirical results

3.1. Data

This study uses weekly data for stock prices of China’s Shanghai Composite Index, Brazil’s BOVESPA Index, Russia’s RTX Index, India’s BSE SENSEX Index and South Africa’s FTSE/JSE Index over the period from January 9, 2011, to April 25, 2021. The selected stock markets are the representative markets in each country. For comparison purpose, we analyze two sub-periods: the first is from January 6 to December 29, 2019, before the outbreak of COVID-19 pandemic in China; the second is the COVID-19 period from January 5, 2020, to April 25, 2021. All data are transformed in log returns by $r_t = lnR_t - lnR_{t-1}$ where $R_t$ is the stock price at time $t$.

To compute the value of $\Delta CoVaR$ in two subperiods, rolling window method is adopted. Thus, data from January 9, 2011, to December 30, 2018, is treated as in-sample data for the first sub-period and data from January 9, 2011, to December 29, 2019, is the in-sample data for the second sub-period. Data in the two sub-periods are treated as out-of-sample data. For example, there are 459 observations in the first sub-period. Data from the 1st to the 408th are in-sample data and from the 409th to the 459th are out-of-sample data. The value of $\Delta CoVaR$ for country $i$ are calculated from the historical return. For example, for country $i$, $\Delta CoVaR$ at $t=409$ are calculated by the data from the 1st to the 408th and $\Delta CoVaR$ at $t=410$ are calculated by the data from the 2nd to the 409th. Therefore, $\Delta CoVaR$ in the two subperiods could be obtained. All calculations are done in R software.

|                      | Mean  | S.D.  | Max  | Min  | Skewness | Kurtosis | J-B    | ADF    |
|----------------------|-------|-------|------|------|----------|----------|--------|--------|
| Pre-event            |       |       |      |      |          |          |        |        |
| China                | 0.000 | 0.029 | 0.091| -0.143| -0.839   | 6.561    | 263.50 | -18.51*|
| India                | 0.000 | 0.021 | 0.071| -0.079| -0.002   | 3.748    | 9.51   | -19.64*|
| Brazil               | 0.000 | 0.030 | 0.166| -0.105| 0.219    | 4.911    | 65.35  | -20.34*|
| Russia               | -0.001| 0.039 | 0.147| -0.180| -0.317   | 4.900    | 68.16  | -20.20*|
| SA                   | 0.001 | 0.019 | 0.065| -0.065| 0.054    | 3.380    | 2.64   | -20.78*|
| China                | 0.000 | 0.029 | 0.091| -0.143| -0.806   | 6.506    | 284.85 | -19.61*|
| India                | 0.001 | 0.021 | 0.070| -0.079| -0.018   | 3.837    | 13.43  | -20.82*|
| COVID-19             |       |       |      |      |          |          |        |        |
| Brazil               | 0.001 | 0.030 | 0.166| -0.105| 0.150    | 4.904    | 71.03  | -21.72*|
| Russia               | 0.000 | 0.037 | 0.147| -0.180| -0.377   | 5.195    | 103.04 | -21.21*|
| SA                   | 0.001 | 0.019 | 0.065| -0.065| 0.031    | 3.308    | 1.898  | -21.76*|

Notes: SA stands for South Africa. ADF are the empirical statistics of the Augmented Dickey and Fuller (1979) unit root test. An asterisk (*) indicates rejection of the null hypothesis at 1%.
Table 1 summarizes descriptive statistics for stock market returns. Besides, unit root test is accomplished to test the stationarity of data. The skewness of China, Brazil and Russia are far from zero, indicating that the log returns are skewed. The kurtoses are all greater than 3, indicating a heavy tailed distribution of the log returns. The significant results of the Jarque-Bera statistics show evidence that BRICS returns exhibit a non-normal distribution. Results of ADF test tell that all the data are stationary.

3.2. Marginal model results
We first apply ARMA-GJR-GARCH model to in-sample data to select the best distribution for each country. Four distributions—normal, skewed normal, skewed student t and skewed generalized t distribution are adopted and Bayesian information criterion (BIC) is used to select the best-fit distribution. Table 2 displays the selected distribution for each country in each period and the corresponding BIC value.

Table 2. Selected distribution for five countries in two-subperiods.

|                | China | India | Brazil | Russia | SA  |
|----------------|-------|-------|--------|--------|-----|
| Pre-event      |       |       |        |        |     |
| Distribution   | sstd  | snorm | sstd   | snorm  | snorm|
| BIC            | -1798.16 | -1980.14 | -1661.19 | -1503.61 | -2060.65 |
| COVID-19       |       |       |        |        |     |
| Distribution   | sstd  | snorm | sstd   | snorm  | snorm|
| BIC            | -2034.367 | -2258.69 | -1899.97 | -1752.8 | -2325.22 |

Notes: “sstd” and “snorm” represents skewed student t and skewed normal distribution., respectively.

3.3. Results for risk spillover
This section shows the risk spillovers from China to Brazil, Russia, India and South Africa and that in reverse. Comparisons across countries and between two sub-periods are made.

Table 3. Average risk spillovers between China and other BRICS countries.

|                | 2019 | COVID-19 period |
|----------------|------|-----------------|
| C→B            | 0.0094 | 0.0171 |
| C→R            | 0.0309 | 0.0326 |
| C→I            | 0.0092 | 0.0198 |
| C→S            | 0.0164 | 0.1200 |
| B→C            | 0.0104 | 0.0109 |
| R→C            | 0.0240 | 0.0250 |
| I→C            | 0.0253 | 0.0266 |
| S→C            | 0.0459 | 0.0373 |

Table 3 summarizes the risk spillover effect between China and other BRICS countries in 2019 and COVID-19 period. Numbers in the table are the mean values of ∆CoVaR computed through bivariate copulas. The value of ∆CoVaR shows how much one country adds to 1% VaR of another country when the former moves from its median state to its 1% VaR level, e.g., China adds 0.9% to Brazil with its 1% VaR movement in 2019. To show the strength of the effect, we take the absolute value of our results which is originally negative. The values of ∆CoVaR in COVID-19 period are greater than that in pre-event period, implying that bidirectional spillover effect between China and other BRICS countries has been strengthened by COVID-19 pandemic, except for the risk spillover from South Africa to China. This result is different from the findings of Hanif et al. [19] in which they concluded that the magnitude of spillovers is higher from the US to China during pre-COVID-19 and from China to the US during the COVID-19 pandemic. In COVID-19 period, South Africa received 12% risk from China which is nearly eight times larger than it did in 2019. This means that South Africa was vulnerable from 2020 onward. For Brazil and India, risk spillovers from China in COVID-19 period roughly doubled. Although 1.7% and 1.9 % increase in risk seems to be small but it is nonnegligible considering the loss of the whole stock market in the country. Spillover effect from other countries to...
China change slightly in COVID-19 period, indicating that stock market of China is strong when faced with shocks from other countries.

In Figure 1 and 2, we display the development tendency of risk spillovers in two sub-periods. In Figure 2, there exists co-movement between two countries’ risk increase in most of the time, specifically from July 2020 onward because bidirectional risk spillovers rise and fall at almost the same time. However, in Figure 1, strong co-movement relationship is not seen. This implies that the COVID-19 pandemic strengthened the relationship between China and other BRICS countries. During the epidemic, BRICS countries enhanced coordination to fight the disease together. At the 12th BRICS Summit, Chinese President Xi Jinping made a speech—“Fighting COVID-19 in Solidarity and Advancing BRICS Cooperation Through Concerted Efforts”. The speech stressed the importance of enhancing solidarity and coordination and appealed to other four countries to come together to meet the COVID-19 challenge. In 2020, China donated tons of medical supplies to other BRICS countries and shared anti-epidemic experience with them via video conference. Other four countries also gave China timely help. For example, Russia sent anti-pandemic expert to China and delivered 23 tons of medical supplies to Wuhan in February 2020. At the same time, India and Brazil donated 15 tons and 200,000 disposable masks to China, respectively. South Africa’s Standard Bank and enterprises donated $61,576 and 30,000 masks in March 2020. Five countries also cooperated in vaccine R&D. BRICS New Development Bank even offered loans to five countries to help them fight against the disease. There is no doubt that relationship among five countries has been tightened in COVID-19 period.

![Figure 1](image1.png)

**Figure 1.** Risk Spillovers between China and other BRICS countries in 2019.

In Figure 2, risk spillovers from China to Brazil, Russia and India increased sharply at the end of March. Spillover effect from China to South Africa increased to more than 0.1. This is exact the time when the disease started to spread in four countries. For South Africa, newly confirmed cases
surpassed 1000 for the first time in May 24, when risk spillover from China peaked. This means the spillover effect has been influenced by COVID-19 to a large extent. Compared with those in 2019, risk spillovers from other BRICS countries to China experienced bigger ups and downs. This provides the evidence that COVID-19 has caused more turbulence in risk spillovers. In addition, trajectories of red lines are similar except for R→C, which indicates that the spillover effect from Russia and China is more influenced by Russian stock market than by Chinese stock market.

![Figure 2. Risk Spillover between China and other BRICS countries in COVID-19 period.](image)

4. Conclusions
In this paper, we apply CoVaR-copula approach to measure the risk spillover effect between China and other BRICS countries in COVID-19 period. Data of representative stock market in each country are used and divided into two sub-periods. By making comparison between the results before and during the epidemic, we found that COVID-19 pandemic strengthened co-movement between China and other four countries. Thus, paying attention to the linkage among these countries could help to timely manage spillover risk caused by next shock from the pandemic. Compared with 2019, COVID-19 period witnessed stronger risk spillover effect. In particular, the value of ΔCoVaR between China and South Africa increased to 12%, showing the vulnerability of the financial market in South Africa. Compared with other BRICS countries, China’s stock market is strong when faced with shocks from other countries during the pandemic. Brazil, Russia, India, and South Africa should improve the defence capability of their financial markets for external risk. Risk spillovers from China to other countries increased dramatically when COVID-19 spread in those countries. Hence, we can conclude that the method we use, which is flexible and tractable is accurate and practical. This method is suggested to be applied in future studies for systemic risk measurement.
References
[1] Su X 2020 Measuring extreme risk spillovers across international stock markets: A quantile variance decomposition analysis The North American Journal of Economics and Finance 51 https://doi.org/10.1016/j.najef.2019.101098
[2] Abuzayed B, Bouri E Al-Fayoum N and Jalkh N 2021 Systemic risk spillover across global and country stock markets during the COVID-19 pandemic Economic Analysis and Policy 71 180-197
[3] Jiang Y, Fu Y and Ruan W 2019 Risk spillovers and portfolio management between precious metal and BRICS stock markets Physica A: Statistical Mechanics and its Applications 534 https://doi.org/10.1016/j.physa.2019.04.229
[4] McIver R P and Kang S H 2020 Financial crises and the dynamics of the spillovers between the U.S. and BRICS stock markets Research in International Business and Finance 54 https://doi.org/10.1016/j.ribaf.2020.101276
[5] Kielmann J, Manner H and Min A 2021 Stock market returns and oil price shocks: A CoVaR analysis based on dynamic vine copula models Empirical Economics https://doi.org/10.1007/s00181-021-00273-9
[6] Shi K 2021 Spillovers of Stock Markets among the BRICS: New Evidence in Time and Frequency Domains before the Outbreak of COVID-19 Pandemic Journal of Risk and Financial Management 14 (112) https://doi.org/10.3390/jrfin14030112
[7] Lien D, Lee G, Yang L and Zhang Y 2018 Volatility spillovers among the U.S. and Asian stock markets: A comparison between the periods of Asian currency crisis and subprime credit crisis The North American Journal of Economics and Finance 46 187-201
[8] Kang S H, Uddin G S, Troster V and Yoon S-M 2019 Directional spillover effects between ASEAN and world stock markets Journal of Multinational Financial Management 52-53 https://doi.org/10.1016/j.mulfin.2019.100592
[9] Bae K-H, Karolyi A and Stulz R M 2009 A new approach to measuring financial contagion The Review of Financial Studies 16 (3) 717-763
[10] Bekерт G and Wu G 2020 Asymmetric volatility and risk in equity markets The Review of Financial Studies 13 (1) 1-42
[11] Chollete L, Heinen A and Valdesogo A 2009 Modeling international financial returns with a multivariate regime switching copula Journal of Financial Economics 7 (4) 437-480
[12] Das S and Uppal R 2004 Systematic risk and international portfolio choice The Journal of Finance 59 (6) 2809-34
[13] Fang L, Chen B, Yu H and Qian Y 2018 Identifying systemic important markets from a global perspective: Using the ADCC ΔCoVaR approach with skewed-t distribution Finance Research Letters 24 137-144
[14] Shahzad H S J, Arreola-Hernandez J, Bekiros S, Shahbaz M and Kayani G 2018 A systemic risk analysis of islamic equity markets using vine copula and delta CoVaR modeling Journal of International Financial Markets, Institutions and Money 56 104-127
[15] Glosten L R, Jagannathan R and Runkle D E 1993 On the relation between the expected value and the volatility of the nominal excess return on stocks Journal of Finance 48 (5) 1779-1801
[16] Adrian T and Brunnermeier M K 2011 CoVaR American Economic Review 106 1705-1741
[17] Reboredo C J and Ugolini A 2015 Systemic risk in European sovereign debt markets: A CoVaR-copula approach Journal of International Money and Finance 51 214-244
[18] Sklar A 1959 Fonctions de Riepartition á n Dimensions et Leurs Marges Publications de l’Institut Statistique de l’Université de Paris 8 229-231
[19] Hanif W, Mensi W and Vo X V 2021 Impacts of COVID-19 outbreak on the spillovers between US and Chinese stock sectors Finance Research Letters 40 https://doi.org/10.1016/j.frl.2021.101922