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Markets Dependence in Times of Turmoil: Evidence from US and Asia-Pacific Stock Markets

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ABSTRACT

The US stock market collapse of 2020 was caused by the COVID-19 shock, exerting profound impacts on global stock markets. In this article, we analyze the downside and upside contagion and the tail dependence risks of the US stock market index on China, Hong Kong, Japan, and South Korea. We establish our empirical findings through a robust modelization of a conditional VaR (CoVaR), ΔCoVaR, and copula models. The empirical results reveal wide spillover effects from the US to East Asian stock markets. These spillover effects are aggravated in the COVID-19 period when compared to the full sample period. This impact deluges to the Chinese market only via Hong Kong. The findings show that indirect spillovers on the Chinese stock market are heavier than direct spillovers. The study highlights different features of the US and Chinese spillovers. These findings provide useful support for policymakers and risk managers involved in the East Asian stock markets.

INTRODUCTION

The COVID-19 shock created a highly volatile period for the US stock market, which also exerted profound effects on global stock markets. At the same time, the US was experiencing these effects, turmoil was felt in other stock markets, particularly in the East Asia area. In March 2020, the US stock market halted many times. In this respect, the spillover risks to the East Asian stock markets are important to study because the East Asia area is closely correlated with the US.

Strong risk aversion induced by the COVID-19 shock spread across global financial markets from February to March 2020. In particular, the US stock market was hit hard by tremendous and abrupt uncertainty caused by the pandemic. Under these conditions, the issue of judging the degree to which some stock market indexes affect the performance of other financial equity markets becomes pertinent and is worth examining (Zehri, 2020a). Hence, investigating the risk contagion of the US stock market return to East Asian markets is an interesting topic full of practical implications.

The issue has been analyzed from multiple viewpoints including Granger-causality (Liu et al., 2021; Da Fonseca and Gottschalk, 2020), or cointegration, under the studies of Kim (2009), Hyde et al. (2007), or linear and nonlinear regression, as in Bekiros (2014), and Golosnoy et al. (2015), and vine copula modeling (Jiang et al., 202). Regarding the previous works, our work has the merit of performing a sound empirical examination employing modified Iterative Cumulative Sum of Squares (ICSS) algorithm applied by many researchers (Ewing and Malik, 2016) to detect underlying structural breaks in the unconditional variance of stock returns. The span of the periods of instability is decided according to the identified breaks. In terms of the modeling approach, our research is broadly linked to the studies of Shahzad et al. (2018) and Xiao (2020) who employed copula and CoVaR models to investigate the spillover effects, systemic and tail dependence risks of some stock markets indexes. We also employ multivariate copula to model the dependency structure of the East-Asian and the US stock markets. The dependency structures are used to identify risk spillovers (Adrian and Brunnermeier, 2016; Shahzad et al., 2018). The robustness of the spillover effect is verified through the bootstrap Kolmogorov-Smirnov (KS) test used by several scholars (Reboredo and Ugolini, 2015). Based on these useful empirical results, we analyze the differences in the risk spillovers. In addition to the above-mentioned contribution to existing literature, this paper has chosen a key analysis period. The period of 2015-2020 is very significant for addressing the issue of spillover effect. In this period, there are two special crises: the 2015 Chinese stock market crash caused by deleveraging effects and the 2020 US stock market drop due to the COVID-19 shock. A major contribution of our paper, which has not been addressed by the previous literature, is to compare the two spillovers effect of the US-COVID-19 shock and the Chinese 2015 crisis. We detail the characteristics of each spillover effect, and we identify the differences in propagation on East Asian countries.

Our empirical findings highlight that greater downside spillover effects existed from the US to East Asian stock markets, particularly throughout the COVID-19 period. The conditional spillovers present are significant and confirm the strong links between the US and the East Asian stock markets. The indirect spillover effect of the US stock market on the Chinese stock market is more significant than the direct spillover. This finding highlights the strong dependence of the Chinese stock market on the fluctuations in the US stock market, especially when China controls transactions in Hong Kong. The results offer important evidence on the differences in the risk spillovers. First, the Chinese stock market exerted direct and indirect spillovers to East Asian stock markets during the full sample period. However, the direct contagions are reduced, and the indirect effects become insignificant during its period of instability. Second, the contagion of the US to East Asian stock markets is distinct from that of the Chinese market because of dependent structures with other stock markets, especially in indirect dependency during the full period. In addition, the contagion of the US stock market to the other stock markets is exacerbated during the period of instability due to the COVID-19 shock.

This paper is organized as follows: Section 1 displays the literature review. Section 2 analyzes the data. Section 3 discusses and interprets the empirical findings. Section 4 concludes.

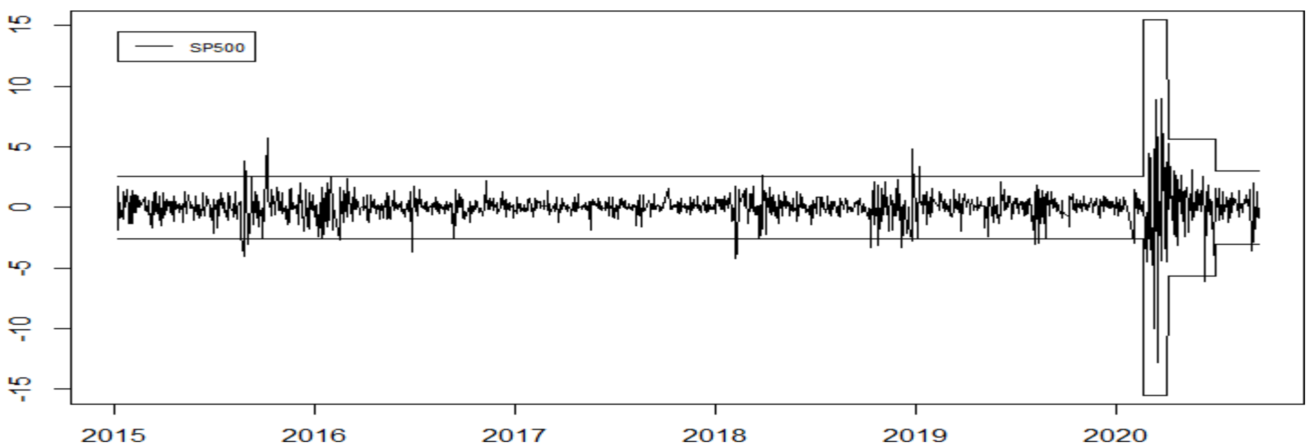
1. LITERATURE REVIEW

The relevant literature on spillover risk can be shared with two stands. One recent investigated the spillover effect caused by the COVID-19 shock. This pandemic disease has left profound effects on international financial markets (Janiak et al., 2021). Policymakers made difficult decisions to limit these effects (for instance, city isolation, flight interdiction, and employment interruption) to avoid the propagation of the COVID-19. As a result, the economic consequences were substantial and costly (Deb et al., 2020) and caused powerful market risk spillover, or contagion impact, in particular (Okorie and Lin, 2021). Several recent studies have highlighted this spillover risk of COVID-19 shock (Liu et al., 2021). Many studies reveal a significant increase in correlations between several stock markets for the period of high volatility following the appearance of the pandemic disease (Nguyen and Le, 2021). For instance, Okorie and Lin (2021) found that the COVID-19 shock increased spillover channels in the global stock markets. Liu et al. (2021) analyzed the risk of contagion on the industrial sector before and after the highly volatile COVID-19 period. They used the causal forest and elaborate network approaches and found that the spillover risk in this sector was quite high. Shahzad et al. (2021) studied the contagion effect of China to neighbor stock markets and found an unstable form of transmission that became more stable and stronger in the period of COVID-19.

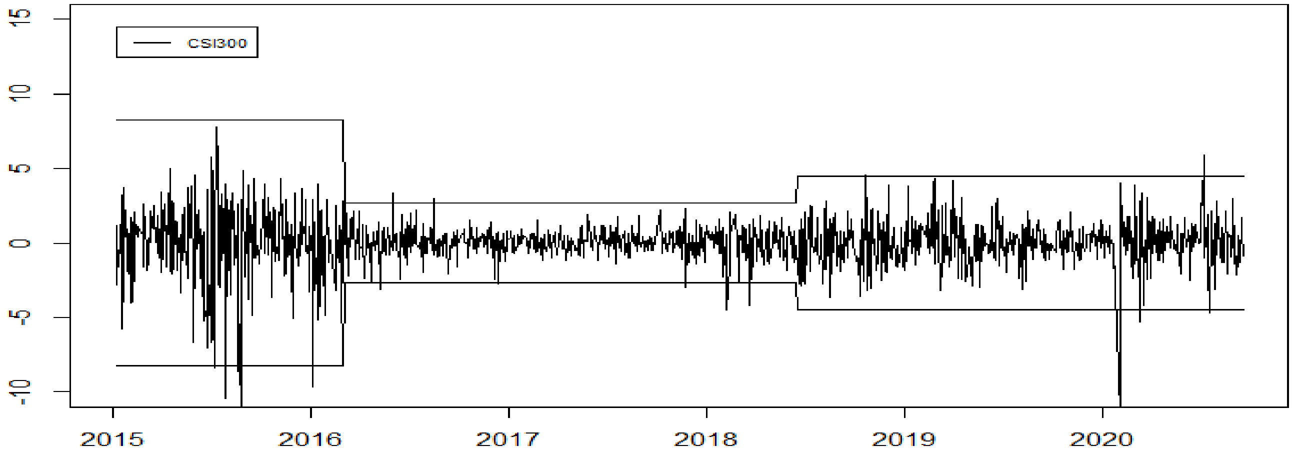
Another group of studies examined the volatile spillover effects of stock markets, focusing on the empirical approaches used to capture the potential contagion effect. Particularly, emphasis is given to studies employing the generalized autoregressive conditional heteroskedasticity (GARCH) with structural breaks and copula quantile regression, as in our empirical analysis. Multiple studies explore spillover or contagion within stock markets and compare findings before and after high-volatility events (e.g., Jitmaneeroj, 2018). Most of these studies address this spillover risk through analyzing volatile and conditional correlations, generally using the GARCH approach. It was sometimes necessary to extend the GARCH approach to other empirical methods likely to shed more light on the risk spillover among stocks markets (Moon and Yu, 2010).

2. DATA ANALYSIS

The selected stock markets for analysis include the Standard & Poor's Index (S&P 500, US), the Shanghai Shenzhen Index (CSI 300, China), the Hang Seng Index (HS, Hong Kong), the Nikkei Index (N225, Japan), and the KOSPI Composite Index (KS, South Korea). These stock indexes describe their market shifts. This data[1] is sourced from Yahoo Finance, covering January 1, 2015-October 20, 2020.
The choice of this analysis period is made for several reasons; essentially it covers the period of COVID-19. For comparison with a stable period, the analysis period is extended for 5 years before the pandemic, and the 2015 period corresponds to the Chinese crisis, which can also have a contagion effect on neighboring Asian countries. We will also consider the spillover impact of the 2015 Chinese crisis and compare it with the crisis that interests us most in this paper, the spillover effect of the US stock market during COVID-19.



[1] We follow Xiao, Y. (2020) to complete the missing data using Last Observation Carried Forward (LOCF) method.



CSI300
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10
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2016
2017
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2019
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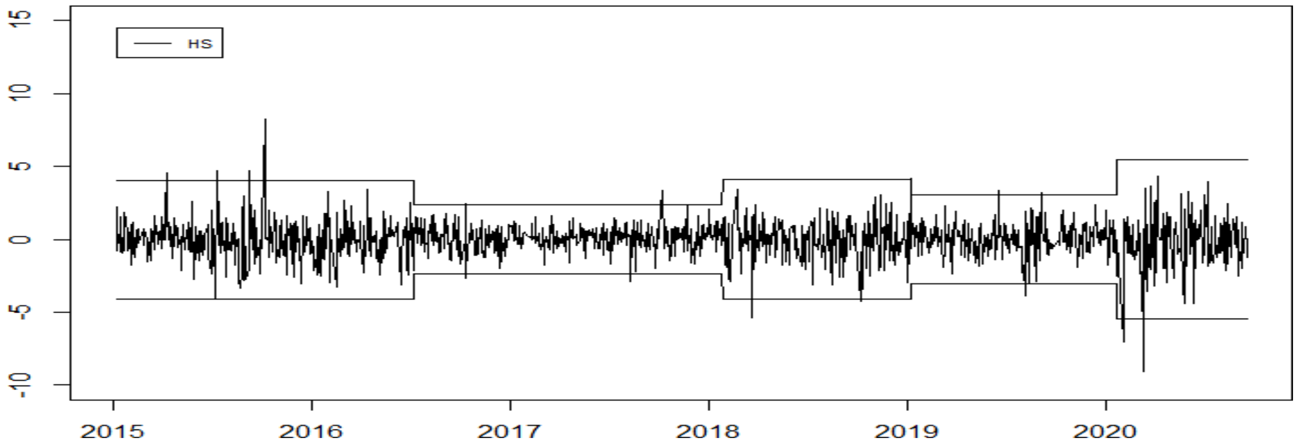

HS
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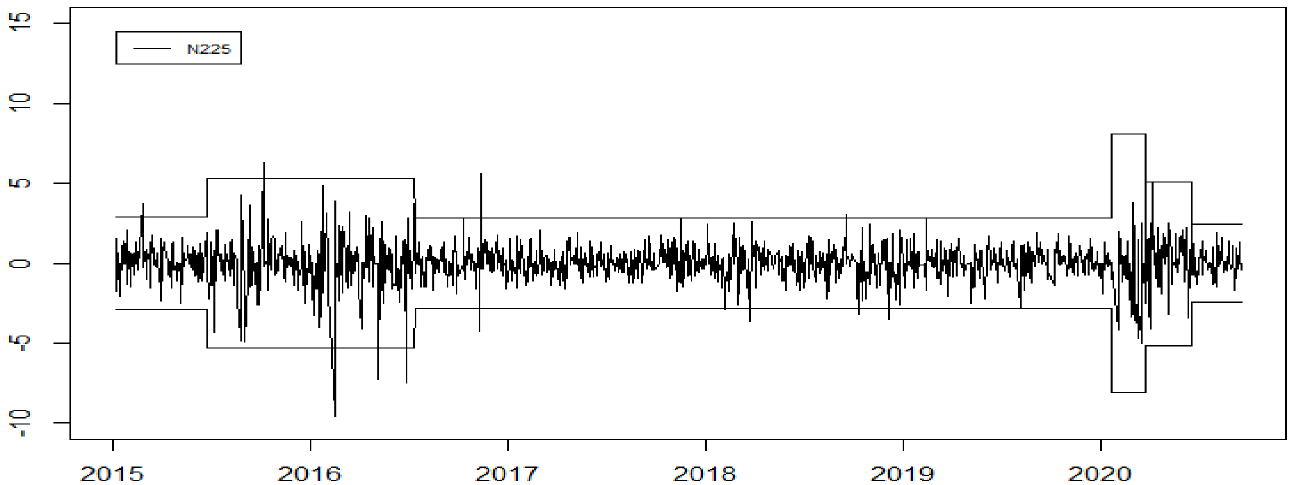

N225
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2020

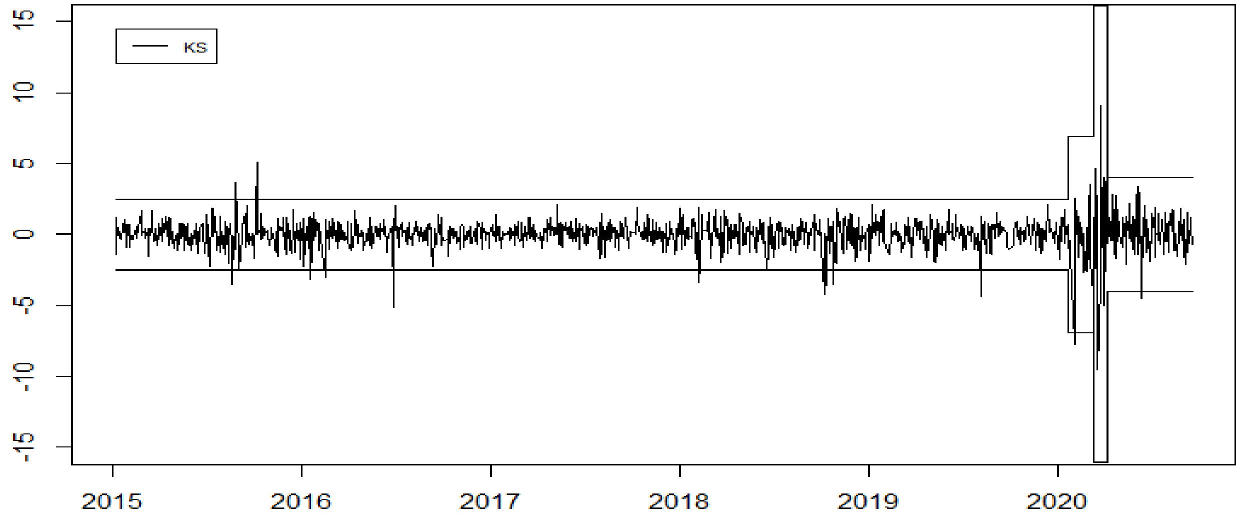

Figure 1. Total return indexes volatility

Source: Author's creation

In Fig.1, the index returns reflect the volatile dynamics of the stock markets. In Table 1, the underlying volatility structural points of stock markets are identified by the modified ICSS algorithm. During the 2015 period of instability in the Chinese stock market, the crisis occurred, and the CSI 300 Index slumped about 2000 points from 5353 to 3354 within three months. In this period, all stock markets presented an interval of intensive volatility, and the Japan and Hong Kong stock markets displayed stronger volatility groupings than the other stock markets.

Table 1. Structural breaks in volatility

	USA *SP500*	*China* *CSI300*	*Hong Kong* *HS*	*Japan* *N225*	*South Korea* *KS*
P_1	2 Jan., 2015 -2 Mar.,2016	5 Jan.,2015 -21 Feb., 2020	5 Jan.,2015 -9 Jul., 2016	4 Jan.,2015 -23 Jun., 2016	4 Jan.,2015 -20 Jan., 2020
P_2	3 Mar., 2016 -14 Jun., 2018	21 Feb., 2020 -6 Apr., 2020	9 Jul., 2016 -28 Jan., 2018	26 Jun., 2016 -12 Jul., 2016	23 Jan., 2020 -11 Mar., 2020
P_3	14 Jun., 2018 -18 Sept., 2020	7 Apr., 2020 -2 Jul., 2020	29 Jan., 2018 -7 Jan., 2019	13 Jul., 2016 -22 Jan., 2020	12 Mar., 2020 -9 Apr., 2020
P_4			21 Jan., 2020 -19 Sept., 2020	26 Mar., 2020 -18 Jun., 2020	
P_5				17 Jun., 2020 -16 Sept., 2020	

Source: Author's creation

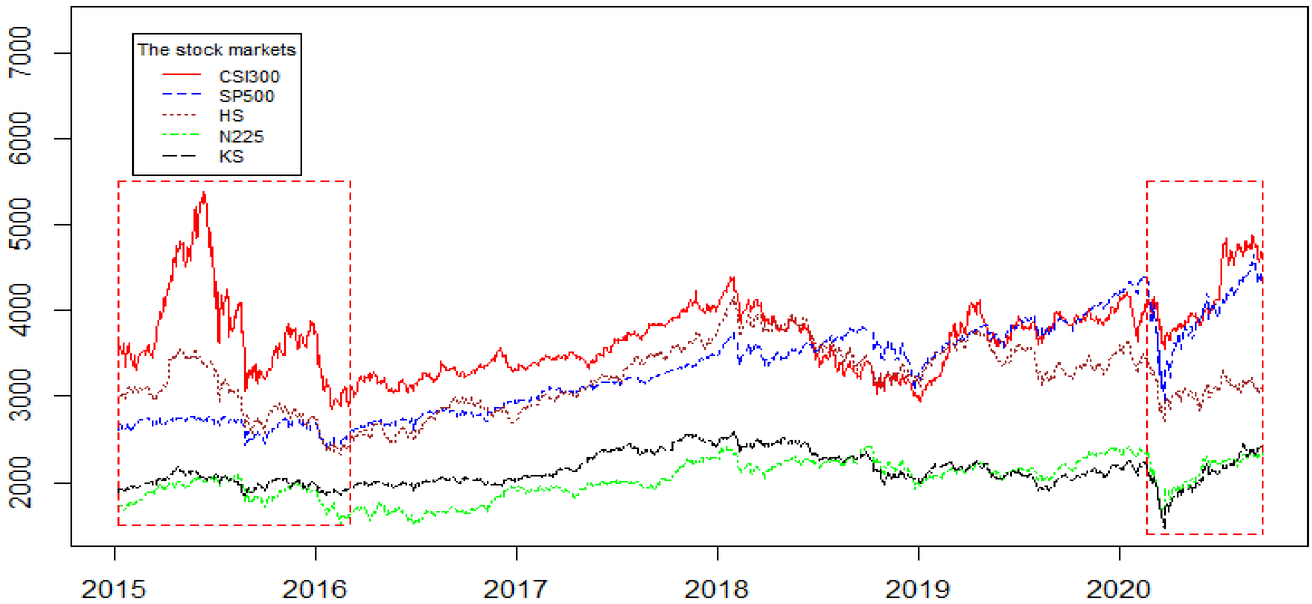

Figure 2. Evolution of stock markets indices

Source: Author's creation

In Figure 2, two special periods are noted in terms of high volatility clustering (the Chinese and US stock markets drops). From a visual perspective, the full period is more stable than the two special periods. As for relative comparison, the full period and the COVID-19 period will be used in the empirical analysis.

The left and right red frames represent periods surrounding the Chinese and US stock markets during the crisis, respectively. Assuming the spillover effect of Chinese stock markets on neighboring Asian countries is obvious, this paper focuses more on the US stock market collapse (during the COVID-19 period).

Table 2 reports descriptive statistics for the five indexes during two kinds of periods. For the full sample period, the mean is too low while the standard deviation is high showing an increased statistical dispersion. The distribution of the five indexes is asymmetric and may be subject to sudden fluctuations in the event of an external shock. The statistics of the US stock market are alike during its instability period. The East Asian stock markets are impacted by the risk spillovers of the two largest stock markets as they have an extreme downside risk during the US period of instability (Zehri, 2020b).

For the full sample period, the five indexes display important leptokurtic, compared with a normal distribution. The return series normality is rejected based on Jarque-Bera tests. The stationarity of these indexes is verified by rejecting the null hypothesis of the presence of unit root. The Augmented Dickey-Fuller (ADF) tests allow this result at a 1% significance level. The Phillips Perron (PP) test also draws the same conclusion in terms of rationality. The presence of ARCH effects is ensured by Q^2 (20) and ARCH (20) at a 1% significance level.

Table 2. Descriptive statistics for index returns

	USA SP500	China CSI300	Hong Kong HS	Japan N225	South Korea KS
	The full period				
Min	-11.4352	-10.9426	-8.1314	-8.7542	-6.8991
Max	9.1183	6.6402	7.8492	5.4382	8.9504
Mean	0.0291	0.0208	0.002	0.0193	0.0203
Std.dev	1.1546	1.5211	1.3139	1.3108	1.0902
Skewness	-1.0715***	-1.1899***	-0.2977***	-0.5897***	-1.1983***
Kurtosis	20.2967***	7.1925***	4.9548***	7.1539***	15.8085***
Jarque-Bera	2308.197	3861.0274***	1482.7693***	2358.1471***	1612.989***
ADF	-11.076***	-10.085***	-10.106***	-10.747***	-10.312***
PP	-39.923***	-35.659***	-35.649***	-35.481***	-37.749***
$Q^2(20)$	1945.5***	581.94***	96.36***	193.35***	1341***
ARCH(20)	50.86***	11.43***	2.997***	6.247***	31.69***
VaR(0.05)	-1.6844	-2.4239	-1.9752	-1.8056	-1.385
VaR(0.01)	-3.4523	-5.2902	-3.1965	-3.6951	-3.5136
	The COVID-19 period				
Min	-10.8452	-4.7461	-7.9514	-5.0087	-7.8291
Mean	-0.0932	0.0573	-0.2537	-0.0316	-0.1095
Std.dev	4.1271	2.3022	2.0633	2.1994	2.7922
VaR(0.05)	-4.2984	-3.4182	-3.7420	-3.5652	-4.3367
VaR(0.01)	-9.2947	-3.335	-5.4473	-5.0476	-8.0437

Notes: Jarque-Bera statistics is the test for normal distribution; Lagrange Multiplier test for heteroskedasticity is the ARCH(20). Ljung-Box Q-statistics of order 20 is the Q^2 (20). ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Source: Author's creation

Table 3 reports the linear dependency of the stock market indexes. The coefficients of correlation show differences between the two types of periods. The periods of instability exhibit special characteristics compared to the full period. More specifically, the correlation of any market with the US during the full period is over 0.35. However, we find the correlation of the Hong Kong market with the Chinese market is stronger than the Chinese market with other markets. This evidence demonstrates that the Hong Kong stock market is greater linked to the Chinese market.

Table 3. Pearson correlation coefficients

Correlation	*CSI300*	*SP500*	*HS*	*N225*	*KS*
The full period					
CSI300	1.0000	-	-	-	-
SP500	0.4013	1.0000	-	-	-
HS	0.5978	0.5792	1.0000	-	-
N225	0.3466	0.6123	0.5172	1.0000	-
KS	0.4068	0.7073	0.633	0.6071	1.0000
The COVID-19 period					
CSI300	1.0000	-	-	-	-
SP500	0.6389	1.0000	-	-	-
HS	0.7139	0.5962	1.0000	-	-
N225	0.4821	0.6966	0.5546	1.0000	-
KS	0.6112	0.792	0.7098	0.7044	1.0000

Notes: Pearson's correlation coefficient reflects linear relationships of the markets.

Source: Author's creation

3. METHODOLOGY AND EMPIRICAL RESULTS

Our empirical methodology is broadly related to the works of Shahzad et al. (2018) and Xiao (2020) who used copula and CoVaR models to examine the contagion, systemic and tail dependence risks of some stock markets indexes. We apply multivariate copula to model the dependency structure of the East-Asian and the US stock markets. The dependency structures are used to identify risk spillovers (Adrian and Brunnermeier, 2016; Shahzad et al., 2018). The robustness of the spillover effect is verified through the bootstrap Kolmogorov-Smirnov (KS) test used by several scholars (Reboredo and Ugolini, 2015).

$$r_t = \mu + \rho r_{t-1} + \epsilon_t, \epsilon_t = h_t z_t$$

$$\ln(h_t^2) = \omega + d_1 P_1 + \cdots + d_n P_n + \alpha[|z_{t-1}| - E|z_{t-1}|] + \gamma z_{t-1} + \beta ln(h_{t-1}^2)$$

In this model, μ is mean and h_t is conditional variance. z_t is an autonomous random variable. α designate the magnitude impact that means a relevant impact on instability, and γ determine the direction of effect that identifies unequal impacts on instability. Favorable shocks to instability are defined by the total of coefficients α + γ, conditional on the event that the innovation ϵ_t is bigger than zero or not; the harmful shocks, α - γ, alternatively. Following Ewing and Malik (2010) and Rapach and Strauss (2008), $P_1, \ldots, P_n$ are multiple dummy variables with the value '1' when the variance process owns a structural change.

For the extreme value, the Peaks Over Threshold (POT) approach is employed in our empirical analysis. Surplus dispersion above the limit η is defined as:

$$F_\eta(z) = P(z - \eta \leq z | Z > \eta) = \frac{F(z + \eta) - F(\eta)}{1 - F(\eta)}$$

An asymptotic generalized Pareto distribution (GPD) is reached for large thresholds of the series innovations. Simultaneously, the middle part of the full distribution is completed by a cumulative distribution function.

$$F_{\xi,\beta}(z) = \begin{cases} \frac{k^l}{n}\left(1 + \xi^{l\frac{-z_t+\eta^l}{\beta^l}}\right) if \;\; z_t < \eta^l \\ \varphi(z_t) \qquad\qquad if \quad \eta^l < z_t < \eta^u \\ 1 - \frac{k^u}{n}\left(1 + \xi^{u\frac{z_t-\eta^u}{\beta^u}}\right)^{\frac{-1}{\xi^u}} \; if \qquad z_t > \eta^u \end{cases}$$

In this model, ξ is the form criterion, β is the local, and η^l define a lower threshold and η^u the upper. z_t is the innovation cleaned through the conditional variance model and $\varphi(z_t)$ is the observed distribution. Estimating quantile regression parameters is done by solving the following minimization problem:

$$\min_{\beta\in\mathbb{R}^k}\{(\textstyle\sum_{i=1} p - I_{\{y_t\le x_t\ \beta\}})(\ y_t - x_t\ \beta)\}$$

We attempt to measure risk spillovers with conditional quantile regression. The conditional quantile regression copula is shown:

$$C_{v|u_1}(v|u_1) = P(V \le v|U_1 = u_1) = \frac{\partial C_{v,u_1}(v,u_1)}{\partial u_1}$$

Based on this transformation, conditional quantile function can be estimated through modeling an inverse marginal distribution and a conditional copula quantile function.

$$y_\alpha^{y|x_1,x_2} = F_y^{-1}\left(C_{V|U_1,U_2}^{-1}(\alpha|u_1,u_2)\right)$$

The multivariate copula framework is estimated for calculating conditional quantile function $C_{v|u_1}$.

The VaR at the quantile τ is defined as:

$$\mathrm{P}(y \le VaR_\tau) = \tau$$

$$Var_\tau^y = \mathrm{F}^{-1}(\tau)$$

The conditional VaR (CoVaR) of Y given X = x is given by:

$$F_{Y|X=x}\left(CoVaR_\tau^{y|x_1}\right) = P\left(Y \le CoVaR_\tau^{y|x_1}|X_1 = x_1\right)$$

and the conditional copula quantile is defined as:

$$CoVaR_\tau^{y|x_1} = F_y^{-1}\left(C_{V|U_1}^{-1}(\tau|u_1)\right)$$

In this formula, $CoVaR_\tau^{y|x_1}$is the quantile τ of the variable '*y*' conditional on variable 'x_1.' The conditional copula quantile regression can be employed in measuring spillover effects as the explanatory variable has a crucial role in the CoVaR.

In that case, the PIT of argument X_1 is equal to a lower probability. The significance level of its VaR can represent the probability of its crisis. The corresponding conditional copula quantile formula is defined as:

$$CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(\beta)} = F_y^{-1}\left(C_{V|U_1}^{-1}(\tau|\beta)\right)$$

In this formula, $F_{x_1}^{-1}(\beta)$ is the inverse distribution function of X_1. The market X_1 is in a turmoil state if β takes $Fx_1(VaR_\beta^1)$. On the contrary, the market X_1 is in a normal state if β takes $Fx_1(X_{0.5}^1)$, for $X_{0.5}^1$ is the median value of X_1.

To determine the contagion effects of one financial market on another we draw on the approach of Shahzad et al. (2018) and Xiao (2020). In these studies, relative spillover effects are measured as follow:

$$\Delta CoVaR_\tau^{y|x_1} = (CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(\beta)} - CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(x_{0.5}^1)})/\ CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(x_{0.5}^1)}$$

$$\Delta CoVaR_\tau^{y|x_1,x_2} = (CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(\beta),x_2} - CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(x_{0.5}^1),x_2})/\ CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(x_{0.5}^1),x_2}$$

To identify the contagion effects, we use the KS test, developed by Abadie (2002), to assess the occurrence of spillovers.

$$KS_m = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x|F_m(x) - G_n(x)|$$

Where $F_m(x)$ is the cumulative CoVaR distribution functions in an intense condition and $G_n(x)$ in regular condition. *m* and *n* are the two samples size. We test the rejection of the following null hypothesis:

$$H_0^1: CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(\beta)} = CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(x_{0.5}^1)}$$

$$H_0^2: CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(\beta),x_2} = CoVaR_\tau^{y|x_1=F_{x_1}^{-1}(x_{0.5}^1),x_2}$$

3.1 Results of the GARCH with structural breaks model

The GARCH (1,1) is used to examine the volatility of our five return indexes. The empirical estimation of the GARCH model with structural breaks is reported in Table 4.

Table 4. The estimated parameters.

	USA SP500	*China CSI300*	*Hong Kong HS*	*Japan N225*	*South Korea KS*
μ	0.0393**	0.0398**	0.02778	0.0403	0.0183
	(0.0170)	(0.0192)	(0.0195)	(0.0306)	(0.0287)
ρ	-0.0799***	-0.0154	-0.0034	0.0195	-0.0194
	(0.0307)	(0.0292)	(0.1577)	(0.0241)	(0.0291)
$\omega \times^{10000}$	-0.0514***	0.1874***	0.0982***	0.0157	-0.1876***
	(0.0081)	(0.0627)	(0.0117)	(0.0359)	(0.0353)
α	-0.3234***	-0.0856***	-0.1327***	-0.2078***	-0.1491***
	(0.0412)	(0.0193)	(0.0199)	(0.0195)	(0.0289)
β	0.8255***	0.7358***	0.8121***	0.7354***	0.5413***
	(0.0204)	(0.0297)	(0.0392)	(0.0307)	(0.0874)
γ	0.0931***	0.1529***	0.0594	0.0257	0.2205***
	(0.0118)	(0.0291)	(0.0399)	(0.0355)	(0.0421)
P_1	0.2458***	-0.2907***	-0.1859***	0.1521***	0.2294***
	(0.0526)	(0.0617)	(0.0499)	(0.0397)	(1.7665)
P_2	0.1419***	-0.2069***	0.0305	-0.0343*	1.7916***
	(0.0271)	(0.0322)	(0.0181)	(0.0216)	(0.4516)
P_3	0.1549***	-	-0.2055***	0.2745***	0.4522***
	(0.0165)		(0.0409)	(0.0914)	(0.1093)
P_4	-	-	0.1374***	0.1594***	-
			(0.0215)	(0.0514)	

P_5	-	-	-	-0.0878*** (0.0246)	-
$Q_2(20)$	11.631 [0.967]	9.9585 [0.8734]	13.372 [0.9012]	14.131 [0.6985]	18.852 [0.5172]
ARCH (20)	0.4914 [0.8791]	0.4125 [0.9547]	0.7025 [0.8269]	0.8257 [0.6837]	0.9292 [0.5492]
AIC	2.3944	3.3976	3.1082	2.9590	2.5809
BIC	2.3982	3.3877	3.1458	3.0004	2.6147
LL	-1588.673	-2412.363	-2124.827	-2037.975	-17.588
BDS	-1.1125 [0.3175]	-0.1878 [0.8277]	0.8245 [0.4575]	0.5908 [0.5107]	-0.8531 [0.3295]

Notes: Lagrange Multiplier test for heteroskedasticity is the ARCH (20). Ljung-Box Q-statistics of order 20 is the Q^2 (20). The fitting of models is tested by the Akaike information criterion, Bayesian information criterion, and Log-likelihood noted AIC; BIC; and LL, respectively. ***, ** and * denote significance at 1%, 5% and 10%, respectively. The hypothesis that series are i.d.d is tested through the BDS test. Round brackets are used for the standard errors and square brackets for p values.

Source: Author's creation

The parameter β reflects volatility persistence. In general, β is close to 1 but it decreases to some extent when the structural breaks are incorporated into the models. For all series, the parameter γ is significant at 1% level for China, US, and South Korea markets, which indicates the existence of leverage effect. Structural breaks detected through the modified ICSS method are significant. The detected breakpoints indicate that the volatile dynamics of the stock markets vary with some financial events. The fitting quality of the models is verified according to the values of AIC, BIC, and LL.

3.2 Copula model results

Based on the PIT data, we estimated the dependency structure for the full sample and the COVID-19 periods. The estimated copulas were selected according to the best AIC value. The pair copulas indicated unconditional and conditional dependency among stock markets. Correlation differences reported in Table 5 confirm the heterogeneity of the dependency structure during the two types of periods.

Considering the full sample, we find a symmetric direct correlation of the Chinese stock market to the neighbors' East Asian stock markets. In light of Kendal values, the dependency between the Hong Kong and Chinese markets is the strongest (0.43). In indirect dependency, the Chinese conditional on the Hong Kong market is positively correlated with the other markets. There exists an indirect link between the Chinese and the other markets through Hong Kong.

For the period of instability in the Chinese stock market, the direct structures are similar to the full period. However, the indirect dependency of other stock markets and the Chinese market have changed these values from positive to negative or decreased them slightly. The evidence of the indirect dependency shows that the Chinese market is correlated with other East Asian markets through the Hong Kong market.

In another case, the estimated copulas for the full period in the US market showed obvious differences compared to the full period of the Chinese market. As for the direct correlation, the larger correlation values highlighted stronger dependency in extreme situations. In addition, the conditional copulas demonstrate that Hong Kong is a bridge linking the US market with the Chinese market. This finding is significantly different from the results of the full period in the Chinese market. The period of instability in the US market is very special because of the major crisis that occurred. Subsequently, the dependency structure among the stock markets changed under the huge risk shock, compared with the full period. The estimated copulas show novel situations in terms of the dependency structure. In the direct case, the dependency of other markets on the US market is greater than in other periods according to Kendal's values. In this case, the finding is different from the instability of the Chinese market, as this period involves a more expansive and severe risk contagion. Furthermore, the indirect dependency structure indicates that the stock markets are interwoven. In this situation, the US market dependent on South Korea, Japan, and Hong Kong stock markets is correlated with Chinese, Hong Kong, and South Korea markets, respectively. In this period, their multivariate system became so complicated under the big shock. This case reflects the risk contagion caused by the extreme panic spreads across the global financial market. The risk spillovers in this period are massive. In the next section, we will compute risk spillovers based on these important dependency structures.

Table 5. Estimates for copula parameters

	Direct dependency				*Indirect dependency*		
US spillover effect	SP500 HS	SP500 CSI300	SP500 N225	SP500 KS	SP500 CSI300|HS	-	-
The full sample period							
Copula Name	t	Normal	t	t	Normal	-	-
Para$_1$	0.62 (0.02)	0.29 (0.02)	0.58 (0.02)	0.59 (0.02)	0.07 (0.03)	-	-
Para$_2$	13.23 (5.61)	-	12.46 (4.51)	7.84 (2.36)	-	-	-
Tau	0.43	0.25	0.45	0.31	0.02	-	-
AIC	-624.73	-199.05	-597.99	-523.2	**-1137.55**	-	-
LL	-2.25	-087	-1.97	-1.75	-3.59	-	-
The COVID-19 period							
US spillover effect	SP500 HS	SP500 CSI300	SP500 N225	SP500 KS	SP500 CSI300|HS	SP500 HS|KS	SP500 KS|N225
Copula	Normal	Normal	t	RG	F	G	Normal
Para$_1$	0.59 (0.04)	0.48 (0.04)	0.57 (0.03)	1.31 (0.09)	0.41 (0.12)	1.31 (0.07)	0.37 (0.04)
Para$_2$	-	-	6.17 (3.51)	-	-	-	-
Tau	0.38	0.40	0.38	0.42	0.18	0.11	0.21
AIC	-61.84	-29.58	-65.4	-76.18	**-124.03**	**-174.12**	**-184.68**
LL	-0.61	-.27	-0.67	-0.85	-1.27	-5.12	-6.24

Notes: Copula Name: t: Student(t); N: Normal; F: Frank; C: Clayton; RG: Rotated Gumbel G: Gumbel. Symmetric dependence is defined by Normal and Frank copulas, the other copulas for asymmetric dependence. Para$_1$ and Para$_2$ denote of the evaluated copula parameters. the Kendal's coefficient is presented by 'Tau'. LL is the Log-Likelihood. AIC is Akaike information criteria. the best copula fit is identified by lower values of AIC and LL.

Source: Author's creation

3.3 Measuring risk spillover

CoVaR is used to evaluate the dependency relationships that may exist between stock markets. The risk spillovers based on the estimated copulas are computed through the CoVaR approach. Table 6 reports the results of the CoVaR and ΔCoVaR across stock markets.

Table 6. The BTKS tests of asymmetric risk spillover (CoVaR and ΔCoVaR measurements)

	Direct dependency				*Indirect dependency*		
US spillover effect	SP500 HS	SP500 CSI300	SP500 N225	SP500 KS	SP500 CSI300|HS	-	-
The full period							
CoVaR	-2.8229 (0.7977)	-3.3169 (1.6287)	-2.7382 (1.1284)	-2.3188 (1.6155)	-2.0955 (1.1243)	-	-
ΔCoVaR	**1.1130** (0.0141)	0.6919 (0.0197)	1.4995 (0.0172)	1.1658 (0.2025)	0.2051 (0.1844)	-	-
BTKS	0.7033 [0.0000]	0.395 [0.0000]	0.7991 [0.0000]	0.8733 [0.0000]	0.2031 [0.0000]	-	-
The COVID-19 period							
	SP500 HS	SP500 CSI300	SP500 N225	SP500 KS	SP500 CSI300|HS	SP500 HS|KS	SP500 KS|N225
CoVaR	-3.012 (0.3502)	-6.8592 (1.4326)	-2.7462 (0.6839)	-1.818 (0.1956)	-4.9271 (1.7564)	-1.5692 (0.5735)	-1.4563 (0.3916)
ΔCoVaR	1.1243 (0.0176)	**1.1237** (0.1454)	**1.1937** (0.0754)	**1.6838** (0.087)	**1.8561** (2.3163)	0.4105 (0.0742)	0.7562 (0.3052)
BTKS	0.9154 [0.0000]	0.941 [0.0000]	0.9252 [0.0000]	0.8731 [0.0000]	0.7157 [0.0000]	0.4155 [0.0000]	0.7938 [0.0000]

Notes: The table reports the mean values of CoVaR and ΔCoVaR. In the round bracket, we display their standard deviation. BTKS tests the null hypothesis that CoVaR in the intense shift is equal to it in regular circumstances. The alternative hypothesis is: CoVaR in the intense shift is greater than it in the regular circumstances. In square brackets, we display the *p*-value. The figure is underlined if the CoVaR and ΔCoVaR are larger in the direct or indirect dependence. The figure is in bold if the ΔCoVaR is larger in the full period or the instability period.

Source: Author's creation

For the full period, direct risk spillovers of China's highly volatile stock market are distinguishable from the indirect ones dependent on the Hong Kong market. This case is consistent with the estimated dependency degree evaluated by Kendal's coefficient in Table 5. At the same time, from this useful finding, it is evident that the spillover from the Chinese contingent on Hong Kong to the other markets is weaker, though the indirect spillovers still exist. On the other hand, the spillovers in the unstable period of the Chinese market display great discrepancy, compared to the full period. In the direct aspect, the contagion of the Chinese market to other stock markets is weaker than the ones in the full period, except for the spillover to Japan.

For the full and unstable periods in the US stock market, the evidence on the dependency structure reported in Table 5 documented some special characteristics. Hence, the risk spillovers of the US to the other markets are distinct from the Chinese market. The empirical results for the full sample and COVID-19 periods confirm the graphical proof. We found that CoVaR and ΔCoVaR mean values are close and standard deviations have equivalent extent. The CoVaR descriptive statistics computed through the copula approach also give the same results. The decrease in the CoVaR values highlights a rise in the spillover risk. The decrease is particularly shown for the direct dependency of the US to Hong Kong, China; and the indirect dependency on China via Hong Kong. This result is also confirmed by the estimates of the ΔCoVaR parameters. The positive sign of these estimates emphasizes identical shifts across stock markets returns.

CONCLUSION

This paper provides new understandings of the interdependence and spillover risk effects during times of instability using the empirical analysis of the US and East Asian stock markets indexes. The acquired findings provide relevant proof of the distinctions in the risk spillovers. First, the Chinese stock market created direct and indirect contagion to other stock markets during the full sample period. In contrast, the corresponding direct risk spillovers were weakened, and moreover, the indirect impacts became trivial throughout its period of instability. Second, the spillovers of the US market to other stock markets are different from the Chinese due to diverse dependency structures with other stock markets, particularly the indirect dependency during the full sample period. Further, the risk spillovers of the US stock market to other stock markets was aggravating during its period of instability due to the COVID-19 shock.

Investors in the East Asian markets should be aware of the interdependence of the markets, especially any movement in the Chinese market, as a result of these special factors. These special factors are especially prevalent during periods of instability. In addition, the risk spillovers resulting from disruptions in the US stock market should be considered. When adjusting strategies, investors must pay attention to risk contagion in the East Asian stock markets. This is even more important during times of unstable events. When faced with situations where prices are plunging, capital adequacy is essential.

Our findings are relevant for investors in the East Asian stock markets who hope to safeguard portfolios from the extreme movement in one market, which affects the stocks in other markets. Investors in the Chinese stock market should proceed with caution when stock market crashes occur in either the East Asia or US markets, as these markets are interrelated. A stock market crash in China would be devastating due to their fragile, emerging market. The risk spillovers would create destructive results for the market.

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