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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 1st, 2014 to June 30th, 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.

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 (Amaratunga, Cabrera, Ghosh, et al., 2021; Ashraf, 2020; Baveja, Kapoor, & Melamed, 2020; Corbet, Larkin, & Lucey, 2020; Sharif, Aloui, & Yarovaya, 2020; Zhang, Hu, & Ji, 2020). Based on daily stock return data from 64 countries over the period of January 22, 2020 to April 17, 2020, Ni Toi and Pochea (2020) show 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, Ni Toi and Pochea (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.

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contagion (Akhtaruzzaman, Boulker, & Sensoy, 2021; Alqaralleh, Canepa, & Zanetti, 2020; Calvo & Reinhart, 1996; Dornbusch, Park, & Claessens, 2000; Eichengreen, Rose, & Wyplosz, 1996; Forbes & Rigobon, 2002; Gunay, 2020; Zhu, Yang, & Ye, 2018; Zorgati & Lakhal, 2020; Zorgati, Lakhal, & Zabbi, 2019), but the definition of contagion and how it could be measured is still contestable. According to Gravelle, Kichian, and Morley (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 Rigobon (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 (Chiang, Jeon, & Li, 2007; Collins & Biekpe, 2003; Forbes & Rigobon, 2002). 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, & 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 (Caballlos-Rocha, Gomez-Gonzalez, & Melo-Velandia, 2019; Fenech & Vesga, 2019; Ni Toi & Pechea, 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, Li, and Li (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, Hou, Hu, and Oxley (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, Liu, and Wang (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 4th, 1999, to May 13th, 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, Yuan, Li, and Wang (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 1st, 2014 to June 30th, 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 (Forbes & Rigobon, 2002; Mash & Mash, 1999; Yang et al., 2005). 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
returns is positive for all markets except for Singapore and Malaysia and (MERV) over the period of January 1st, 2014 to June 30th, 2021. We select the first date of the pre-COVID-19 period as January 1st, 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 30th, 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 Africa. Our sample covers both the periods before (January 1st, 2014–December 30, 2019) and during Covid–19 (December 31, 2019–June 30th, 2021).

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

According to Bruneau, Flageollet, and Peng (2015),

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 (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.

Fig. 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.

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, Mendes, & Vieira, 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 3 reports the results of the estimates of the mean and variance}

\[ \tau_c(X, Y) = 1 - 4 \int_0^1 \frac{\partial C(u, v)}{\partial u} \frac{\partial C(u, v)}{\partial v} \, dudv \]

\[ \rho_c(X, Y) = 12 \left( C(u, v) - uv \right) \, dudv \]

In this study, we use Kendall’s τ to evaluate global dependence structures, and the τ 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. Then we conclude about the existence and the intensity of financial contagion.

At this level, and using Kendall’s τ, two tests are necessary:

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

\[ H_0: \Delta \tau = \tau_{\text{covid}} - \tau_{\text{pre-covid}} \leq 0 \]
\[ H_1: \Delta \tau = \tau_{\text{covid}} - \tau_{\text{pre-covid}} > 0 \]

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

\[ H_0: \Delta \tau_{A-B} = \left( \tau_{A-B}^{\text{covid}} - \tau_{A-B}^{\text{pre-covid}} \right) \leq 0 \]
\[ H_1: \Delta \tau_{A-B} = \left( \tau_{A-B}^{\text{covid}} - \tau_{A-B}^{\text{pre-covid}} \right) > 0 \]

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 (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.

\[ H_0: \Delta \tau = \tau_{\text{covid}} - \tau_{\text{pre-covid}} \leq 0 \]
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\[ H_0: \Delta \tau_{A-B} = \left( \tau_{A-B}^{\text{covid}} - \tau_{A-B}^{\text{pre-covid}} \right) \leq 0 \]
\[ H_1: \Delta \tau_{A-B} = \left( \tau_{A-B}^{\text{covid}} - \tau_{A-B}^{\text{pre-covid}} \right) > 0 \]
Table 1

Descriptive statistics.

| Markets          | Taiwan | Singapore | Hong Kong | Malaysia | Indonesia | India | Vietnam |
|------------------|--------|-----------|-----------|----------|-----------|-------|---------|
| Obs              | 1889   | 1889      | 1889      | 1889     | 1889      | 1889  | 1889    |
| Min              | -233.24| -7.637    | -9.051    | -5.4047  | -6.8050   | -14.101| -11.326 |
| Max              | 233.19 | 5.894     | 4.924     | 6.6262   | 4.653     | 8.5948 | 7.8296  |
| Mean             | 0.0378 | -0.0014   | 0.0114    | 0.0095   | 0.0168    | 0.0488 | 0.0116  |
| StDev            | 7.6455 | 0.863     | 1.142     | 0.6851   | 0.9747    | 1.0891 | 1.430   |
| Skewness         | -0.7374| -0.592    | -0.617    | -0.2870  | -0.5957   | -1.533 | -0.593  |
| Kurtosis         | 11.314 | 10.302    | 4.266     | 10.3827  | 24.110    | 5.4074 | 5.4074  |
| J.B              | 658.955*** | 4888.28*** | 1558.33*** | 8593.44*** | 1990.5*** | 4660.4*** | 2520.1*** |
| Q(10)            | 44.167*** | 29.135*** | 7.428     | 21.855** | 14.022    | 64.789*** | 26.476*** |

| Markets          | South Korea | Australia | China | United States | Mexico | Brazil | Argentina |
|------------------|--------------|-----------|-------|---------------|--------|--------|-----------|
| Obs              | 1889         | 1889      | 1889  | 1889          | 1889   | 1889   | 1889      |
| Min              | -8.7669      | -10.009   | -8.872| -12.765       | -6.638 | -15.993| -47.6922  |
| Max              | 8.251        | 6.354     | 6.369 | 8.968         | 4.1805 | 13.022 | 9.773     |
| Mean             | 0.027        | 0.0181    | 0.0279| 0.0450        | 0.0093 | 0.0491 | 0.1208    |
| StDev            | 0.9733       | 0.9757    | 1.386 | 1.104         | 0.9699 | 1.642  | 2.652     |
| Skewness         | -0.285       | -1.284    | -1.115| -1.059        | -0.5194| -1.048 | -3.398    |
| Kurtosis         | 10.974       | 14.438    | 7.892 | 22.128        | 4.618  | 14.861 | 57.769    |
| J.B              | 9531.6***    | 16971***  | 5399.83*** | 38988*** | 1769.8*** | 17775*** | 266905*** |
| Q(10)            | 30.948***    | 84.591*** | 30.355*** | 332.93*** | 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.

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

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.}

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

**3.2. Data transformation**

The second step consists of transforming the filtered returns, returning 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). **Fig. 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 $[0,1]$.²

**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 0 with the transformed data from the previous step as input to the algorithm. The initial parameter theta 0 is obtained from Kendall’s empirical tau (Bouye, Durrleman, Nikeghbali, Riboulet, & Roncalli, 2000).

**Table 4** shows that the empirical Kendall $\tau$ increases from stable 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 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

| Country  | Model                  | AIC     | BIC     | Persistence |
|----------|------------------------|---------|---------|-------------|
| 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)   | 2.9073  | 2.9367  | 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 5** presents the estimation of the copula parameters using the CML method for stable and crisis periods.
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.

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 (Rivers & Vuong, 2002; Vuong, 1989). The AIC criterion is used to assess the quality of the estimates and to judge the selection of the most suitable copula (Dias & Embrechts, 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.

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.

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.

The test of the intensity of financial contagion between 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 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 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.

### 3.6. Economic implications

Beyond a major health crisis, the Covid-19 pandemic has triggered...
| Country         | Copulas       | Dependence parameter | Degree of freedom | LLF    | AIC    | BIC    |
|----------------|---------------|----------------------|-------------------|--------|--------|--------|
| China/Vietnam  | Clayton       | 0.1224               | (0.3212)          | 14.18  | -26.37 | -20.52 |
|                | Gumbel        | 1.0507               | (1.247)           | 7.53   | -13.06 | -7.22  |
|                | Frank         | 0.6108               | (1.6934)          | 12.87  | -23.74 | -17.89 |
|                | t-student     | 0.1124               | (30)              | 14.01  | -24.02 | -12.33 |
|                | Gaussian      | 0.1123               | (30)              | 15.23  | -28.46 | -22.61 |
|                | Survival Gumbel | 1.0663            | (1.194)           | 14.66  | -27.33 | -21.48 |
|                | China/Malaysia| Clayton             | 0.1247            | (0.462) | 15.8   | -29.6  |
|                | Gumbel        | 1.0547               | (1.1241)          | 8.1    | -14.2  | -8.35  |
|                | Frank         | 0.6458               | (2.094)           | 14.46  | -26.92 | -21.08 |
|                | t-student     | 0.1144               | (30)              | 15.37  | -26.92 | -15.06 |
|                | Gaussian      | 0.1246               | (0.840)           | 16.84  | -31.67 | -25.83 |
|                | Survival Gumbel| 1.0618           | (1.273)           | 15.65  | -29.31 | -23.46 |
|                | China/Indonesia| Clayton           | 0.1658            | (0.324) | 25.14  | -48.28 |
|                | Gumbel        | 1.0868               | (1.188)           | 20.89  | -39.28 | -33.93 |
|                | Frank         | 0.7735               | (1.864)           | 20.64  | -39.28 | -33.43 |
|                | t-student     | 0.1454               | (30)              | 28.14  | -52.28 | -40.59 |
|                | Gaussian      | 0.1531               | (0.282)           | 27.35  | -52.7  | -46.85 |
|                | Survival Gumbel| 1.0835           | (1.276)           | 27.03  | -52.07 | -46.22 |
|                | China/Singapore| Clayton          | 0.1357            | (0.316) | 16.04  | -30.09 |
|                | Gumbel        | 1.0634               | (1.162)           | 12.81  | -23.61 | -17.77 |
|                | Frank         | 0.6387               | (1.2619)          | 14.07  | -26.15 | -20.3  |
|                | t-student     | 0.1132               | (30)              | 18.23  | -32.46 | -20.77 |
|                | Gaussian      | 0.1114               | (0.2633)          | 15.35  | -28.7  | -22.85 |
|                | Survival Gumbel| 1.0795           | (1.170)           | 20.1   | -38.2  | -32.35 |
|                | China/South Korea| Clayton       | 0.4358            | (0.794) | 136.59 | -271.17|
|                | Gumbel        | 1.2108               | (1.4235)          | 101.37 | -200.75| -194.9 |
|                | Frank         | 1.9114               | (3.5225)          | 121.27 | -240.54| -234.69|
|                | t-student     | 0.3224               | (30)              | 140.16 | -276.31| -264.62|
|                | Gaussian      | 0.3258               | (0.5166)          | 137.04 | -272.08| -266.24|
|                | Survival Gumbel| 1.2435           | (1.436)           | 144.56 | -287.13| -281.28|
|                | China/Australia| Clayton           | 0.4635            | (0.734) | 157    | -311.99|
|                | Gumbel        | 1.2325               | (1.46)            | 117.54 | -233.07| -227.23|
|                | Frank         | 2.007                | (3.495)           | 130.99 | -259.98| -254.14|
|                | t-student     | 0.3331               | (30)              | 160.41 | -316.82| -305.13|
|                | Gaussian      | 0.3417               | (0.518)           | 153.05 | -304.11| -298.26|
|                | Survival Gumbel| 1.2641           | (1.467)           | 165.36 | -328.72| -322.87|
|                | China/Hong Kong| Clayton           | 0.8157            | (1.231) | 362.14 | -722.29 |
|                | Survival Gumbel| 1.2641           | (1.467)           | 165.36 | -328.72| -322.87|

(continued on next page)
| Country       | Copulas         | Dependence parameter | Degree of freedom | LLF      | AIC       | BIC       |
|--------------|----------------|----------------------|-------------------|----------|-----------|-----------|
| China/India  | Clayton        | 0.2314               | (0.632)           | 47.24    | (12.99)   | (24.98)   |
|              | Gumbel         | 1.1224               | (1.331)           | 40.43    | (10.19)   | (18.37)   |
|              | Frank          | 1.197                | (2.420)           | 41.87    | (11.02)   | (16.73)   |
|              | t-student      | 0.217                | (0.417)           | 52.43    | (13.17)   | (22.34)   |
|              | Survival Gumbel| 1.1335               | (1.335)           | 49.47    | (14.22)   | (27.48)   |
| China/Taiwan | Clayton        | 0.3617               | (0.6003)          | 102.94   | (12.35)   | (22.69)   |
|              | Gumbel         | 1.163                | (1.2704)          | 61.15    | (7.67)    | (13.34)   |
|              | Frank          | 1.5532               | (2.2612)          | 81.66    | (9.72)    | (17.45)   |
|              | t-student      | 0.2734               | (0.3917)          | 95.65    | (11.14)   | (18.28)   |
|              | Survival Gumbel| 1.1917               | (1.3231)          | 107.08   | (12.06)   | (22.11)   |
| China/USA    | Clayton        | 0.1603               | (0.547)           | 26.46    | (12.35)   | (26.9)    |
|              | Gumbel         | 1.0741               | (1.382)           | 15.32    | (11.85)   | (21.81)   |
|              | Frank          | 0.757                | (2.581)           | 17.07    | (12)      | (22)      |
|              | t-student      | 0.1330               | (0.185)           | 26.33    | (12.49)   | (20.89)   |
|              | Survival Gumbel| 1.1917               | (1.3231)          | 107.08   | (12.06)   | (22.11)   |
| China/Argentina | Clayton | 0.4421               | (0.869)           | 142.76   | (21.73)   | (42.84)   |
|              | Gumbel         | 1.2107               | (1.484)           | 96.01    | (20.83)   | (38.76)   |
|              | Frank          | 1.8715               | (3.622)           | 116.72   | (22.55)   | (43.73)   |
|              | t-student      | 0.330                | (0.545)           | 140.12   | (23.78)   | (45.88)   |
|              | Survival Gumbel| 1.2423               | (1.537)           | 150.19   | (23.88)   | (45.66)   |
| China/Brazil | Clayton        | 0.2407               | (0.7131)          | 50.87    | (11.05)   | (20.07)   |
|              | Gumbel         | 1.1312               | (1.3787)          | 44.04    | (16.26)   | (30.52)   |
|              | Frank          | 1.220                | (2.9214)          | 50.27    | (15.18)   | (28.36)   |
|              | t-student      | 0.2194               | (0.4731)          | 58.43    | (17.09)   | (30.17)   |
|              | Survival Gumbel| 1.1331               | (1.482)           | 55.88    | (17.76)   | (32.77)   |
| China/Mexico | Clayton        | 0.2865               | (0.664)           | 69.13    | (12.98)   | (23.81)   |
|              | Gumbel         | 1.1376               | (1.280)           | 46.53    | (7.48)    | (14.12)   |
|              | Frank          | 1.3408               | (2.537)           | 61.19    | (12.56)   | (22.66)   |

(continued on next page)
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, Li, and Huang (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 pandemic has a strong impact on the U.S. stock market.

Table 5 (continued)

| Country    | Copulas  | Dependence parameter | Degree of freedom | LLF     | AIC      | BIC      |
|------------|----------|----------------------|-------------------|---------|----------|----------|
|            | 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) |

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               | 7.52               | 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                  |
| (Gumbel)      |                 | (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)      | –                     | –                     |

Table 7

Contagion test.

| Markets       | Δτ     | p-value | Contagion? |
|---------------|--------|---------|------------|
| 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     | 0.1999 | 1.41e-12| Yes        |
| China/Argentina| 0.1524 | 0       | Yes        |
| China/Brazil  | 0.1688 | 0       | Yes        |
| China/Mexico  | 0.1647 | 0       | Yes        |

Table 8

Intensity test of financial contagion between Asian and American markets.

| Market | South Korea | Vietnam | Singapore | Taiwan | Hong Kong | Malaysia | India | Indonesia | Australia |
|--------|-------------|---------|-----------|--------|-----------|----------|-------|-----------|----------|
| USA    | 0.0396      | 0.0726  | 0.1153    | 0.13   | 0.102     | 0.0467   | 0.0727 | 0.0897    | 0.0601   |
| Brazil | 0.0172      | 0.0505  | 0.0932    | 0.1079 | 0.0799    | 0.0246   | 0.0501 | 0.0676    | 0.0385   |
| 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   |

Table 9

Intensity test of financial contagion between American markets.

| Market | Brazil | Mexico | Argentina |
|--------|--------|--------|-----------|
| USA    | 0.0221 | 0.0041 | 0.0385    |
| Brazil | 0.0164 | 0.0123 |           |
| Mexico |        |        |           |
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, 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 30th, 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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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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