

# **Financial Contagion Intensity during the COVID-19 Outbreak: A Copula Approach**

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## **Abstract**

The sudden and rapid spread of the novel coronavirus (COVID-19) has had a severe impact on financial markets and economic activities all over the world. The purpose of this paper is to investigate the existence and intensity of financial contagion during the COVID-19 outbreak. We use daily series of stock indexes of 10 Asian countries (Taiwan, Hong Kong, Singapore, India, Indonesia, Malaysia, South Korea, Vietnam, Australia and China) and 4 American countries (the United-States, Brazil, Mexico, and Argentina) over the period starting from January 1<sup>st</sup>, 2014 to June 30<sup>th</sup>, 2021. Based on a copula approach, the results show that all studied markets are affected by the COVID-19 outbreak and the presence of financial contagion for all American and Asian countries. The results also show that contagion is more intense for American countries than Asian ones. These findings have practical implications, especially for investors, risk managers, and policy makers. The latter should continue to provide liquidity to the international market during this pandemic.

**Keywords:** COVID-19 outbreak, financial contagion, intensity, copula approach

**JEL classification:** C5-C58-G1

## **1 Introduction**

Over the past 30 years, financial crises have followed one another (Asian crisis, 1997; technological crisis, 2000; subprime crisis, 2007; and sovereign debt crisis, 2011–2013). Actually, all over the world, people are suffering from Covid-19. The World Health Organization declared the outbreak of Covid-19 as a global pandemic on March 11, 2020. This pandemic has shaken the global financial markets, which entered a period of enormous financial distress.

Following the outbreak of the pandemic, the literature on its economic and financial effects started and has been increasingly developed ever since (Sharif et al., 2020; Corbet et al., 2020; Ashraf, 2020; Baveja et al., 2020; Amaratunga et al., 2021; Zhang et al., 2020).

Based on daily stock return data from 64 countries over the period of January 22, 2020 to April 17, 2020, Ashraf (2020) shows that equity returns have declined as the number of confirmed Covid-19 cases has increased. From their side, Sharif et al. (2020) used the Granger causality test and the wavelet method to analyze the connectivity between the economic policy uncertainty, the shock market, geopolitical risk, and U.S. oil price volatility shock during the recent spread of Covid-19. The authors conclude that Covid-19 risk can be considered an economic crisis. For the Bitcoin market, Corbet et al. (2020) demonstrate that the volatility relationship between the major Chinese stock exchanges and Bitcoin has evolved during the Covid-19 outbreak. Moreover, Conlon and McGee (2020) prove that a small allocation to Bitcoin considerably increases the risk of portfolio decline: cryptocurrencies are evolving in parallel with the S&P 500 as the crisis is developing. Xu and Lien (2021) investigated the effect of the COVID-19 outbreak on foreign exchange dependencies for Brazil, Russia, India, China and South Africa (BRICS) economies. To measure currency dependencies, the authors use the Copula-based GAS approach and found negative effects of the COVID-19 on currency dependencies in BRICS. They also show that oil shocks exert a small effect on currency dependencies in BRICS.

Globally, the financial markets were affected by the Covid-19 outbreak. Wang et al. (2020) investigated the impact of volatility on international financial markets during the Covid-19 pandemic and found that the latter considerably influences the international financial market, especially in countries with severe outbreaks. Following this crisis, contagion has become one of the most debated topics in international finance. Several authors investigate financial contagion (Calvo and Reinhart, 1996; Eichengreen et al., 1996; Dornbusch et al., 2000;

Forbes and Rigobon, 2002; Zhu, Y. et al. 2018; Zorgati et al., 2019; Zorgati and Lakhali, 2020; Akhtaruzzaman et al., 2021; Alqaralleh H. et al., 2020; Gunay, 2020), but the definition of contagion and how it could be measured is still contestable. According to Gravelle et al. (2006) and Davidson (2020), financial contagion occurs when there is a statistically significant increase in cross-market correlation following the occurrence of major shocks and between stable and crisis periods.

Eichengreen et al. (1996) and Forbes and Regoban (2002) provide the most commonly used definition of financial contagion. According to Eichengreen et al. (1996), contagion is “a significant increase in the likelihood of a crisis in one country, conditional on the occurrence of a crisis in another country.” Forbes and Rigobon (2002) consider contagion as “a significant increase in cross-market linkages after a shock to one country (or countries group).” Contagion occurs when the degree of co-movement between two markets is high during the stability period and persists in the crisis period. This definition emphasizes the importance of other links through which shocks are transmitted, including trade and finance.

There is an increasing number of studies on financial contagion during the Covid-19 pandemic. For instance, Akhtaruzzaman et al. (2021) investigated how financial contagion occurred between China and G7 countries through financial and non-financial companies during Covid-19. They examined the occurrence of financial contagion through increased Dynamic Conditional Correlations (DCC) during the Covid-19 period and found that financial firms are more prominent in transmitting contagion than nonfinancial firms. The authors also prove that China and Japan have transmitted more spillovers than they received during the Covid-19 period. Alqaralleh et al. (2020) also investigated the contagion effect between the US markets and five major markets in the world during the Covid-19 outbreak and show that correlations were largely dynamic over time before December 2019. Moreover, Gunay (2020) examined the impact of the Covid-19 outbreak on financial contagion in six stock markets: Italy, the United States, Spain, the United Kingdom, Turkey, and China. He showed that this pandemic has led to a severe version of contagion. Zorgati and Garfatta (2021) examined the effect of spatial proximity on financial contagion during the COVID-19 outbreak using local correlation approach. They used daily stock index series of Asian, American, and European countries from January 1, 2014 to January 30, 2021. They showed the existence of spatial financial contagion effect between China and geographically distant countries. However, this effect was absent for geographically close countries.

Different approaches are used to conclude about the existence of financial contagion. The most common method used to test for financial contagion is the correlation approach (Forbes and Rigobon, 2002; Collins and Biekpe, 2003 and Chiang et al. 2007). However, the simple and adjusted correlation approaches present short-term relationships between the stock markets and do not take into account the direction of causality between markets. Some authors favor the use of cointegration approach when dealing with time series of stock market indexes (Yang, Kolari and Min, 2005). However, this approach only tests the existence of causalities, without specifying the propagation channels. Recently, the literature uses the copula approach to explain the dependencies between financial markets (Fenech and Vosgha, 2019 Cubillos-Rocha et al.2019; Ni toi and Pochea, 2020)). This method tests both the existence and the intensity of financial contagion.

Several researches were concerned about the mechanisms of financial risk transmission under the COVID-19 pandemic, as well as differences between different types of countries. Indeed, Guo et al. (2021) studied the tail risk of contagion between 19 international financial markets during the Covid-19 outbreak. The authors used the FARM-selection approach and the time-varying financial network model and concluded that the Covid-19 outbreak increases the number of contagion channels in the international financial system. Corbet et al. (2021) examined the presence of financial contagion among several Chinese coronavirus concept-based stock indices during the COVID-19 outbreak. They used a regime-switching skew-normal (RSSN) methodology to test for contagion through the correlation and channels while considering structural breaks in the different moments. Lately, Luo et al (2021) studied the multiscale financial risk contagion using Empirical Mode Decomposition Copula models (EMD-Copula-CoVaR). Based on a sample of nine international stock markets from January 4<sup>th</sup>, 1999, to May 13<sup>th</sup>, 2021. They found that financial risk contagion is significant at all-time scales.

This paper extends previous papers and aims at investigating the presence of financial contagion and its intensity during the Covid-19 outbreak using a copula approach. This approach has been used in numerous studies that investigate financial contagion during crises. For instance, Rodriguez (2007) examined financial contagion during the Asian and Mexican crisis using switching-parameter copulas. He found evidence of changing dependence during crisis periods. Recently, Zorgati et al. (2019) studied the financial contagion phenomenon in the context of the subprime crisis and found that there is a contagion between the United States and other American countries using a copula approach. They also found that American

countries record high levels of contagion intensity compared with Asian countries during the subprime crisis.

Wang et al. (2021) investigate financial contagion and contagion channels during the global financial crisis (GFC). They use a dynamic mixture copula-extreme value theory (DMC-EVT) model for 39 currencies against the gold ounce in Europe, North America, Latin America, South America, Asia, Africa, and Oceania. They show the existence of financial contagion in the forex market during the GFC. They also show that wealth constraints are the contagion channels during this crisis.

This paper extends the work of Wang et al. (2021) who tested whether financial contagion exists in the forex market and whether it is driven by economic fundamentals or investors. The purpose of this study is to investigate the intensity of financial contagion during the Covid-19 based on the copula approach which is appropriate for this purpose.

The contribution of this paper is twofold. First, to the best of our knowledge, this is the first study to investigate the intensity of financial contagion during the Covid-19 outbreak. Our study covers the period of January 1<sup>st</sup>, 2014 to June 30<sup>th</sup>, 2021, and the sample includes Asian and American markets. Indeed, several studies were concerned about the mechanisms and pathways of financial risk transmission under the COVID-19 pandemic, as well as differences between different types of countries. We try to fill this void by examining how intense contagion is in America compared with Asian countries.

Second, this paper is based on the copula approach, which is robust compared with the correlation, cointegration, and GARCH approaches (Masih and Masih, 1999; Yang et al., 2005; Forbes and Regoban, 2002). The copula approach allows also to capture nonlinear dependencies. In addition, any multivariate distribution may be estimated using a copula model. The copula approach is also appropriate as it allows us to measure the intensity of the contagion for the studied countries.

The rest of this paper is structured as follows. Section 2 presents data and methodology followed by results and discussion in section 3. The final section concludes the paper.

## **2. Data and Methodology**

### **2.1 Data description**

We use daily series of stock indexes of nine Asian countries (Taiwan (TWII), Hong-Kong (HSI), Singapore (STI), India (BSESN), Indonesia (JKSE), Malaysia (KLSE), South Korea

(KS11), Vietnam (VNM), Australia (AORD) and China (SSE)). Four American countries (the United-States (SP500), Brazil (BVSP), Mexico (MXX), and Argentina (MERV))<sup>1</sup> over the period of January 1<sup>st</sup>, 2014 to June 30<sup>th</sup>, 2021. We select the first date of the pre-COVID-19 period as January 1<sup>st</sup>, 2014, to separate it from the subprime crisis (2007) and sovereign debt crisis (2011–2013). We select countries affected by the outbreak of Covid-19 and for which data were available from January 2014 to June 30<sup>th</sup>, 2021. We choose countries which belong to the same region as China, and the countries mostly affected by COVID-19 belonging to the region of America. Our sample covers both the periods before (January 1<sup>st</sup>, 2014–December 30, 2019) and during Covid–19 (December 31, 2019– June 30<sup>th</sup>, 2021).<sup>2</sup>

## **2.2. Descriptive statistics**

Table 1 presents descriptive summary of different stock indexes' returns during the total period. We show that the mean of stock indexes' returns is positive for all markets except for Singapore and Malaysia and is close to zero for all markets. Furthermore, the skewness value of returns is far from zero and negative for all stock indexes. This result indicates that the distribution of return is negatively skewed and there is a long tail on the left.

The kurtosis value is greater than 3 indicating the non-normality of indexes' returns and the existence of extreme values. Finally, the Jarque-Bera's statistic shows that stock market indexes' returns do not follow a normal distribution where, the Box Pierce Ljung portmanteau test of order 10 shows that most index returns are uncorrelated.

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<sup>1</sup>We note that the data are obtained from the website: <http://fr.finance.yahoo.com/>

<sup>2</sup> December 31<sup>st</sup> 2019, is the date when the first case of Covid-19 was reported to the World Health Organization by China (2020).

**Table 1. Descriptive statistics**

Markets	Taiwan	Singapore	Hong Kong	Malaysia	Indonesia	India	Vietnam
<b>Obs</b>	1889	1889	1889	1889	1889	1889	1889
<b>min</b>	-233.24	-7.637	-9.051	-5.4047	-6.8050	-14.101	-11.326
<b>max</b>	233.19	5.894	4.924	6.6262	4.653	8.5948	7.8296
<b>mean</b>	0.0378	-0.0014	0.0114	-0.0095	0.0168	0.0488	0.0116
<b>StDev</b>	7.6455	0.863	1.142	0.6851	0.9747	1.0891	1.430
<b>Skewness</b>	-0.7374	-0.592	-0.617	-0.2870	-0.5895	-1.533	-0.593
<b>Kurtosis</b>	11.314	10.302	4.266	10.3827	4.880	24.110	5.4074
<b>J.B</b>	658505***	8488.2***	1558.3***	8534***	1990.5***	46604***	2420.1***
<b>Q(10)</b>	441.67***	29.135***	7.428	21.855**	14.022	64.789***	26.476***
Markets	South Korea	Australia	China	United States	Mexico	Brazil	Argentina
<b>Obs</b>	1889	1889	1889	1889	1889	1889	1889
<b>min</b>	-8.7669	-10.009	-8.872	-12.765	-6.638	-15.993	-47.6922
<b>max</b>	8.251	6.354	6.369	8.968	4.1805	13.022	9.773
<b>mean</b>	0.027	0.0181	0.0279	0.0450	0.0093	0.0491	0.1308
<b>StDev</b>	0.9733	0.9757	1.386	1.104	0.9699	1.642	2.652
<b>Skewness</b>	-0.285	-1.284	-1.115	-1.059	-0.5194	-1.048	-3.398
<b>Kurtosis</b>	10.974	14.438	7.892	22.128	4.618	14.861	57.769
<b>J. B</b>	9531.6***	16971***	5309.8***	38988***	1769.8***	17775***	266905***
<b>Q(10)</b>	30.948***	84.591***	30.355***	319.39***	37.351***	95.349***	6.761

Notes: We use the Jarque–Bera test to check whether the return distribution is normal. The Box–Pierce–Ljung statistic, Q (10) statistic is distributed as a  $\chi^2$  with 10 degrees of freedom. \*, \*\*, and \*\*\* are significance levels at the 10%, 5%, and 1%, respectively.

## 2.3 Methodology

We use the copula approach, which is more robust than many other approaches, namely the cointegration and correlation approaches. Indeed, the copulas approach allows to capture nonlinear dependencies. In addition, any multivariate distribution may be estimated using a copula model by estimating the marginal distributions and the copula function independently. The correlation coefficient is an exhaustive measure of linear dependence for normal variables. However, it fails to capture nonlinear dependence. Furthermore, Cointegration and Granger's causality approaches only test the existence and direction of causalities, without specifying the intensity of financial contagion.

The copula approach is appropriate to measure the existence as well as the intensity of financial contagion. The notion of copulas was introduced by Sklar (1959) and then by Genest and Makay (1986). Nelson (2006) defines copulas as follows: “Copulas are functions that join or couple multivariate functions to their one-dimensional margins.” According to Bruneau et al. (2015), “A copula of dimension J is a multivariate distribution function C defined on the hypercube  $[0,1]^J$  and whose marginals are uniform over  $[0,1]$ .” Sklar’s theorem is stated as



follows: Let  $H$  be a distribution function of marginal functions  $F_1, F_2 \dots F_d$ , if it exists, then a copula  $C$ , such that:

$$H(x_1, x_2, \dots, x_d) = C(F_1(x_1), F_2(x_2), \dots, F_d(x_d)) \quad \forall x \in (x_1, x_2, \dots, x_d) \mathbb{R}^d. \text{ }^3$$

In the literature, there are a variety of families of copulas. In this study, we apply the most used copulas in finance, namely, Gaussian, Student, Gumbel (1960), Clayton (1978), Frank (1979) and the survival Gumbel copula.

We characterize the dependence structure between markets using copulas or measures derived from the same copula, such as Spearman's  $\rho$  or Kendall's  $\tau^4$ .

For two-dimensional variables  $X$  and  $Y$ , we obtained the  $\tau$  and the  $\rho$  from the copulas' functions,

$$\tau_C(X, Y) = 1 - 4 \int_{I^2} \frac{\partial C(u, v)}{\partial u} \frac{\partial C(u, v)}{\partial v} dudv$$

$$\rho_s(X, Y) = 12 \int_{I^2} (C(u, v) - uv) dudv$$

In this study, we use Kendall's  $\tau$  to evaluate global dependence structures, and the  $\tau$  is the basis of the developed contagion tests.

To assess the existence of financial contagion, we follow a four-step methodology:

**Step 1:** We estimate the ARMA-GARCH model to remove heteroskedastic and autoregressive effects from stock indexes. Moreover, we recover standardized residuals called filtered returns.

**Step 2:** We divide the filtered returns into pre-Covid-19 and Covid-19 periods and transform the data into uniforms.

**Step 3:** We use the distribution obtained to estimate different copulas by canonical maximum likelihood (CML) methods and adopt the AIC to select the most adequate copula.

**Step 4:** We implement the bootstrap technique to compute the variance-covariance matrix of the indicators and parameters of the selected copula.<sup>5</sup> We then conclude about the existence and the intensity of financial contagion.

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<sup>3</sup> We use bivariate continuous copulas in this study.

<sup>4</sup> Nelsen (2006)

<sup>5</sup> Trivedi and Zimmer (2005)

At this level, and using Kendall's  $\tau$ , two tests are necessary:

Test 1: Contagion existence test during the Covid-19 outbreak

$$\begin{cases} H_0 = \Delta\tau = \tau_{\text{covid}} - \tau_{\text{pre-covid}} \leq 0 \\ H_1 = \Delta\tau = \tau_{\text{covid}} - \tau_{\text{pre-covid}} > 0 \end{cases}$$

Test 2: Contagion intensity test during the Covid-19 outbreak

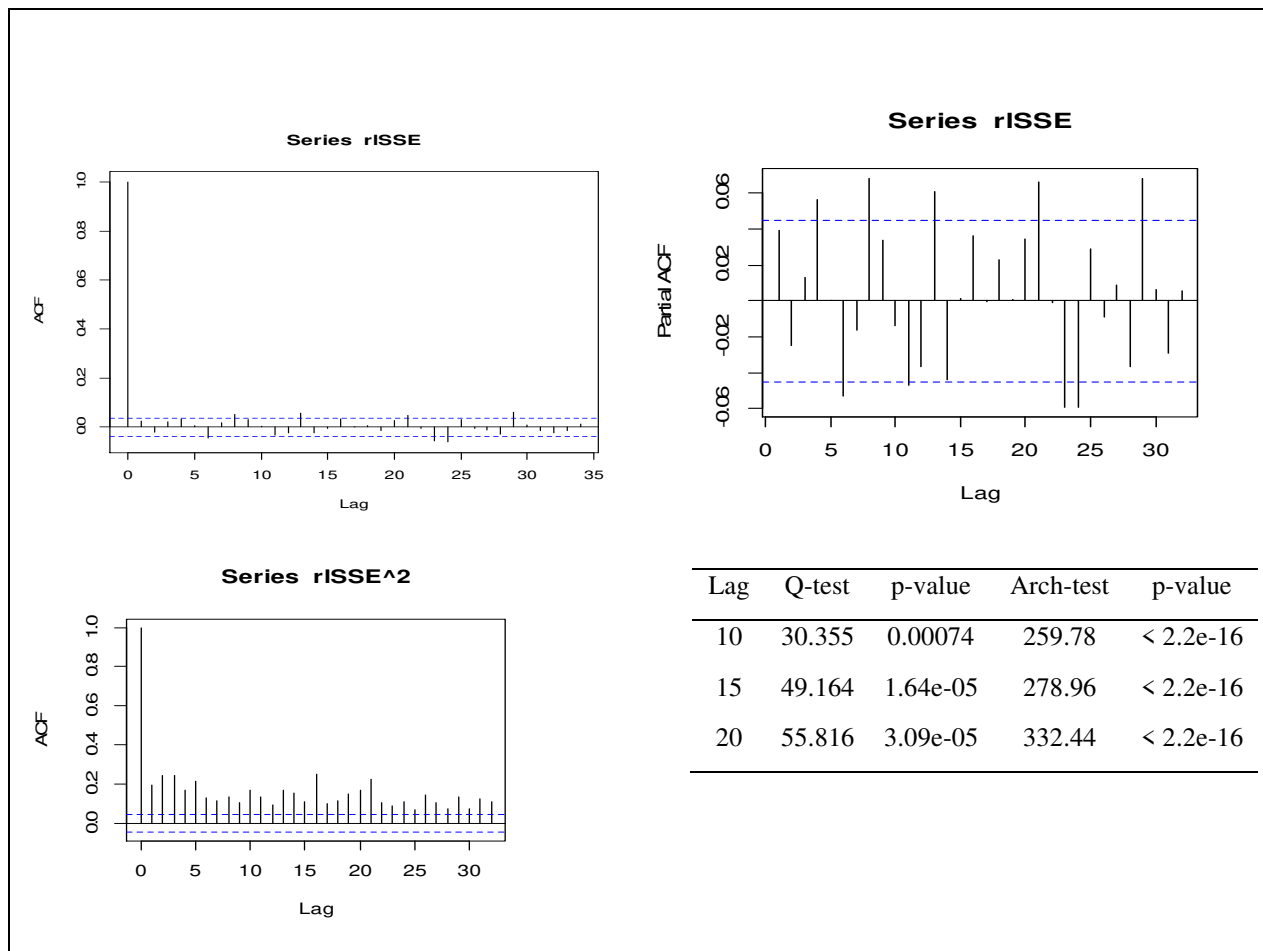
$$\begin{cases} H_0 = \Delta\tau_{A-B} = (\tau_{\text{covid}}^A - \tau_{\text{pre-covid}}^A) - (\tau_{\text{covid}}^B - \tau_{\text{pre-covid}}^B) \leq 0 \\ H_1 = \Delta\tau_{A-B} = (\tau_{\text{covid}}^A - \tau_{\text{pre-covid}}^A) - (\tau_{\text{covid}}^B - \tau_{\text{pre-covid}}^B) > 0 \end{cases}$$

### 3 Results and discussion

#### 3.1 Estimating ARMA-GARCH model

We start with the study of the correlogram of stock index series of various markets for the total period. We study the autocorrelation, partial autocorrelation, and autocorrelation of squared return functions of China's index (SSE). We also apply the test for the absence of autocorrelation Ljung-box-Pierce (1978) residuals to determine whether the series of daily returns are autocorrelated or not. Then, we study the test of Engle, the ARCH-test, to test the null hypothesis of homoscedasticity.

Figure 1 shows the presence of the AR and ARCH effect in the stock index return series of all markets (p-values below the 5% threshold); therefore, the processes are poor.



**Fig. 1. ACF, Partial ACF and ACF of squared returns, Q-Test and ARCH-test of functions of China's index (SSE)**

To remove the heteroskedastic and autoregressive effects from stock indexes, we use ARMA-GARCH models. The Box-Jenkins method allows us to determine the ARMA model for each stock index return. The GARCH model (1, 1) is used to correct the volatility problem. This model is especially suitable in financial time series (Horta et al., 2010).

Table 2 presents the results of the estimation models. The results show that the persistence measure is close to 1 for all markets. This means that the shock will persist over the long term.

**Table 2. Model estimation results**

<b>Country</b>	<b>Model</b>	<b>AIC</b>	<b>BIC</b>	<b>Persistence</b>
Vietnam	ARMA(0,0)-GARCH(1,1)	3.3077	3.3223	0.986
Malaysia	ARMA(1,2)-GARCH(1,1)	1.6813	1.7048	0.993
Indonesia	ARMA(2,2)-GARCH(1,1)	2.5017	2.5193	0.981
Singapore	ARMA(2,1)-GARCH(1,1)	2.177	2.2014	0.976
South Korea	ARMA(0,2)-GARCH(1,1)	2.3848	2.4053	0.979
Australia	ARMA(0,1)-GARCH(1,1)	2.3073	2.3367	0.980
Hong Kong	ARMA(0,0)-GARCH(1,1)	2.924	2.9396	0.992
India	ARMA(0,0)-GARCH(1,1)	2.5424	2.5571	0.973
Taiwan	ARMA(0,1)-GARCH(1,1)	2.4527	2.4703	0.984
China	ARMA(2,3)-GARCH(1,1)	2.9191	2.9514	0.998
USA	ARMA(1,0)-GARCH(1,1)	2.2868	2.3249	0.999
Argentina	ARMA(0,0)-GARCH(1,1)	4.3639	4.3786	0.978
Brazil	ARMA(2,2)-GARCH(1,1)	3.484	3.484	0.963
Mexico	ARMA(2,2)-GARCH(1,1)	2.5206	2.5470	0.97885

Table 3 reports the results of the estimates of the mean and variance equations for different markets studied. We notice that  $\mu$  and  $\omega$  refer respectively to the constant associated with the equation of the mean and the constant associated with the equation of variance and that the error term follows a standard Gaussian distribution.

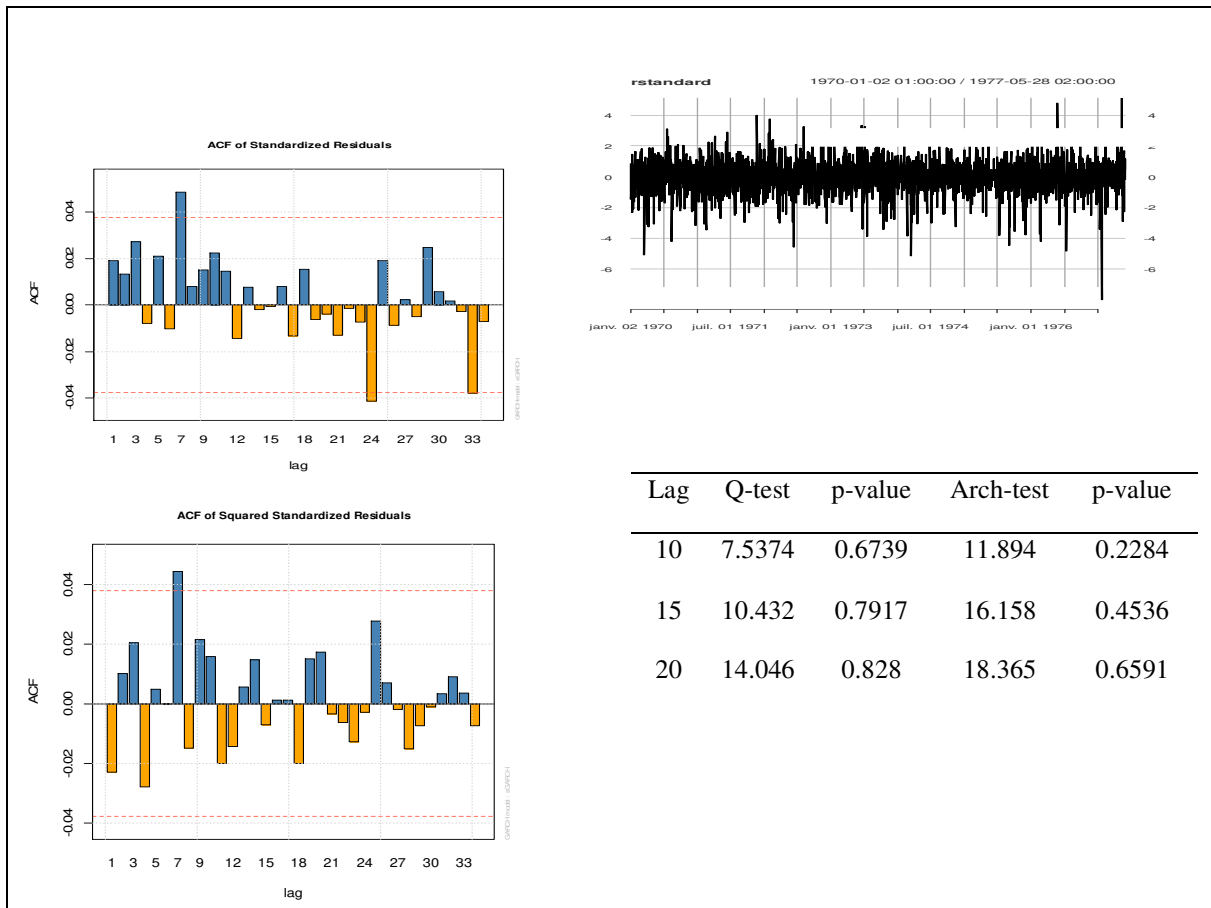
**Table 3. The estimates of the equations of the mean and the variance for financial markets**

Markets	Parameters	Estimate	Std error	t-value
Vietnam	mu	0.0454	0.025	1.803
	omega	0.0327	0.014	2.277
	garch(1)	0.079	0.017	4.563
	arch(1)	0.9067	0.020	44.14
Malaysia	mu	-0.0032	0.010	-0.3008
	ar(1)	-0.0056	1.2224	-0.0466
	ma(1)	0.0599	1.2223	0.094
	ma(2)	0.0091	0.0237	0.385
	omega(1)	0.0042	0.0018	2.368
	garch(1)	0.083	0.015	5.294
	arch(1)	0.910	0.016	55.832
	Indonesia	mu	0.0518	0.016
ar(1)		-0.6254	0.1152	-5.715
ar(2)		-0.8423	0.1141	-7.5589
ma(1)		0.6561	0.085	6.575
ma(2)		0.8465	0.1123	8.273
omega		0.0222	0.012	1.800
garch(1)		0.0858	0.025	3.338
arch(1)		4.5322	0.034	26.231
Singapore		mu	0.021	0.0155
	ar(1)	0.786	0.1511	5.204
	ar(2)	0.00012	0.024	0.004
	ma(1)	-0.769	0.149	-5.136
	omega	0.015	0.006	2.546
	garch(1)	0.090	0.019	4.637
	arch(1)	0.885	0.025	34.863
	South Korea	mu	0.0552	0.0159
ma(1)		-0.0187	0.0221	-0.845
ma(2)		0.0533	0.023	2.2904
omega		0.022	0.0082	2.724
garch(1)		0.093	0.019	4.898
arch(1)		0.885	0.0234	37.802
Australia	mu	0.084	0.026	3.579
	ma(1)	0.0254	0.014	1.078
	omega	0.0162	0.0059	2.7305
	garch(1)	0.0988	0.019	5.185
	arch(1)	0.8820	0.0227	68.7993
Hong Kong	mu	0.0063	0.0212	2.982
	omega	0.0113	0.0046	2.4417
	garch(1)	0.039	0.0066	5.9783
	arch(1)	0.9525	0.0068	139.16
India	mu	0.0817	0.017	4.682
	omega	0.0244	0.007	3.470
	garch(1)	0.0686	0.013	5.233
	arch(1)	0.904	0.016	56.145
Taiwan	mu	0.0802	0.0165	4.859
	ma(1)	0.0221	0.2305	0.962
	omega	0.506	0.0787	6.440
	garch(1)	0.2275	0.0488	4.655
	arch(1)	0.2513	0.060	4.148
China	mu	0.0554	0.0016	2.9466
	ar(1)	0.880	0.015	75.6925
	ar(2)	-0.9765	0.0052	-191.04
	ma(1)	0.419	0.0078	-94.869
	ma(2)	1.007	0.0005	2724.3
	ma(3)	0.0131	0.0007	20.821
	omega	0.015	0.0072	2.17

	garch(1)	0.077	0.0221	3.515
	arch(1)	0.921	0.020	45.268
USA	mu	0.0141	0.036	10.552
	ar(1)	-0.0417	0.0172	-2.514
	omega	0.0262	0.0070	3.70
	garch(1)	0.0808	0.0399	5.52
	arch(1)	0.7781	0.0328	63.675
Argentina	mu	0.1988	0.041	4.795
	omega	1.1897	0.0838	2.262
	garch(1)	0.1207	0.032	3.768
	arch(1)	0.8581	0.037	62.661
Brazil	mu	0.0976	0.028	3.485
	ar(1)	-1.227	0.022	-54.508
	ar(2)	-0.2450	0.023	-10.613
	ma(1)	1.1910	0.00003	3614.82
	ma(2)	0.2129	0.0007	271.71
	omega	0.0789	0.024	2.26
	garch(1)	0.0873	0.015	5.679
	arch(1)	0.8762	0.021	40.997
Mexico	mu	0.0269	0.0151	1.774
	ar(1)	0.946	0.3012	3.140
	ar(2)	-0.1879	0.2843	-0.660
	ma(1)	-0.880	0.3058	-2.879
	ma(2)	0.092	0.2907	0.3164
	omega	0.0201	0.0076	2.650
	garch(1)	0.0853	0.0167	5.088
	arch(1)	0.892	0.0212	41.974

Following the estimation of the ARMA-GARCH models, we recover the residuals resulting from this estimation (filtered returns). We apply the same procedure to ensure that autocorrelation and heteroskedasticity are corrected.

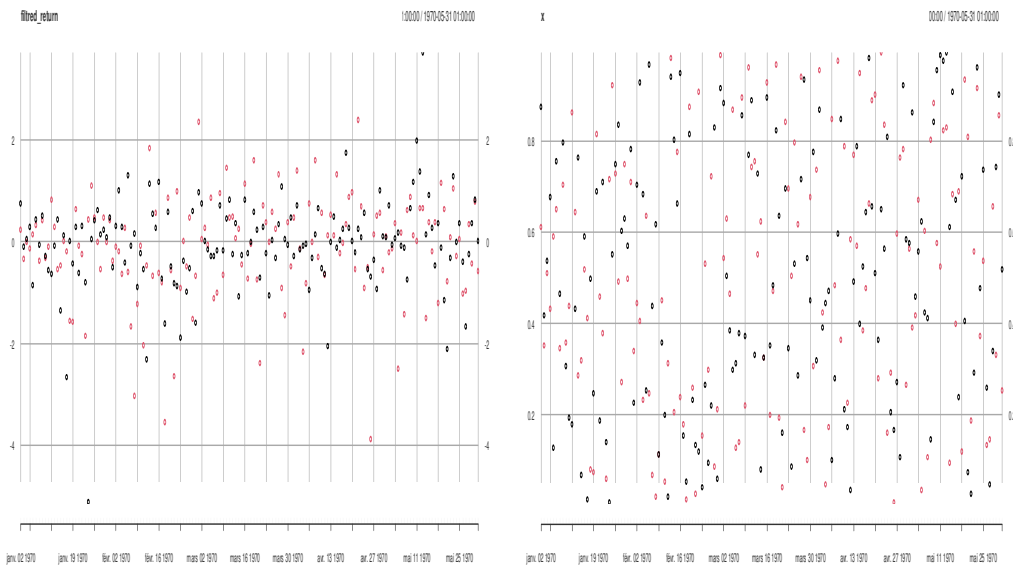
Figure 2 shows that the residuals are not correlated (p-values above the 5% threshold); therefore, the chosen processes are of good quality. Furthermore, we note that the heteroscedasticity problem is well corrected (p-values above the threshold of 5%).



**Fig. 2.** Autocorrelation function of the standardized innovations of China's index (SSE), the standardized innovations, autocorrelation function of the squared standardized innovations, Q-test and ARCH-test

### 3.2 Data transformation

The second step consists of transforming the filtered returns, resulting from the ARMA–GARCH model for stable and crisis periods. We study the following market couples: China/Taiwan, China/Hong Kong, China/Singapore, China/India, China/Indonesia, China/Malaysia, China/South Korea, China/Vietnam, China/United States, China/Brazil, China/Mexico, and China/Argentina). The stable period starts from 01/01/2014 to 30/12/2019, and the crisis period starts from 31/12/2019 to 30/06/2021 (363 observations). Figure 3 illustrates the representation of the filtered returns of China and U.S. markets before and after transformation uniform. This transformation is necessary because the bivariate copula function operates in the space  $[0,1]$ .<sup>2</sup>



**Figure 3. Bivariate representation of the filtered returns of the SSE and U.S. markets during the crisis period before and after uniform transformation of margins**

### 3.3 Estimation of copulas

After data transformation, we now estimate the copulas. We treat the most commonly used copulas in finance, namely, the elliptical copulas: Gaussian and t-Student, and some Archimedean copulas: Gumbel (1960), Clayton (1978), and Frank (1979) and the survival copula Gumbel.

To estimate the copula parameters using canonical maximum likelihood (CML), we consider an initial parameter  $\theta$  with the transformed data from the previous step as input to the algorithm. The initial parameter  $\theta$  is obtained from Kendall's empirical tau (Bouye et al., 2000).

Table 4 shows that the empirical Kendall's tau increases from stability to crisis period for all financial markets. Moreover, the value of Kendall's tau is higher in the American region than in the Asian region, which leads us to conclude that the American region is more at risk of financial contagion than the region of Asia.



**Table 4. Values of empirical Kendall's tau for pre-Covid and Covid period**

	China /Vietnam	China /Malaysia	China/ Indonesia	China/ Singapore	China/South Korea	China /Australia	China/ Hong Kong
<b>Pre-covid period</b>	0.0665	0.0707	0.0847	0.0699	0.2032	0.2111	0.3491
<b>Covid period</b>	0.1835	0.2336	0.1746	0.1393	0.3531	0.3252	0.4324
	China/India	China/Taiwan	China/USA	China/ Argentina	China/Brazil	China/Mexico	
<b>Pre-covid period</b>	0.1200	0.1676	0.0765	0.1994	0.1317	0.1452	
<b>Covid period</b>	0.2419	0.2394	0.1519	0.3546	0.2730	0.3041	

Table 5 presents the estimation of the copula parameters using the CML method. The results remain unchanged. They show that the value of the estimated parameters of the copulas in the period of crisis is higher than that of the period of stability. This increase is due to the co-movements between the markets, which became more pronounced following the Covid-19 outbreak.

In addition, we notice that all the values of the coefficient of dependency are positive. This result suggests that Asian markets and America's markets depend on China's market, the country from which Covid-19 originated.

**Table 5. Estimated Copulas during the pre-Covid and Covid periods**

Country	Copulas	Dependence parameter	Degree of freedom	LLF	AIC	BIC
China/Vietnam	Clayton	0.1224		14.18	-26.37	-20.52
		(0.3212)		(4.75)	(-5.45)	(-2.89)
	Gumbel	1.0507		7.53	-13.06	-7.22
		(1.247)		(5.11)	(-8.29)	(-5.29)
	Frank	0.6108		12.87	-23.74	-17.89)
		(1.6934)		(5.63)	(-9.86)	(-6.95)
	t-student	0.1124	30	14.01	-24.02	-12.33
Gaussian	0.1123	(30)	(5.98)	(-7.96)	(-2.94)	
	(0.334)		15.23	-28.46	-22.61	
Survival Gumbel	1.0603		14.66	-27.33	-21.48	
	(1.194)		(4.62)	(-6.48)	(-3.59)	
China/Malaysia	Clayton	0.1247		15.8	-29.6	-23.75
		(0.462)		(6.68)	(-11.33)	(-8.42)
	Gumbel	1.0547		8.1	-14.2	-8.35
		(1.1241)		(6.76)	(-11.52)	(-8.81)
	Frank	0.6458		14.46	-26.92	-21.08
		(2.094)		(7.94)	(-13.89)	(-10.78)
	t-student	0.1144	30	15.37	-26.92	-15.06
Gaussian	0.1246	(30)	(8.08)	(-12.15)	(-6.15)	
	(0.335)		16.84	-31.67	-25.83	
Survival Gumbel	1.0618		15.65	-29.31	-23.46	

		(1.273)		(7.54)	(-13.07)	(-10.16)
China/Indonesia	Clayton	0.1658		25.14	-48.28	-42.44
		(0.324)		(3.87)	(-5.68)	(-2.57)
	Gumbel	1.0868		20.89	-39.28	-33.93
		(1.188)		(4.01)	(-6.23)	(-3.12)
	Frank	0.7735		20.64	-39.28	-33.43
		(1.864)		(6.43)	(-10.99)	(-7.88)
	t-student	0.1454	30	28.14	-52.28	-40.59
	(0.284)	(30)	(5.26)	(-6.34)	(-1.39)	
Gaussian	0.1531		27.35	-52.7	-46.85	
	(0.282)		(5.64)	(-9.18)	(-6.17)	
Survival Gumbel	1.0835		27.03	-52.07	-46.22	
	(1.276)		(4.12)	(-6.61)	(-4.14)	
China/Singapore	Clayton	0.1357		16.04	-30.09	-24.24
		(0.316)		(4.08)	(-6.16)	(-3.15)
	Gumbel	1.0634		12.81	-23.61	-17.77
		(1.162)		(4.58)	(-7.15)	(-4.14)
	Frank	0.6387		14.07	-26.15	-20.3
		(1.2619)		(3.2)	(-4.4)	(-1.39)
	t-student	0.1132	20.09	18.23	-32.46	-20.77
	(0.262)	(30)	(4.59)	(-5.39)	(1.63)	
Gaussian	0.1114		15.35	-28.7	-22.85	
	(0.2633)		(4.54)	(-7.09)	(-4.07)	
Survival Gumbel	1.0795		20.1	-38.2	-32.35	
	(1.170)		(4.31)	(-6.42)	(-3.23)	
China/South Korea	Clayton	0.4358		136.59	-271.17	-265.33
		(0.784)		(17.79)	(-32.68)	(-29.67)
	Gumbel	1.2108		101.37	-200.75	-194.9
		(1.4235)		(16.76)	(-29.32)	(-26.31)
	Frank	1.9114		121.27	-240.54	-234.69
		(3.5225)		(21.87)	(-41.92)	(-36.92)
	t-student	0.3224	19.06	140.16	-276.31	-264.62
	(0.5166)	(30)	(20.46)	(-36.64)	(-29.73)	
Gaussian	0.3258		137.04	-272.08	-266.24	
	(0.5185)		(21.55)	(-39.82)	(-35.19)	
Survival Gumbel	1.2435		144.56	-287.13	-281.28	
	(1.436)		(19.75)	(-38.32)	(-33.43)	
China/Australia	Clayton	0.4635		157	-311.99	-306.15
		(0.734)		(16.46)	(-31.73)	(-26.81)
	Gumbel	1.2325		117.54	-233.07	-227.23
		(1.46)		(17.38)	(-32.96)	(-20.85)
	Frank	2.007		130.99	-259.98	-254.14
		(3.495)		(21.38)	(-40.76)	(-37.75)
	t-student	0.3331	12.09	160.41	-316.82	-305.13
	(0.518)	(30)	(20.54)	(-37.09)	(-31.07)	
Gaussian	0.3417		153.05	-304.11	-298.26	
	(0.535)		(21.67)	(-39.34)	(-36.53)	
Survival Gumbel	1.2641		165.36	-328.72	-322.87	
	(1.467)		(18.59)	(-35.17)	(-33.26)	
China/Hong Kong	Clayton	0.8157		362.14	-722.29	-716.44
		(1.231)		(30.02)	(-58.04)	(-54.03)
	Gumbel	1.4847		363.62	-725.25	-719.4
		(1.620)		(38.71)	(-73.88)	(-71.51)
	Frank	3.5310		371.6	-741.2	-735.35
		(4.772)		(33.42)	(-67.56)	(-61.72)
	t-student	0.5380	17.52	426.9	-849.81	-838.12
	(0.642)	9.19	(38.93)	(-72.97)	(-67.65)	
Gaussian	0.5317		423.41	-844.82	-838.98	
	(0.758)		(38.76)	(-74.81)	(-71.87)	
Survival Gumbel	1.5003		411.7	-821.56	-815.72	

		(1.730)		(35.87)	(-68.72)	(-65.63)
China/India	Clayton	0.2314		47.24	-92.47	-86.63
		(0.632)		(12.99)	(-24.98)	(-21.97)
	Gumbel	1.1224		40.43	-78.86	-73.02
		(1.331)		(10.19)	(-18.37)	(-15.36)
	Frank	1.197		41.87	-81.73	-75.89
		(2.420)		(11.02)	(-20.83)	(-16.73)
	t-student	0.217	30	52.43	-100.87	-89.18
	(0.417)	(30)	13.17	(-22.34)	(-16.32)	
Gaussian	0.2321		51.94	-101.87	-96.03	
	(0.428)		(13)	(-24.11)	(-21.09)	
Survival Gumbel	1.1335		49.47	-96.95	-91.1	
	(1.335)		(14.22)	(-27.48)	(-23.63)	
China/Taiwan	Clayton	0.3617		102.94	-203.88	-198.03
		(0.6003)		(12.35)	(-22.69)	(-19.68)
	Gumbel	1.163		61.15	-120.3	-114.46
		(1.2704)		(7.67)	(-13.34)	(-10.33)
	Frank	1.5532		81.66	-161.31	-155.47
		(2.2612)		(9.72)	(-17.45)	(-14.44)
	t-student	0.2734	22.55	95.65	-187.29	-175.6
	(0.3917)	(30)	(11.14)	(-18.28)	(-12.26)	
Gaussian	0.2730		93.41	-184.83	-178.98	
	(0.3985)		(11.09)	(-20.17)	(-17.16)	
Survival Gumbel	1.1917		107.08	-212.16	-206.32	
	(1.3231)		(12.06)	(-22.11)	(-19.1)	
China/USA	Clayton	0.1603		26.46	-50.91	-45.07
		(0.547)		(9.17)	(-16.34)	(-13.83)
	Gumbel	1.0741		15.32	-28.64	-22.8
		(1.382)		(11.85)	(-21.81)	(-17.56)
	Frank	0.757		17.07	-32.14	-26.29
		(2.581)		(12)	(-22)	(-17.79)
	t-student	0.1330	15.32	26.33	-48.65	-36.96
	(0.185)	(30)	(12.49)	(-20.89)	(-13.96)	
Gaussian	0.1345		21.8	-41.6	-35.75	
	(0.428)		(12.49)	(-22.87)	(-18.96)	
Survival Gumbel	1.0954		30.42	-58.84	-52.99	
	(1.386)		(11.05)	(-20.07)	(-16.1)	
China/Argentina	Clayton	0.4421		142.76	-283.5	-277.67
		(0.869)		(21.73)	(-42.84)	(-37.82)
	Gumbel	1.2107		96.01	-190.02	-184.17
		(1.484)		(20.83)	(-38.76)	(-35.44)
	Frank	1.8715		116.72	-231.43	-225.59
		(3.622)		(22.55)	(-43.73)	(-39.69)
	t-student	0.330	21.95	140.12	-276.24	-264.55
	(0.545)	(30)	(23.78)	(-45.88)	(-39.89)	
Gaussian	0.321		137.87	-273.75	-267.9	
	(0.547)		(24.92)	(-47.92)	(-43.67)	
Survival Gumbel	1.2423		150.19	-298.39	-292.54	
	(1.537)		(23.88)	(-45.66)	(-41.65)	
China/Brazil	Clayton	0.2407		50.87	-99.73	-93.89
		(0.7131)		(16.26)	(-30.52)	(-27.51)
	Gumbel	1.1312		44.04	-86.09	-80.24
		(1.3787)		(13.72)	(-25.45)	(-22.44)
	Frank	1.220		50.27	-98.54	-92.7
		(2.9214)		(15.18)	(-28.36)	(-25.35)
	t-student	0.2194	20.13	58.43	-112.85	-101.16
	(0.4731)	(30)	(17.09)	(-30.17)	(-24.15)	
Gaussian	0.2166		55.83	-109.65	-103.81	
	(0.4751)		(17.12)	(-32.24)	(-29.23)	
Survival Gumbel	1.1331		55.88	-109.76	-103.92	

		(1.482)		(17.76)	(-32.77)	(-29.15)
China/Mexico	Clayton	0.2865		69.13	-136.26	-130.42
		(0.664)		(12.98)	(-23.81)	(-20.31)
	Gumbel	1.1376		46.53	-91.06	-85.22
		(1.280)		(7.48)	(-14.12)	(-10.75)
	Frank	1.3408		61.19	-120.38	-114.54
		(2.537)		(12.56)	(-22.66)	(-19.65)
	t-student	0.2342	30	68.67	-133.34	-121.65
		(0.467)	(30)	(13.31)	(-22.21)	(-16.27)
Gaussian	0.2332		67.73	-133.46	-127.62	
	(0.434)		(13.65)	(-25.83)	(-22.19)	
Survival Gumbel	1.1508		68.05	-134.11	-128.26	
	(1.343)		(12.62)	(-23.12)	(-21.31)	

### 3.4 Selection of the most suitable dependency structure

To select the most suitable copula, which best represents the dependency structure between the Chinese market and other studied markets, we rely on the information criterion of Akaike (AIC). We also refer to the Likelihood Ratio Tests (Vuong, 1989; Rivers and Vuong, 2002). The AIC criterion is used to assess the quality of the estimates and to judge the selection of the most suitable copula (Dias, 2004).

Table 6 presents the results on copulas selected for the Asian and American markets during both the pre-Covid-19 and Covid-19 periods. We find that during the pre-Covid-19 period, the Gaussian copula best represents the dependency structure between the Chinese market and the markets of Vietnam, Malaysia, Indonesia, and India. Frank's copula best describes dependency between the market of China and those of South Korea, Australia, Indonesia, and Malaysia during the Covid-19 period.

**Table 6. Copulas selected in pre Covid–19 (Covid–19) periods**

Markets	Copula selected	Dependence parameter	Degrees of freedom	Kendall's tau	Upper tail dependence	Lower tail dependence
China/Vietnam	Gaussian	0.1123	-	0.0708	-	-
	(Gaussian)	(0.334)	-	(0.1891)	-	-
China/Malaysia	Gaussian	0.1246	-	0.0731	-	-
	(Frank)	2.094	-	(0.2173)	-	-
China/Indonesia	Gaussian	0.1531	-	0.0912	-	-
	(Frank)	(1.864)	-	(0.1924)	-	-
China/Singapore	Survival Gumbel	1.0795	-	0.0704	-	0.09
	(Gumbel)	(1.162)	-	(0.146)	(0.19)	-
China/South Korea	Survival Gumbel	1.2435	-	0.1914	-	0.25
	(Frank)	(3.5225)	-	(0.343)	-	-
China/Australia	Survival Gumbel	1.2641	-	0.2132	-	0.27
	(Frank)	(3.495)	-	(0.3440)	-	-

China/Hong Kong	t-student	0.5380	17.52	0.3657	0.3	0.3
	(Gaussian)	(0.758)	-	(0.4546)	-	-
China/India	Gaussian	0.2321	-	0.1334	-	-
	(Survival Gumbel)	(1.335)	-	(0.2521)	-	(0.33)
China/Taiwan	Survival Gumbel	1.1917	-	0.1615	-	0.21
	(Clayton)	(0.6003)	-	0.2224	-	(0.31)
China/USA	Survival Gumbel	1.0954	-	0.0871	-	0.11
	(Gaussian)	(0.428)	-	0.278	-	-
China/Argentina	Survival Gumbel	1.2423	-	0.2121	-	0.25
	(Gaussian)	(0.547)	-	(0.3645)	-	-
China/Brazil	t-student	0.2194	20.13	0.1328	-	-
	(Survival Gumbel)	(1.482)	-	(0.3016)	-	(0.37)
China/Mexico	Clayton	0.2865	-	0.1284	-	0.09
	(Gaussian)	(0.434)	-	(0.2931)	-	-

### 3.5 The bootstrap technique

The copulas selected in our study are not the same in the two sub-periods. In such a case, we cannot compare the estimated dependency parameters. We study the global dependence between the Chinese market and the American and Asian markets and then calculate the Kendall tau relative to these markets for both sub-periods.

To conclude on the hypothesis of contagion, we apply the bootstrap technique to obtain standard errors for the various test statistics.

The increase in Kendall tau values during times of crisis compared with those during periods of stability shows the existence of financial contagion. Indeed, according to Horta et al. (2010), there is a contagion phenomenon if dependency is higher in times of crisis.

The results reported in Table 7 allow us to conclude on the existence of contagion between the Chinese market and the markets of the Asian and American regions. The results show that the variation of the tau of Kendall is positive for all countries, suggesting that there is contagion of the COVID-19 outbreak for all markets studied. To determine the probability of  $\Delta \tau$ , we use 1000 replications (R=1000) in the bootstrap procedure.

Kendall's tau is relatively higher in the American region (the United States, Mexico, Argentina, and Brazil) compared with the Asian region (Vietnam, Taiwan, Hong Kong, etc.). We then conclude that the American region is more affected by the Covid-19 outbreak than the Asian region. Otherwise, the market of the United-States shows the most significant increase in Kendall's tau and therefore the highest dependence compared with other markets.

**Table 7. Contagion test**

<b>Markets</b>	$\Delta \tau$	<b>p- value</b>	<b>Contagion?</b>
China/Vietnam	0.1183	2.01e-07	Yes
China/Malaysia	0.1442	1.47e-09	Yes
China/Indonesia	0.1012	8.65e-07	Yes
China/Singapore	0.0756	0.0009	Yes
China/South Korea	0.1516	0	Yes
China/Australia	0.1308	1.36e-05	Yes
China/Hong Kong	0.0889	0	Yes
China/India	0.1187	1.57e-14	Yes
China/Taiwan	0.0609	0	Yes
China/USA	0.1909	1.41e-12	Yes
China/Argentina	0.1524	0	Yes
China/Brazil	0.1688	0	Yes
China/Mexico	0.1647	0	Yes

We now investigate the intensity of the financial contagion between Asian and American markets, then between different American markets, and finally between Asian markets. We use the bootstrap results and test contagion intensity during the Covid-19 outbreak.

$$\begin{cases} H_0 = \Delta \tau_{A-B} = (\tau_{\text{covid}}^A - \tau_{\text{pre-covid}}^A) - (\tau_{\text{covid}}^B - \tau_{\text{pre-covid}}^B) \leq 0 \\ H_1 = \Delta \tau_{A-B} = (\tau_{\text{covid}}^A - \tau_{\text{pre-covid}}^A) - (\tau_{\text{covid}}^B - \tau_{\text{pre-covid}}^B) > 0 \end{cases}$$

Table 8 shows that all values are positive and subsequently, we conclude that markets A (American region) are highly intensive relative to markets B (Asian regions). In addition, American markets are more intense to contagion than Asian markets.

**Table 8. Intensity test of financial contagion between Asian and American markets**

$\Delta \tau_{A-B}$	<b>South Korea</b>	<b>Vietnam</b>	<b>Singapore</b>	<b>Taiwan</b>	<b>Hong Kong</b>	<b>Malaysia</b>	<b>India</b>	<b>Indonesia</b>	<b>Australia</b>
USA	0.039	0.0726	0.1153	0.13	0.102	0.0467	0.0722	0.0897	0.0601
Brazil	0.0172	0.0505	0.0932	0.1079	0.0799	0.0246	0.0501	0.0676	0.038
Mexico	0.0131	0.0464	0.0891	0.1038	0.0758	0.0205	0.046	0.0635	0.0339
Argentina	0.0008	0.0341	0.0768	0.0915	0.0635	0.0082	0.0337	0.0512	0.0216

The test of the intensity of financial contagion between the different American markets is presented in Table 9. The results show that the most intense country with financial contagion during the Covid-19 outbreak is the United States, followed by Brazil, Mexico and Argentina. Argentina is nevertheless the least intense American country for contagion.

**Table 9. Intensity test of financial contagion between American markets**

$\Delta\tau_{A-B}$	Brazil	Mexico	Argentina
USA	0.0221	0.0262	0.0385
Brazil		0.0041	0.0164
Mexico			0.0123

Table 10 shows that the highest intensity of contagion in the Asian region is recorded in the South Korean market, followed by Malaysia, Australia, India, Vietnam, and Indonesia. However, Hong Kong, Singapore, and Taiwan register the lowest intensity of contagion.

**Table 10. Intensity test of financial contagion between Asian markets**

$\Delta\tau_{A-B}$	South Korea	Singapore	Taiwan	Hong Kong	Malaysia	India	Indonesia	Australia
Vietnam	-0.0333	0.0427	0.0574	0.0318	-0.0259	-0.0004	0.0171	-0.0125
South Korea		0.078	0.0907	0.0627	0.0074	0.0329	0.0504	0.0208
Singapore			0.0147	-0.0133	-0.0686	-0.0431	-0.0256	-0.0552
Taiwan				-0.028	-0.0833	-0.0578	-0.0403	-0.0699
Hong Kong					-0.0553	-0.0298	-0.0123	-0.0419
Malaysia						0.0255	0.043	0.0134
India							0.0175	-0.0121
Indonesia								-0.0296

### 3.6 Economic implications

Beyond a major health crisis, the Covid-19 pandemic has triggered an economic crisis that has already resulted in massive unemployment. This pandemic spread rapidly, infecting millions of people, and has practically stopped economic activities. In addition, the Covid-19 pandemic has affected the financial markets. Indeed, many stock markets (both in developed and emergent countries) have recorded a drop of 30% or more. According to He and Harris (2020), the Covid-19 pandemic could cause fear, shock, and panic among domestic and international investors. From their side, Wang et al. (2020) show that investors shape their feelings towards the pandemic and can significantly influence the stock markets. Indeed, when the stock market moves down due to perceived high risk, investors become relatively pessimistic and tend to wait until a recovery begins before entering the market.

Specifically, the Covid-19 pandemic has had a negative impact on several stock markets, namely, those of Europe, America, and Asia. For instance, Baker et al. (2020) found that the pandemic has a strong impact on the U.S. stock market. He and Harris (2020) show that the COVID-19 pandemic has a negative short-term impact on stock markets of China, Italy, South Korea, France, Spain, Germany, Japan, and American countries.

Our findings support the fact that the Covid-19 pandemic has shaken financial markets all over the world. Indeed, we show the existence of financial contagion for all American and Asian countries. We also show that contagion is more intense for American countries than Asian countries. Indeed, the United States did not react on time to the pandemic and lost valuable time in managing the crisis.

#### **4. Conclusion**

The purpose of our study is to examine the presence of financial contagion and its intensity during the Covid-19 outbreak based on a copula approach. We use daily series of stock indexes of 10 Asian countries (Taiwan, Hong Kong, Singapore, India, Indonesia, Malaysia, South Korea, Singapore, Vietnam, and China) and four American countries (United States, Brazil, Mexico, and Argentina) over the period of January 1, 2014 to June 30<sup>th</sup>, 2021.

Using the copula approach, we show that the variation of the tau of Kendall is positive for all countries. We then conclude that there is contagion during the COVID-19 outbreak for all studied markets. We also find that the American region is more affected by the Covid-19 outbreak than the Asian region. Otherwise, the markets of the United States and Brazil show the most significant increase in Kendall's tau and therefore the highest dependence. By testing the intensity of financial contagion, we show that American markets are more intense to contagion than Asian markets. We find that the most intense country for financial contagion during the Covid-19 outbreak is the United States, followed by Brazil, Mexico, and Argentina.

For the Asian region, the country with the most intense contagion is the market of South Korea, followed by Malaysia, Australia, India, Vietnam, and Indonesia. However, Hong Kong, Singapore, and Taiwan recorded the lowest intensity of contagion. Indeed, the geographical proximity of these countries to China allows them to react quickly to this pandemic and put in place several restrictive measures (physical distancing, socio-economic restrictions, hygienic measures, etc.) to minimize the risk and limit the spread of the outbreak.



Our results are consistent with those of Baker et al. (2020) who found that the Covid-19 outbreak has a strong impact on the stock market in the United States. Furthermore, Guo et al. (2021) show the existence of contagion for American (Brazil, United States, and Canada) and Asian markets (Australia, Hong Kong, Korea, Singapore, and Taiwan) during the Covid-19 outbreak. Moreover, our findings are consistent with those of Zorgati et al. (2019). They found that American markets (Brazil, Argentina, Canada, and the United States) have high levels of contagion intensity compared with the Asian markets (Hong Kong, Australia, Korea, China, and Singapore) during the subprime crisis.

To limit the contagion associated to the subprime crisis, policymakers in the USA designed an appropriate monetary policy that ensures the liquidity of the domestic stock market and protects it from contagion. They reevaluated the global financial system to limit the recession by taking appropriate actions. Furthermore, financial risk managers provided support to financial institutions in trouble to reduce the perceived risks of investors.

Our study examines the intensity of financial contagion during the Covid-19 outbreak. Our results provide implications, especially for investors, risk managers, and policymakers. The latter should continue to provide liquidity to the international market during this pandemic.

Following these findings, investors seek to optimize their portfolios. Indeed, in the course of the Covid-19 outbreak, international stock markets have experienced extremely volatile periods that have increased market risk and credit risk for international investors.

Our results may also be helpful for regulators and policymakers as they should consider the increase in dependencies during market distress as a potential risk to financial stability. Therefore, regulatory policies should aim to prevent extreme risk shocks from spreading to global stock markets to maintain domestic financial stability, especially in the case of COVID-19 waves in the future.

Research on the subject of contagion during Covid-19 is in its nascent stages. For future research, we suggest studying the transmission channels of the Covid-19 outbreak in Asian, American, European and African regions.

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