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A Time-Varying Copula Approach to Investigate the Dependence Structures of BRICS Stock Markets Before and After COVID-19

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ABSTRACT

In this study, changes in the dependence structures of BRICS countries' stock markets before and after the World Health Organization's Covid-19 emergency declaration were examined using the time-varying (TV) copula method. The return series of the stock markets were divided into two periods, namely before COVID-19 (BC) and after COVID-19 (AC). The novel time-varying flexy copula (TVFC) proposed in the study provides a more flexible structure and produces better results than the TV single copula and the TV optimal copula in comparative analyses. In addition, risk spillovers between market indices were explored using the CoVaR-Copula method. According to the results, the interdependence coefficients of all countries were higher in the AC period than in the BC period with the exception of the China – South Africa pair. Moreover, the dependence coefficient of India with other BRICS countries was quite high compared to the other pairs. Based on the risk spillover results, it was concluded that the Chinese stock market index was the index least affected by the other BRICS countries in the AC period compared to the BC period.

KEYWORDS

BRICS; copula; COVID-19; stock markets; time-varying copula

JEL

C18; C58; G11; G15; G32

1. Introduction

On January 30, 2020 , a Public Health Emergency of International Concern (PHEIC) was declared by the World Health Organization (WHO) due to the worldwide spread of coronavirus (WHO, 2020). Then the virus, named COVID-19, was declared a global pandemic by the WHO on March 11, 2020 . The fear and anxiety caused by uncertainty about the virus affected not only people's lives but also the global economy. In other words, the pandemic, which negatively affected many economic activities around the world, particularly affected the behavior of investors in stock markets, which was reflected in stock prices and stock market indices (Eren 2021). The impact of the COVID-19 pandemic on countries' financial markets is supported by the studies by Chowdhury, Ishrat Khan, and Kumar Dhar (2022), Christos, Charalampos, and Eleni (2021), So, Chu, and Chan (2021), Ashraf (2020), Baker et al. (2020), Liu et al. (2020), Sharif, Aloui, and Yarovaya (2020), and Topcu and Gulal (2020).

The BRICS countries were chosen as the main subject of the present study because their GDP represents 24.3% of the world's GDP, accounts for 41.2% of the world's population according to 2020 data on the World Bank's website (https://www.worldbank.org/), and they correspond to 26% of the world's land area. The term BRICS stands for the five emerging economies of Brazil, Russia, India, China, and South Africa. Existing studies involving BRICS countries have focused on intermarket comparisons considering these countries as representatives of emerging markets (e.g., Muguto and Muzindutsi (2022); Wen et al. (2022); Biswas, Majumder, and Dawn (2022); Song, Liu, and Sriboonchitta (2019); Yang and Hamori (2013)); and intramarket evaluations (e.g., Ijumba (2013);

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Guoxiang and Gao (2019); Kannadhasan and Das (2019); Hendriks (2019); Dong et al. (2020)). The BRICS countries, which have also been referred to as the engine of global growth over the past 20 years, suffered extremely from the decline in global demand for primary export items due to the pandemic Dash, Sethi, and Kumar Dash (2021). The stock markets of most countries recovered in a short period after the negative financial shock faced by the stock markets, as the lethality of the virus did not materialize as feared and gradual normalization steps were taken in many countries. Therefore, how much did the COVID-19 pandemic affect the dependence structures of BRICS countries' stock markets? To answer this question, in the present study a time-varying flexy copula (TVFC) approach is proposed, which is a modified version of a time varying copula, to evaluate the dependence structures of BRICS countries' stock markets before and after COVID-19.

The time-varying copula is widely used in the literature to evaluate the dependence structures of stock markets. It provides better results than a time-invariant copula since the structure of a model may change constantly when working with stock market datasets (Yang, Yang, and Hamori 2018). A number of studies have been performed with time-varying single copulas to examine the dependence structures of BRICS countries (Ji et al. 2020; Yang, Yang, and Hamori 2018; Kumar et al. 2019; Jiang et al. 2020; Cheng, Liu, and Sriboonchitta 2021).

Our paper makes three main contributions to the existing literature. (1) We introduce the TVFC approach, which extends the classical time-varying single copula and the time-varying optimal copula (TVOC) of Liu, Ji, and Fan (2017a) a step further by leaving the copula families more flexible. The fit performance of the TVFC is found satisfactory compared to the time-varying single copula and TVOC approaches applied to the BRICS dataset. (2) We assess the dependence structures of BRICS countries' stock markets before and after the PHEIC declaration. This study fills the gap in the literature by taking the effect of COVID-19 into account on the dependence structures of BRICS countries. The impact of COVID-19 on the dependence structures is revealed as remarkable changes occur after the PHEIC declaration. (3) We further develop our study to analyze risk spillovers of BRICS countries' stock markets before and after the PHEIC declaration using the CoVaR-Copula method. Among the BRICS countries, China was the most resistant to market fluctuations during COVID-19.

The remainder of this paper is organized as follows: Section 2 introduces the methodologies. Section 3 presents the data and its descriptive statistics. Section 4 reports the empirical results. Section 5 concludes the paper.

2. Method

2.1. Time Varying Copula

Copulas have become very popular recently and used for analyzing multivariate extremes and dependence between variables (Hamma, Ghorbel, and Jarboui 2018). A brief introduction to copula theory is given in Appendix 1 in the supplementary material. Copula analysis in financial studies is usually within the time-invariant framework. Therefore, the parameters resulting from copula analysis have a structure that does not change over time. However, it should be taken into account that dependence structures may change constantly, especially when working with stock market datasets. Therefore, the time-varying copula approach, in which the dependence structures are constantly updated, has received much attention recently (Zhang and Zhao 2021). Unlike the time-invariant copula, a window length is defined in a time-varying copula. Then the selected copula family and parameters are computed for time t, and the analysis continues by rolling the window by one step. In this way, the copula family and its parameters are calculated not only for a given interval but the parameters are also calculated separately for each time interval. The most important step in this approach is the determination of the window length because the results of time-varying copula analysis are very sensitive to window length (Charfeddine and Benlagha 2016). The limitation of the time-varying single copula approach is that the selected copula family is constant for each time point. As the copula parameters change from day to day, the copula families may also change from day

to day. Therefore, in the present study a structure is proposed in which the copula families also remain flexible.

2.2. Time-Varying Flexy Copula

When performing time-varying copula analysis, selected copula families are usually applied for a given time interval and the results are interpreted by selecting the copula family with the most appropriate information criterion value. The studies by Qiang et al. (2018), Qiang, Liu, and Fan (2019), and Lee, Hong, and Yang (2018) are some examples that can be attributed to this approach. This approach is referred to as "time-varying single copula" in the present study, as in the studies by Wen, Bouri, and Cheng (2019) and Liu, Ji, and Fan (2017b). The TVOC approach used by Liu, Ji, and Fan (2017a) selects the optimal copula from the three sets of copulas based on the dependency structure of two variables. If the variables are significantly negative dependent, the copula family is selected from the set of normal, t, 90° rotated Clayton, 270° rotated Clayton, 90° rotated Gumbel, and 270° rotated Gumbel copulas. However, if the variables are significantly positive dependent, the copula family is selected from the set of normal, t, Clayton, 180° rotated Clayton, Gumbel, and 180° rotated Gumbel copulas. Otherwise, the optimal copula family is selected from the set of normal, t, Clayton, 90° rotated Clayton, 180° rotated Clayton, 270° rotated Clayton, Gumbel, 90° rotated Gumbel, 180° rotated Gumbel, and 270° rotated Gumbel copulas. Unlike the commonly used copula approaches, in our study we aimed for a better structure based on a natural selection achieved in a single step selecting the most appropriate copula from the extended set of copulas included in the R package VineCopula (Schepsmeier et al. 2015), namely independence, normal, t, Clayton, Gumbel, Frank, Joe, BB1 (Clayton – Gumbel), BB6 (Joe – Gumbel), BB7 (Joe – Clayton), BB8 (Joe – Frank), 180° rotated Clayton, 180° rotated Gumbel, 180° rotated Joe, 180° rotated BB1, 180° rotated BB6, 180° rotated BB7, 180° rotated BB8, 90° rotated Clayton, 90° rotated Gumbel, 90° rotated Joe, 90° rotated BB1, 90° rotated BB6, 90° rotated BB7, 90° rotated BB8, 270° rotated Clayton, 270° rotated Gumbel, 270° rotated Joe, 270° rotated BB1, 270° rotated BB6, 270° rotated BB7, 270° rotated BB8, Tawn type 1, 180° rotated Tawn type 1, 90° rotated Tawn type 1, 270° rotated Tawn type 1, Tawn type 2, 180° rotated Tawn type 2, 90° rotated Tawn type 2, and 270° rotated Tawn type 2 copulas for each window. In this way, we aimed not only to extend the selection set of the copula family but also to let the algorithm decide on the most appropriate copula family and therefore the direction of the dependency.

In the present study, a brand new time-varying flexy copula (TVFC) approach was used to examine the dependence structures of BRICS countries' market indices before and after the COVID-19 PHEIC declared by the WHO. In this way, it was aimed to take the time-varying copula approach a step further by keeping the copula families flexible. Once the log-return series were obtained, the copula families, dependence values, and lower and upper tail dependence values for each day were obtained by fitting the 65-day rolling-window procedure. Let T be the time span included in the study. Thus, T copula families belonging to two series are to be determined. The copula families were determined using an algorithm consisting of the following steps:

(1) Obtain the filtered values of two series.
(2) Convert these values into values with uniform distribution on [0,1].
(3) Apply all the copula families one by one to day t (current day) and the past 64 days to get the information for day t and obtain the log-likelihood (LL), Akaike information criteria (AIC), and Bayesian information criteria (BIC) values for each copula family.
(4) Determine the most appropriate copula family based on the best LL, AIC, and BIC values.
(5) Go to the next day $(t=t+1)$ and return to step 3. Exit when the processes for the last day are complete.

The algorithm is repeated for each pair to determine the most appropriate copula family. Appendix 2 in the supplementary material contains a graphical process summarizing step 3, step 4, and step 5.

Since five countries were included in the study, these steps were repeated for a total of 10 return series pairs.

2.3. Conditional Value-At-Risk Methodology

Value at risk (VaR) is one of the most common and useful methods for measuring the risk of a single asset. However, the VaR value of a single asset may not reflect systemic risk on its own. Therefore, conditional VaR (CoVaR), proposed by Adrian and Brunnermeier (2011) and generalized by Girardi and Ergün (2013), has been used in the literature to assess the tail dependence and risk spillovers between financial instruments. Appendix 3 in the supplementary material summarizes the CoVaR methodology. In our study, the risk spillovers of the BRICS countries' stock indices were examined with the CoVaR.

3. Data

We considered the daily natural logarithmic returns of BRICS market indices (Brazil's Bovespa, Russia's RTS, India's Nifty 50, China's Shanghai Composite, and South Africa's Top 40). Let $P_{(t)}$ be the price of an index at time t; the daily natural logarithmic return calculation used in almost every study in the finance literature is given as $R_t = lnP_t - lnP_{t-1}$, where P_t is the closing price of an index at time t and $P_{t\text{-}1}$ is the closing price of an index the day before. In the present study, January 30, 2020 , the day that the PHEIC was declared by the WHO, was chosen as a base day, instead of March 11, 2020 , because almost all countries' stock prices were exposed to huge declines between these two dates. Therefore, in the rest of the article, the expressions "before COVID-19 (BC)" will be used to represent the days before January 30, 2020, and "after COVID-19 (AC)" will be used to represent the days after. From the day the PHEIC was declared to September 8, 2021 , the day the study began, 414 trading days passed. For the analyses, the number of days before the PHEIC declaration was equated to the number of days after the PHEIC declaration. In light of this information the "before the PHEIC declaration" period includes data from July 2, 2018 , to January 30, 2020, while the "after the PHEIC declaration" period begins on January 31, 2020 , and ends on September 8, 2021. Since the window length for measuring time-varying dependencies was decided to be three months (approximately 65 trading days), the dataset in our study covers the period from April 3, 2018 , to September 8, 2021, which corresponds to 892 observations. All variables in the dataset were converted to US dollars so that they are in the same unit. The daily dataset was collected from the website investing.com. Appendix 4 in the supplementary material presents the summary statistics of the BRICS countries' return series and it can be concluded that it is appropriate to use the classical GARCH(1,1) model to filter the returns data.

4. Results

4.1. Copula Results

The analyses were performed using the package VineCopula in R software (R Core Team 2009). Selected copula families before COVID-19 (BC) and after COVID-19 (AC) and their frequencies are given in Appendix 5 in the supplementary material. The table in Appendix 5 shows that the number of independence copulas decreased over the period from AC for all pairs except for the Brazil – Russia and China – South Africa pairs. For the Brazil – Russia pair, the number of the 180 degrees rotated Joe copula, which has only a lower tail dependence structure, was 140 for the BC period (33.8% of the BC period), while this number was 16 for the AC period (3.86%). For the Brazil – India and Brazil – China pairs, the number of the independence copula was 219 (52.9%) and 166 (40%) for the BC period and 13 (3.14%) and 51 (12.3%) for the AC period, respectively. These large decreases indicate that the dependence of the Brazil – India and Brazil – China pairs increased during the AC period.

Appendix 6 in the supplementary document presents the types of the selected copula families as percentages to assess the change in tail dependence structures. In all pairs, there is a general difference in the structure of the tail dependence between the AC and BC periods. The "only lower" tail dependence percentages of the Brazil – Russia, Brazil – South Africa, India – China, and China – South Africa pairs decreased in the AC period. In other pairs, the case was just the opposite. For example, the percentage of the "only lower" copula family of the Russia – India pair was 13.77% in the BC period, while this value increased to 40.1% in the AC period. Thus, it can be concluded that the Russia – India pair in the BC and AC periods had a completely different structure of lower tail dependence.

The lower and upper tail dependence coefficients and Kendall's tau values of the pairs are given in Table 1. According to Table 1, lower tail dependencies of all pairs were higher in the AC period except for the Brazil – Russia and China – South Africa pairs. Moreover, the upper tail dependence values of the Brazil – Russia, Brazil – India, Brazil – China, Brazil – South Africa, Russia – South Africa, and India – China pairs in the AC period were higher than in the BC period.

An examination of the values for the lower tail dependence coefficient of the Russia – India pair in Table 1 reveals that this coefficient averaged 0.05 in the BC period, while it increased to 0.27 in the AC period. These values suggest that the Russia – India pair was more dependent on the presence of negative shocks in the COVID-19 period than in normal periods. When the "no tail dependence" structure of the Russia – India pair in Appendix 6 was examined, it was determined that the value, which was 60.87% in the BC period, decreased to 12.56% in the AC period. Similarly, the lower tail dependencies of these pairs increased in the AC period, as did their dependence coefficient values. Based on the Kendall's tau values given in Table 1, the Russia – India pair had a dependence coefficient of 0.18 in the BC period, while this value increased to 0.31 in the AC period. A similar issue was determined for the Russia – South Africa pair. The percentage of "no tail dependence" of the Russia – South Africa pair given in Appendix 6 decreased from 31.4% in the BC period to 13.53% in the AC period. At the same time, an increase was observed in the lower tail dependence percentages in the AC period. The values of the Russia – South Africa pair in Table 1 show that the dependence coefficient, which was 0.27 in the BC period, increased to 0.37 in the AC period. As indicated in Table 1, the "lower tail dependence" coefficient, which was 0.09 in the BC period, increased to 0.30 in the AC period. No major change was observed in the "upper tail dependence" coefficient between these two, according to

Table 1. Lower tail dependence, upper tail dependence and Kendall's tau values.

	Brazil		Russia		India		China		South Africa	
	BC	AC	BC	AC	BC	AC	BC	AC	BC	AC
Lower tail dependence values										
Brazil	1	1								
Russia	.21	.18	1	1						
India	.06	.22	.05	.27	1	1				
China	.06	.14	.09	.11	.15	.18	1	1		
South Africa	.13	.20	.09	.30	.15	.37	.21	.16	1	1
Upper tail dependence values										
Brazil	1	1	.10	.17	.04	.11	.03	.07	.04	.15
Russia			1	1	.16	.16	.10	.09	.15	.17
India					1	1	.02	.04	.08	.06
China							1	1	.11	.08
South Africa									1	1
Kendall's Tau values										
Brazil	1	1								
Russia	.22	.26	1	1						
India	.04	.22	.18	.31	1	1				
China	.05	.14	.18	.19	.17	.24	1	1		
South Africa	.11	.22	.27	.37	.18	.30	.28	.25	1	1

BC: Before Covid-19; AC: After Covid-19.

the values given in Table 1. A case opposite to these examples is observed for the China – South Africa pair. As seen in Appendix 6, the "no tail dependence" percentage of this pair, which was 28% in the BC period, increased to 33% in the AC period. The Kendall's tau dependence coefficient of China – South Africa given in Table 1 decreased from 0.28 to 0.25. In the AC period, the dependence coefficients of all pairs except the China – South Africa pair increased. In other words, it is undeniable that the dependence between China and South Africa decreased in the period after the COVID-19 emergency declaration. Another finding that distinguishes the China – South Africa pair from the other pairs was that both the lower tail dependence and the upper tail dependence values of the China – South Africa pair were lower in the AC period. As seen in Table 1, the lower and upper tail dependence values of China – South Africa decreased from 0.21 to 0.16 and 0.11 to 0.08, respectively. In other words, the China – South Africa pair was the only pair included in our study whose dependence coefficients decreased after the pandemic warning as well as both their lower and upper tail dependence coefficients.

4.2. Assessing the Copula Results

At this stage, it is evaluated whether the approach proposed in the current study provides a better fit than the approaches commonly used and recommended in the literature. For this purpose, a comparison was made by applying the TVFC; the TVOC of Liu, Ji, and Fan (2017a); and the commonly used time-varying single copulas to the BRICS dataset. The average values of LL, AIC, and BIC calculated for each pair of return series pairs were obtained and are presented in Table 2. The bold values in Table 2 show the best result according to each criterion value. According to the LL and AIC values, it was concluded that the approach proposed in the present study gives more appropriate results compared to the other approaches. According to BIC values, the best result for the Russia – South Africa, India – South Africa, and China – South Africa pairs was the TVOC approach, while the approach applied in our study gave better results for all other pairs. As a result, it was determined that the TVFC approach gave better empirical results almost in terms of all criteria compared to the other approaches.

4.3. Risk Spillover Results

4.3.1. Kolmogorov–Smirnov Bootstrapping Test Results

In the present study, confidence levels of 5% and 95% were set for the VaR values, respectively. In addition, the α- and β-values were set at 0.05 for downside risk spillovers and 0.95 for upside risk spillovers. For the analysis, the window length was determined to be 65 days, as in the TVFC approach. In other words, the VaR and CoVaR values calculated for each day are the results obtained from the 65-day values. Equations (4) and (5) given in Appendix 3 were used to determine the downside and upside risk spillovers, respectively. The results of Kolmogorov – Smirnov bootstrap tests given in Table 3 show that all H_0 hypotheses were rejected ($p < .01$), indicating that there are downside and upside risk spillovers among BRICS countries.

4.3.2. CoVaR Results

Almost all stock exchanges experienced sharp price declines after the PHEIC declaration. These declines were replaced by increases after a while, and many country stock market indices broke their historical records in terms of their currency. This volatility also affected the VaR and CoVaR values of country stock markets. Appendix 7 in the supplementary document shows the VaR and CoVaR plots of the BRICS countries, with the black vertical line in the middle of the plots representing the day of the PHEIC declaration. Considering all the plots in Appendix 7, remarkable changes were observed in VaR and CoVaR values shortly after the PHEIC declaration.

The average downside and upside CoVaR values are presented in Table 3. In terms of downside spillovers, the mean values of downside risk spillovers from Russia to China and from India to China

Table 2. Information criteria values of the chosen copula families.

	Brazil-Russia			Brazil- India			Brazil-China			Brazil- South Africa			Russia-India		
	LL	AIC	BIC	LL	AIC	BIC	LL	AIC	BIC	LL	AIC	BIC	LL	AIC	BIC
TVFC	**6.18**	**−9.81**	**−7.03**	**3.58**	**−4.99**	**−2.63**	**2.78**	**−3.28**	**−0.80**	**5.18**	**−7.96**	**−5.35**	**6.79**	**−10.95**	**−8.08**
TVOC	5.70	−9.18	−6.76	3.03	−4.40	−2.59	1.71	−2.14	−0.75	4.53	−7.27	−5.32	6.24	−10.26	−7.85
Normal	4.52	−7.04	−4.87	2.17	−2.34	−0.17	1.11	−0.22	1.95	3.26	−4.52	−2.35	4.97	−7.95	−5.77
t	5.56	−7.13	−2.78	3.04	−2.08	2.27	1.58	0.83	5.18	4.25	−4.50	−0.15	5.97	−7.94	−3.59
Clayton	4.32	−6.64	−4.47	2.37	−2.73	−0.56	1.28	−0.55	1.62	3.55	−5.10	−2.93	4.91	−7.82	−5.65
Gumbel	4.47	−6.94	−4.76	2.05	−2.10	0.08	1.02	−0.03	2.14	3.07	−4.14	−1.96	4.94	−7.89	−5.71
Frank	4.10	−6.19	−4.02	1.83	−1.67	0.51	0.88	0.23	2.41	2.81	−3.62	−1.44	4.82	−7.64	−5.46
BB7	5.60	−7.20	−2.85	2.99	−1.99	2.36	1.78	0.45	4.80	4.42	−4.84	−0.49	6.16	−8.33	−3.98
R-Gumbel	4.92	−7.84	−5.67	2.50	−3.01	−0.83	1.33	−0.66	1.51	3.70	−5.41	−3.23	5.29	−8.58	−6.40
R-BB7	5.82	−7.64	−3.29	2.99	−1.98	2.37	1.86	0.27	4.62	4.45	−4.89	−0.54	6.00	−8.00	−3.66
	Russia-China			**Russia-South Africa**			**India-China**			**India- South Africa**			**China- South Africa**		
TVFC	**3.99**	**−5.55**	**−2.90**	**9.72**	**−16.93**	−14.19	**5.38**	**−8.56**	**−6.18**	**6.94**	**−11.58**	−9.07	**6.84**	**−11.21**	−8.53
TVOC	3.34	−4.83	−2.84	9.38	−16.61	**−14.28**	4.90	−8.01	−6.08	6.60	−11.24	**−9.10**	6.41	−10.78	**−8.57**
Normal	2.83	−3.66	−1.48	8.21	−14.42	−12.24	4.08	−6.17	−3.99	5.08	−8.16	−5.98	5.89	−9.78	−7.60
t	3.12	−2.23	2.12	9.02	−14.05	−9.70	4.48	−4.95	−0.61	6.05	−8.09	−3.74	5.96	−7.93	−3.58
Clayton	2.58	−3.16	−0.99	7.77	−13.54	−11.36	4.43	−6.85	−4.68	5.88	−9.76	−7.58	5.49	−8.99	−6.81
Gumbel	2.72	−3.44	−1.27	7.67	−13.34	−11.16	3.33	−4.66	−2.49	4.53	−7.06	−4.88	5.03	−8.06	−5.88
Frank	2.65	−3.30	−1.13	7.78	−13.57	−11.40	3.80	−5.60	−3.42	4.86	−7.72	−5.55	5.12	−8.23	−6.06
BB7	3.48	−2.96	1.39	9.29	−14.58	−10.23	4.87	−5.73	−1.38	6.62	−9.25	−4.90	6.55	−9.10	−4.75
R-Gumbel	2.72	−3.45	−1.27	8.52	−15.04	−12.86	4.50	−7.00	−4.83	5.98	−9.96	−7.78	5.74	−9.49	−7.31
R-BB7	3.28	−2.57	1.78	9.27	−14.53	−10.19	4.90	−5.80	−1.45	6.59	−9.18	−4.84	6.44	−8.88	−4.54

TVFC: Time-Varying Flexy Copula; TVOC: Time-Varying Optimal Copula.

Table 3. Averages of VaR and CoVaR values of the indices and KS bootstrap test results.

Spillover		Downside Spillovers					
from	to	BC			AC		
		VaR	CoVaR	p-value	VaR	CoVaR	p-value
Brasil	Russia	−0.019	−0.034	0.0	−0.028	−0.054	0.0
Brasil	India	−0.018	−0.023	0.0	−0.024	−0.052	0.0
Brasil	China	−0.019	−0.026	0.0	−0.018	−0.031	0.0
Brasil	South Africa	−0.017	−0.026	0.0	−0.022	−0.040	0.0
Russia	Brasil	−0.033	−0.057	0.0	−0.044	−0.077	0.0
Russia	India	−0.018	−0.027	0.0	−0.024	−0.054	0.0
Russia	China	−0.019	−0.032	0.0	−0.018	−0.032	0.0
Russia	South Africa	−0.017	−0.029	0.0	−0.022	−0.046	0.0
India	Brasil	−0.033	−0.041	0.0	−0.044	−0.081	0.0
India	Russia	−0.019	−0.027	0.0	−0.028	−0.058	0.0
India	China	−0.019	−0.037	0.0	−0.018	−0.037	0.0
India	South Africa	−0.017	−0.030	0.0	−0.022	−0.047	0.0
China	Brasil	−0.033	−0.042	0.0	−0.044	−0.070	0.0
China	Russia	−0.019	−0.030	0.0	−0.028	−0.049	0.0
China	India	−0.018	−0.034	0.0	−0.024	−0.050	0.0
China	South Africa	−0.017	−0.034	0.0	−0.022	−0.040	0.0
South Africa	Brasil	−0.033	−0.047	0.0	−0.044	−0.076	0.0
South Africa	Russia	−0.019	−0.032	0.0	−0.028	−0.061	0.0
South Africa	India	−0.018	−0.033	0.0	−0.024	−0.059	0.0
South Africa	China	−0.019	−0.043	0.0	−0.018	−0.036	0.0
		Upside Spillovers					
Brasil	Russia	0.018	0.025	0.0	0.026	0.046	0.0
Brasil	India	0.016	0.018	0.0	0.021	0.030	0.0
Brasil	China	0.020	0.023	0.0	0.019	0.029	0.0
Brasil	South Africa	0.016	0.019	0.0	0.021	0.030	0.0
Russia	Brasil	0.029	0.040	0.0	0.039	0.065	0.0
Russia	India	0.016	0.026	0.0	0.021	0.037	0.0
Russia	China	0.020	0.033	0.0	0.019	0.032	0.0
Russia	South Africa	0.016	0.026	0.0	0.021	0.037	0.0
India	Brasil	0.029	0.032	0.0	0.039	0.053	0.0
India	Russia	0.018	0.028	0.0	0.026	0.044	0.0
India	China	0.020	0.029	0.0	0.019	0.030	0.0
India	South Africa	0.016	0.022	0.0	0.021	0.031	0.0
China	Brasil	0.029	0.032	0.0	0.039	0.053	0.0
China	Russia	0.018	0.026	0.0	0.026	0.039	0.0
China	India	0.016	0.021	0.0	0.021	0.030	0.0
China	South Africa	0.016	0.025	0.0	0.021	0.032	0.0
South Africa	Brasil	0.029	0.034	0.0	0.039	0.055	0.0
South Africa	Russia	0.018	0.028	0.0	0.026	0.046	0.0
South Africa	India	0.016	0.022	0.0	0.021	0.033	0.0
South Africa	China	0.020	0.037	0.0	0.019	0.033	0.0

BC: Before Covid-19; AC: After Covid-19.

(−0.032 and −0.037, respectively) were the same in the BC and AC periods. In addition, the downside risk spillover from South Africa to China was higher in the AC period. While the average downside risk spillover from South Africa to China was −0.043 in the BC period, this value was −0.036 in the AC period. For the downside risk spillovers of the other pairs, the value in the AC period was higher than that in the BC period. For example, the downside risk spillovers from Brazil to other BRICS countries and from China to other BRICS countries were lower in the AC period. The upside risk spillover from Russia to China was slightly lower in the AC period. While the average risk spillover from Russia to China was 0.033 in the BC period, this value decreased to 0.032 in the AC period. Similarly, the upside risk spillover from South Africa to China decreased from 0.037 in the BC period to 0.033 in the AC period. For other upside risk spillovers, the value in the AC period was higher than that in the BC period. Upside risk spillovers from Brazil to other BRICS countries, from India to other BRICS countries, and from China to other BRICS countries were higher in the AC period.

Table 4. Averages of ΔCoVaR values.

Spillovers		ΔCoVaR downside			ΔCoVaR upside		
from	to	BC	AC	Overall	BC	AC	Overall
Brasil	Russia	−0.012	−0.020	−0.016	0.047	0.079	0.063
Russia	Brasil	−0.018	−0.026	−0.022	0.079	0.116	0.098
Brasil	India	−0.005	−0.023	−0.014	0.036	0.060	0.048
India	Brasil	−0.007	−0.030	−0.019	0.066	0.104	0.085
Brasil	China	−0.006	−0.011	−0.009	0.043	0.049	0.046
China	Brasil	−0.008	−0.021	−0.015	0.067	0.102	0.085
Brasil	South Africa	−0.007	−0.014	−0.011	0.038	0.056	0.047
South Africa	Brasil	−0.011	−0.025	−0.018	0.070	0.106	0.088
Russia	India	−0.006	−0.023	−0.015	0.046	0.067	0.057
India	Russia	−0.006	−0.023	−0.015	0.049	0.079	0.064
Russia	China	−0.010	−0.011	−0.011	0.055	0.054	0.055
China	Russia	−0.008	−0.015	−0.012	0.048	0.072	0.060
Russia	South Africa	−0.008	−0.018	−0.013	0.046	0.064	0.055
South Africa	Russia	−0.009	−0.026	−0.018	0.051	0.082	0.067
India	China	−0.015	−0.015	−0.015	0.051	0.052	0.052
China	India	−0.013	−0.020	−0.017	0.042	0.060	0.051
India	South Africa	−0.010	−0.020	−0.015	0.043	0.059	0.051
South Africa	India	−0.012	−0.027	−0.020	0.043	0.064	0.054
China	South Africa	−0.013	−0.013	−0.013	0.047	0.059	0.053
South Africa	China	−0.019	−0.014	−0.017	0.060	0.056	0.058

BC: Before Covid-19; AC: After Covid-19.

4.3.3. ΔCoVaR Results

Appendix 8 in the supplementary document presents the downside and upside ΔCoVaR values for the BRICS countries. According to Appendix 8, the magnitude of the upside risk contributions was higher than that of the downside risk contributions. Furthermore, the risk contribution of the other BRICS countries to China on the days of the PHEIC declaration was lower than that of the others. In other words, in the early days when COVID-19 was on the global agenda, the Chinese stock market index seems to have been more resilient than other stock market indices. The average downside and upside ΔCoVaR values are given in Table 4.

Table 4 shows that the risk contributions between almost all countries were greater in the BC period. Only the risk contributions from India to China and from South Africa to China were lower in the AC period. A similar situation exists for the upside risk contributions. Only the risk contributions from India to China and from South Africa to China were lower during the AC period. Brazil was the most affected country when all risk contributions were considered. The values of risk contributions from other BRICS countries to Brazil were higher in both periods.

5. Discussion and Conclusions

The aim in the present study was to evaluate the dependence structures of BRICS countries' stock markets before and after COVID-19 using a time-varying copula. A TVFC approach was proposed to investigate the dynamic dependence structures of BRICS countries before and after the PHEIC declaration by the WHO. The lower tail dependence values of the Brazil – Russia and China – South Africa pairs decreased in the AC period. In the presence of positive shocks, the upper tail dependencies of the Brazil – Russia, Brazil – India, Brazil – China, Brazil – South Africa, Russia – South Africa, and India – China pairs were more interdependent. According to the study by Cheng, Liu, and Sriboonchitta (2021), in which different time ranges and methods were used and weekly returns were evaluated, China and South Africa became more dependent during the COVID-19 pandemic. However, based on the results of our study the dependence of China and South Africa was lower after the COVID-19 declaration. Except for China – South Africa, the interdependence coefficients of all countries were higher in the AC period than in the BC period. Another finding that

distinguishes the China – South Africa pair from the other pairs was that both the lower tail dependence and the upper tail dependence values of this pair were lower in the AC period. The other nine pairs were more interdependent in the BC period. The CoVaR copula method was applied to evaluate the risk spillovers between BRICS countries' stock market indices. Evaluating both upside and downside risk spreads, it is concluded that the Chinese stock market index was the least influenced by other countries in the AC period compared with the BC period. This result is in line with the results of the study by Cheng, Liu, and Sriboonchitta (2021).

Overall, the dependence structures of the BRICS countries changed after the COVID-19 declaration. In particular, the dependence coefficient of India with other BRICS countries was quite high compared to that of the other pairs. Despite the possibility that this increase in correlation may be permanent, investors and portfolio managers need to take the necessary precautions. Based on the risk spillover results, it was concluded that it is important to strengthen the defense characteristics of the stock market indices of BRICS countries other than China. This is because these stock market indices may be vulnerable to extreme movements in the future.

The implications of the present study are twofold. From the methodological point of view, it brings a novel perspective to researchers by proposing the TVFC approach. TVOC, by Liu, Ji, and Fan (2017a), and time-varying single copula approaches were also applied to the dataset used in the study for comparison. When all approaches were applied to the same dataset, the best results were obtained with the TVFC and the TVOC which provides another flexy structure. The dependence structures of two-time series assets may change from day to day. Therefore, the time-varying single copula approach used in time-varying copula analysis may restrict the structure. In the present study, it may be argued that in time-varying copula analysis arranging the structure more flexibly can give better results than restricting the structure to a single copula family. For future studies on time-varying copulas, it is recommended that as many copula families as possible are included in the analysis and comparative analyses can be performed by using existing approaches. From the exploratory point of view, the present study reveals the effects of the COVID-19 pandemic on the BRICS countries' stock markets in terms of risk contagions and types and magnitudes of their interdependencies.

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Data Availability Statement

The data that support the findings of this study were derived from the website investing.com.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

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References

Adrian, T., and M. K. Brunnermeier. 2011. *CoVaR*. NBER Working Paper No: 17454. Cambridge, MA: National Bureau of Economic Research.

Ashraf, B. N. 2020. Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance* 54. doi:10.1016/j.ribaf.2020.101249.

Baker, S. R., N. Bloom, S. J. Davis, K. Kost, M. Sammon, and T. Viratyosin. 2020. The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies* 10 (4):742–58. doi:10.1093/rapstu/raaa008.

Biswas, S., S. Majumder, and S. K. Dawn. 2022. Comparing the socioeconomic development of G7 and BRICS countries and resilience to COVID-19: An entropy–MARCOS framework. *Business Perspectives and Research* 10 (2):286–303. doi:10.1177/22785337211015406.

Charfeddine, L., and N. Benlagha. 2016. A time-varying copula approach for modelling dependency: New evidence from commodity and stock markets. *Journal of Multinational Financial Management* 37:168–89. doi:10.1016/j.mulfin.2016.10.003.

Cheng, Y., J. Liu, and S. Sriboonchitta. 2021. Risk spillovers between China and other BRICS countries during COVID-19 pandemic: A CoVar-copula approach. *Journal of Physics: Conference Series* 1978 (1): 012043. doi:10.1088/1742-6596/1978/1/012043.

Chowdhury, E. K., I. Ishrat Khan, and B. Kumar Dhar. 2022. Catastrophic impact of covid-19 on the global stock markets and economic activities. *Business and Society Review* 127 (2):437–60. doi:10.1111/basr.12219.

Christos, G., N. Charalampos, and K. Eleni. 2021. Impact of COVID-19 on stock markets. *Asian Economics Letters* 2 (2):22974. doi:10.46557/001c.22974.

Dash, D. P., N. Sethi, and A. Kumar Dash. 2021. Infectious disease, human capital, and the BRICS economy in the time of COVID-19. *MethodsX* 8:101202. doi:10.1016/j.mex.2020.101202.

Dong, Z., H. An, S. Liu, Z. Li, and M. Yuan. 2020. Research on the time-varying network structure evolution of the stock indices of the BRICS countries based on fluctuation correlation. *International Review of Economics & Finance* 69:63–74. doi:10.1016/j.iref.2020.04.008.

Eren, B. S. 2021. Short-term effects of covid-19 on emerging markets: An event study. *Malatya Turgut Özal University Journal of Business and Management Sciences* 2 (1):113–33.

Girardi, G., and A. T. Ergün. 2013. Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance* 37 (8):3169–80. doi:10.1016/j.jbankfin.2013.02.027.

Guoxiang, X., and W. Gao. 2019. Financial risk contagion in stock markets: Causality and measurement aspects. *Sustainability* 11 (5):1402. doi:10.3390/su11051402.

Hamma, W., A. Ghorbel, and A. Jarboui. 2018. Copula model dependency between oil prices and stock markets: Evidence from Tunisia and Egypt. *American Journal of Finance and Accounting* 5 (2):111–50. doi:10.1504/AJFA.2018.090370.

Hendriks, J. J. 2019. *Sectoral dependence and contagion within BRICS grouping: An application of the R-vine copulas*. South Africa: University of Johannesburg.

Ijumba, C. 2013. Multivariate analysis of the BRICS financial markets. Doctoral Dissertation.

Jiang, Y., J. Mu, H. Nie, and L. Wu. 2020. Time-frequency analysis of risk spillovers from oil to BRICS stock markets: A long-memory copula-CoVaR-MODWT method. *International Journal of Finance & Economics*. doi:10.1002/ijfe.2326.

Ji, Q., B.-Y. Liu, W.-L. Zhao, and Y. Fan. 2020. Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. *International Review of Financial Analysis* 68:101238. doi:10.1016/j.irfa.2018.08.002.

Kannadhasan, M., and D. Das. 2019. Has co-movement dynamics in Brazil, Russia, India, China and South Africa (BRICS) markets changed after global financial crisis? New evidence from wavelet analysis. *Asian Academy of Management Journal of Accounting & Finance* 15 (1). doi:10.21315/aamjaf2019.15.1.1.

Kumar, S., A. K. Tiwari, Y. Chauhan, and Q. Ji. 2019. Dependence structure between the BRICS foreign exchange and stock markets using the dependence-switching copula approach. *International Review of Financial Analysis* 63:273–84. doi:10.1016/j.irfa.2018.12.011.

Lee, Y., K. Hong, and K. Yang. 2018. Sovereign risk contagion in East Asia: A mixture of time-varying copulas approach. *Emerging Markets Finance and Trade* 54 (7):1513–37. doi:10.1080/1540496X.2018.1445989.

Liu, B.-Y., Q. Ji, and Y. Fan. 2017a. A new time-varying optimal copula model identifying the dependence across markets. *Quantitative Finance* 17 (3):437–53. doi:10.1080/14697688.2016.1205208.

Liu, B.-Y., Q. Ji, and Y. Fan. 2017b. Dynamic return-volatility dependence and risk measure of CoVaR in the oil market: A time-varying mixed copula model. *Energy Economics* 68:53–65. doi:10.1016/j.eneco.2017.09.011.

Liu, H., A. Manzoor, C. Wang, L. Zhang, and Z. Manzoor. 2020. The COVID-19 outbreak and affected countries stock markets response. *International Journal of Environmental Research and Public Health* 17 (8):2800. doi:10.3390/ijerph17082800.

Muguto, L., and P.-F. Muzindutsi. 2022. A comparative analysis of the nature of stock return volatility in BRICS and G7 markets. *Journal of Risk and Financial Management* 15 (2):85. doi:10.3390/jrfm15020085.

Qiang, J., E. Bouri, D. Roubaud, and S. J. H. Shahzad. 2018. Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model. *Energy Economics* 75:14–27. doi:10.1016/j.eneco.2018.08.015.

Qiang, J., B.-Y. Liu, and Y. Fan. 2019. Risk dependence of CoVaR and structural change between oil prices and exchange rates: A time-varying copula model. *Energy Economics* 77:80–92. doi:10.1016/j.eneco.2018.07.012.

R Core Team. 2009. *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. http://www.R-project.org

Schepsmeier, U., J. Stoeber, E. C. Brechmann, B. Graeler, T. Nagler, T. Erhardt, C. Almeida, A. Min, C. Czado, and M. Hofmann. 2015. Package 'VineCopula'. *R Package Version* 2 (5). Retrieved from https://github.com/tnagler/VineCopula

Sharif, A., C. Aloui, and L. Yarovaya. 2020. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis* 70:1–9. doi:10.1016/j.irfa.2020.101496.

So, M. K., A. M. Chu, and T. W. Chan. 2021. Impacts of the COVID-19 pandemic on financial market connectedness. *Finance Research Letters* 38:101864. doi:10.1016/j.frl.2020.101864.

Song, Q., J. Liu, and S. Sriboonchitta. 2019. Risk measurement of stock markets in BRICS, G7, and G20: Vine copulas versus factor copulas. *Mathematics* 7 (3):274. doi:10.3390/math7030274.

Topcu, M., and O. S. Gulal. 2020.The impact of COVID-19 on emerging stock markets. *Finance Research Letters* 36: 101691. doi:10.1016/j.frl.2020.101691.

Wen, X., E. Bouri, and H. Cheng. 2019. The crude oil–stock market dependence and its determinants: Evidence from emerging economies. *Emerging Markets Finance and Trade* 55 (10):2254–74. doi:10.1080/1540496X.2018.1522247.

Wen, F., A. Shui, Y. Cheng, and X. Gong. 2022. Monetary policy uncertainty and stock returns in G7 and BRICS countries: A quantile-on-quantile approach. *International Review of Economics & Finance* 78:457–82. doi:10.1016/j.iref.2021.12.015.

WHO. 2020. *Statement on the second meeting of the international health regulations (2005) emergency committee regarding the outbreak of novel coronavirus (2019-nCov)*.

Yang, L., and S. Hamori. 2013. Dependence structure among international stock markets: A GARCH–copula analysis. *Applied Financial Economics* 23 (23):1805–17. doi:10.1080/09603107.2013.854296.

Yang, L., L. Yang, and S. Hamori. 2018. Determinants of dependence structures of sovereign credit default swap spreads between G7 and BRICS countries. *International Review of Financial Analysis* 59:19–34. doi:10.1016/j.irfa.2018.06.001.

Zhang, K.-S., and Y.-Y. Zhao. 2021. Modeling dynamic dependence between crude oil and natural gas return rates: A time-varying geometric copula approach. *Journal of Computational and Applied Mathematics* 386:113243. doi:10.1016/j.cam.2020.113243.