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The contagion effect of jump risk across Asian stock markets during the Covid-19 pandemic

Yi Zhang [a], Long Zhou [b,*], Yajiao Chen [a], Fang Liu [b]

[a] *School of Economics, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China*
[b] *Business School, Cardiff University, Cardiff CF10 3EU, UK*

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A B S T R A C T

This paper tests the market jump contagion hypothesis in the context of the Covid-19 pandemic. We first use a nonparametric approach to identify jumps by decomposing the realized volatility into continuous and jump components, and we use the threshold autoregressive model to describe the jump interdependency structure between different markets. We empirically investigate the contagion effect across several major Asian equity markets (Mainland China, Hong Kong, Japan, South Korea, Singapore, Thailand, and Taiwan) using the 5-minute high frequency data. Some key findings emerge: jump behaviors occur frequently and make an important contribution to the total realized volatility; jump dynamics exhibit significant nonlinearity, asymmetry, and the feature of structural breaks, which can be effectively captured by the threshold autoregressive model; jump contagion effects are obviously detected and this effect varies depending on the regime.

1. Introduction

In the past 30 years, several severe financial crises have occurred against the background of the continuous deepening of global financial integration, such as the 1997 Asian crisis, the 2000 Internet bubble crisis, the 2003 Latin America crisis, the 2007 subprime crisis, and the 2009 European debt crisis. The common feature of these crises is that they were triggered in one country or region and then spread to other markets in a very short time, causing significant turbulence in the global financial market. Financial crisis has also become the subject of keen interest in the field of financial research, and the issue of financial contagion is a topic of even more debates. It is of concern not only to investors, who want to properly allocate their assets through international market diversity, but also to policy-makers wanting to stabilize the financial market and prevent systemic risks. The most recent manifestation of financial contagion appeared last year. As the outbreak of the Covid-19 pandemic has shaken the global financial markets, it has led to significant turmoil in the global financial markets, and the international major equity markets have suffered a common sharp fall. Accordingly, research about the contagion effect across global financial markets induced by the Covid-19 pandemic has been very popular, and many researchers have studied the topic from different perspectives (Ahelegbey, Giudici and Hashem, 2021; Yang, Luo and Jiang, 2021; Akhtaruzzaman, Boubaker and Sensoy, 2021; Apergis, Christou and Kynigakis, 2019; Zorgati and Garfatta, 2021; Li, 2021; Belhassine and Karamti, 2021; Choi, 2021; Davidovic, 2021; Guo, Li and Li, 2021; Iwanicz-Drozdowska et al., 2021; Lai and Hu, 2021; Luo, Liu and Wang, 2021; BenMim and BenSaïda, 2019; Rao et al., 2021; Zainudin and Mohamad, 2021).

* Corresponding author.
E-mail address: ZhouL11@cardiff.ac.uk (L. Zhou).

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In the literature, the definitions of financial contagion are ambiguous and diverse (Pericoli and Sbracia, 2003). Early studies do not always distinguish between contagion and integration, since they mainly aim at unraveling the channels through which negative shocks are propagated. In fact, two definitions of financial contagion are widely adopted in the existing studies, which refer to the spillover and the co-movement definition respectively. The spillover definition describes financial contagion as when the volatility of asset prices in one market spills over to another (Hohamed & Jawadi, 2011). Meanwhile, the co-movement definition, also referred to as pure contagion, defines financial contagion as a significant increase in market co-movement after an exogenous shock, and this co-movement cannot be interpreted by economic fundamentals (Forbes & Rigobon, 2002). Following the latter definition of financial contagion, our study examines the pure jump contagion based on the observed data series without considering the underlying economic mechanism.

For empirical research, in the past two decades, scholars have developed numerous methodologies for analyzing the financial contagion hypothesis, with the focus mainly on the contagion effect estimation. Among these methods, the three most frequently used approaches are noteworthy. The first approach uses correlation analysis to measure co-movements between markets, and it serves as a measurement of contagion effects. This method corresponds to the definition of financial contagion that is viewed as a rise in the cross-country co-movement of asset prices which cannot be explained by fundamentals. Under this definition, several correlation regression methods have been developed, such as conditional correlation analysis (Dungey and Fry, 2009; Thomas et al., 2007; Anastasopoulos, 2018; Mollah, Quoreshi and Zafirov, 2016; Inci, Li and McCarthy, 2011; Li and Zhu, 2014; Ahlgren and Antell, 2010; Choe et al., 2012), quantile regression analysis (Ye et al., 2016; Ye, Luo and Liu, 2017; Baur and Schulze, 2005; Caporin, Gupta and Ravazzolo, 2020; Chevapatrakul and Tee, 2014; Bianchi, Fan and Todorova, 2020; Deev and Lyócsa, 2020; Soylu and Güloğlu, 2019; Rejeb and Arfaoui, 2016; Baur, Saisana and Schulze, 2004), and local correlation analysis (Zorgati and Lakhal, 2020; Støve, Tjøstheim and Hufthammer, 2014). These scholars do not reject the contagion hypothesis, but they point out the limitations of using correlation for such a purpose.

The copula function is used to test the contagion effect between markets in the second approach used by Fenech and Vosgha, (2019), Hoesli and Reka (2015), Niţoi and Pochea (2020), and Jayech (2016). With a copula model, the multivariate distribution of asset returns can be decomposed into marginal distributions and the copula function, and the joint behavior between the returns in the tails of the distribution can be captured by the copula function. As financial data series always show a non-normal distribution in actual applications, many types of copula functions have been developed to accommodate the real data statistical styles, such as the t-copula, Clayton-copula, Gaussian-copula, and Garch-copula.

The examination of volatility spillover is at the core of the third methodology. The main idea of this approach is to firstly estimate the variance of the returns through the GARCH family model, and then use the dynamic time-varying correlation coefficient to estimate the volatility of asset prices in one country spilling over into another. Many researchers investigate the volatility spillovers among international equity markets over the period of the 2008 global financial crisis (e.g., Pragidis et al., 2015; Reboredo, Rivera and Ugolini, 2016; Diebold and Yilmaz, 2012; Johansson and Ljungwall, 2009; Kenourgios, Samitas and Paltalidis, 2011; BenSaida, Boubaker and Nguren, 2018; Boubaker, Jouini & Lahiani, 2015; Sugimoto, Matsuki & Yoshid, 2014). Kang, Mclver and Yoon (2017) investigate the volatility spillover among six commodity markets using MGARCH models and a spillover index framework, showing that the spillover effects apparently increase during a time of crisis. Furthermore, Yiu, Ho and Choi (2010) use a dynamic conditional-correlation model with seven Asian daily equity-return data series and empirically verify the contagion effect among markets. Recently, since the outbreak of the Covid-19 epidemic has resulted in significant turbulence in the global financial markets, many researchers investigate the volatility spillover among markets during this time. Fur et al. (2016) examine the spillover effect between stock markets by using the ADCC-GARCH model, finding apparent evidence of market contagion during the financial turmoil. Li, Zhuang and Wang (2021) use the GARCH-BEKK technique to construct the spillover index and test the risk contagion effect among different regions in China's stock market. Vo and Tran (2020) combine the EGARCH model with the ICSS algorithm to investigate volatility spillovers from the US equity market to the stock markets of ASEAN economies. Laborda and Olmo (2021) measure volatility spillovers between sectors of economic activity using network connectivity measures. The authors show that volatility spillovers exhibit the ability to predict high episodes of volatility for the S&P 500 index and so are useful as early financial crisis indicators.

As asset returns constantly exhibit non-normal distribution patterns, such as skewness, kurtosis, fat-tail, and asymmetry, it is hard to sufficiently reveal extreme co-movements in asset returns by only using the lower moments under these conditions. In this regard, some recent studies seek to investigate the higher moment interdependency among asset returns and especially to highlight the jump linkages among financial markets. For example, Fry, Martin and Tang (2010) estimate the cross-market contagion effect through an asset-pricing model based on the second and third moments. Asgharian and Bengtsson (2006) examine the higher moment propagation across markets during the financial crisis period, showing that jump linkages among markets change after a significant shift in market structure. Asgharian and Nossman (2011) employ a stochastic volatility model, which incorporates the jump component into the model. The authors test the jump spillover between the U.S. and the European stock markets, finding that jumps generated in the U.S. market largely drive the European market jumps. Jawadi, Louhichi and Cheffou (2015) used a nonparametric method to estimate the jump events in the markets in the U.S. and Germany, U.K., and France. The authors further test the jump contagion among these markets and deliver some meaningful results.

Our work aims to further the understanding of higher moment contagion in asset returns from the perspective of jump events. To this end, we first identified the jumps of each market through a nonparametric technique presented by Barndorff-Nielsen and Shephard (2004). In the literature, many approaches have been developed to estimate discontinuity as well as jump behaviors in the asset price dynamics (e.g., Lee and Mykland, 2008; Heiny and Podolskij, 2021; Corsi, Pirino and Reno, 2010; Dungey and Hvozdyk, 2012; Aït-Sahalia and Xiu, 2016; Pukthuanthong and Roll, 2015). All of these jump testing approaches provide evidence in favor of the presence of discontinuities of returns or jumps. Among these approaches, the nonparametric method proposed by Barndorff-Nielsen and Shephard (2004) stands out, as it can detect precise jump behaviors by decomposing the realized volatility into continuous and jump components, without any pre-specification of the asset pricing model.

Another extension to the present knowledge of financial contagion by our work is that we check the relationships between market jumps through a particular nonlinear analysis framework, namely, the threshold autoregressive model. It is well known that asset returns always show nonlinear, time-varying, and asymmetric characteristics which cannot be sufficiently described by the linear models. Moreover, as some studies (Mandilaras and Bird, 2010; BenSaïda, 2018; Bianchi et al., 2019) point out, financial time series often show a threshold effect, that is, the dynamic shift in the market after an abruptly structural breakpoint. This leads the linkages across markets also to change simultaneously. So, a new specification is required to capture the complex price dynamics as well as the interaction process. Recently, threshold models have been used extensively in the field of financial research due to the advantages they have in describing nonlinearity and structural breaks in the market dynamics (e.g., Tsagkanos, Evgenidis and Vartholomatou, 2017; Evgenidis and Tsagkanos, 2017; Wen, Gong and Cai, 2016; Guidolin and Tam, 2013; Namaki et al., 2011). It is also appropriate for the jump contagion test, as jumps often occur suddenly, and their propagation among markets is expected to be abrupt and simultaneous. Based on these existing works, we consider the threshold autoregressive models to be valid in capturing these market dynamics.

The empirical research provides evidence that jump behaviors frequently occur in stock markets, and this kind of discontinuous price movement is an important component of the total realized volatility. We test the jump contagion linkages among markets using the threshold autoregressive model. The results suggest a significant contagion effect across markets, and this effect shows both nonlinearity and asymmetry. Moreover, it also demonstrates that jump dynamics shift significantly under different market regions, thus supporting the effectiveness of our TAR model.

The remainder of the paper is organized as follows. Section 2 presents the methodology including the nonparametric jump identification technique and the threshold autoregressive model. Section 3 describes the data and empirical results. Section 4 gives the concluding remarks.

2. Methodology

2.1. Jump tests

In a typical jump-diffusion pricing model, the logarithm price process can be expressed as.

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t) \tag{1}$$

in which $p(t)$ is the log price at time$t$, and $\mu(t)$ is a continuous and locally bounded variation process which measures the average rate of growth of the asset price. $\sigma(t)$ represents the volatility of the asset price, and $W(t)$ is the standard Brownian motion. $q(t)$ represents a jump process with jump size $\kappa(t)$ and intensity$\lambda(t)$.

We can use the realized volatility (RV) defined by Andersen et al. (2007) to observe the continuous sample path for asset prices as follows:

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r^2_{t+j\Delta,\Delta} \tag{2}$$

It can be further verified that the realized volatility converges uniformly in probability to a quadratic variation, and in this way, it provides a consistent nonparametric estimation of total variation:

$$RV_{t+1}(\Delta) \to \int_{t-1}^{t} \delta^2(s)ds + \sum_{j=1}^{N_t} \kappa^2_{t,j} \tag{3}$$

where $r_{t,\Delta} \equiv p(t) - p(t-\Delta)$ represents the discretely sampled Δ-period return, N_t is the number of jump events per day t and $\kappa_{t,j}$ denotes the jth intraday jump size.

Since the real stock market is affected by information shocks and investors' irrational sentiment, the movements of financial asset prices are always discontinuous with jump behaviors. In order to make the discrete jump component separate from the realized volatility, Barndorff-Nielsen and Shephard (2004) presented the realized bi-power variation (BV) defined as follows:

$$BV_{t+1}(\Delta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\Delta} |r_{t+j\Delta,\Delta}||r_{t+(j-1)\Delta,\Delta}| \to \int_{t-1}^{t} \delta^2(s)ds, \mu_1 = \sqrt{2/\pi} \tag{4}$$

In the case$\Delta \to 0$, the difference between the realized volatility (RV) and the bi-power variation (BV) is a consistent estimator of the discrete jump variance.

$$Jump_{t+1}(\Delta) = RVt_{t+1}(\Delta) - BV_{t+1}(\Delta) \tag{5}$$

We further use the Z statistics presented by Huang and Tauchen (2005) on the basis of the realized tri-power quarticity (TQ) to identify statistically significant jumps. The representation of the Z statistics is given as.

$$Z_{t+1}(\Delta) \equiv \frac{[RV_t(\Delta) - BV_t(\Delta)]RV_t(\Delta)^{-1}}{\left[(\mu_1^{-4} + 2\mu_1^{-2} - 5)max\left\{1, TQ_t(\Delta)BV_t(\Delta)^{-2}\right\}\right]^{1/2}} \tag{6}$$

in which$TQ_{t+1}(\Delta) \equiv \Delta^{-1}\mu_{\frac{4}{3}}^{-3}\sum_{j=3}^{1/\Delta}\left|r_{t+j\Delta,\Delta}\right|^{4/3}\left|r_{t+(j-1)\Delta,\Delta}\right|^{4/3}\left|r_{t+(j-2)\Delta,\Delta}\right|^{4/3}, \mu_{\frac{4}{3}} \equiv 2^{\frac{2}{3}}\Gamma\left(\frac{7}{6}\right)\cdot\Gamma\left(\frac{1}{2}\right)^{-1}$.

At the significance level of1 - α, the estimator of the discrete jump variance can be obtained as.

$$J_{t+1,\alpha}(\Delta) = I[Z_{t+1}(\Delta)\rangle\phi_\alpha] \times [RV_{t+1}(\Delta) - BV_{t+1}(\Delta)] \tag{7}$$

where $I(\cdot)$ is the indicator function, and t denotes the day.

After the above jump-identifying process, we can further investigate the jump contagion effect across markets by using the threshold models.

2.2. Threshold jump relationships

2.2.1. TAR models

We investigate the contagion effect between jumps across markets in the framework of the threshold autoregressive model (TAR). The TAR model is appealing in modeling the dynamic characteristics of a financial system, such as nonlinearity and mutagenicity. As has been extensively proved, financial markets are highly complex time-varying nonlinear dynamic systems which are coupled through various channels in "normal" times. However, the structure of dependence among the markets will shift after a structural breakpoint in the underlying probability distribution of the data series. In this regard, TAR models are designed to describe the interdependence of dual time series with different market regimes when the underlying dynamics of the data generating processes of the markets are unknown. So, we focus on TAR models and examine our specification via nonlinearity and threshold tests.

TAR models were first presented by Tong and Lim (1980) and have been widely used in the fields of economic and finance research. The basic idea of TAR is that it models on the nonlinear data series using a "piecewise" linear approximation, that is, it separates the global space into multiple subspaces (noted as regimes in the threshold autoregressive model); each regime has the same linear structure. The specification criterion of the regimes depends on the recognition of the threshold value. Generally, a simple two-regime TAR model can be written as follows:

$$\begin{aligned} Y_t &= \alpha_{10} + \sum_{i=1}^{p}\alpha_{1i}Y_{t-i} + \sum_{j=0}^{p}\beta_{1j}X_{1t-j} + \sum_{k=0}^{p}\delta_{1k}X_{2t-k} + \varepsilon_{1t} \ if \ S_t \leqslant c \\ Y_t &= \alpha_{20} + \sum_{i=1}^{p}\alpha_{2i}Y_{t-i} + \sum_{j=0}^{p}\beta_{2j}X_{1t-j} + \sum_{k=0}^{p}\delta_{2k}X_{2t-k} + \varepsilon_{2t} \ if \ S_t > c \end{aligned} \tag{8}$$

where $\left(\alpha_{10}, \alpha_{1i}, \beta_{1j}, \delta_{1k}\right)$ and $\left(\alpha_{20}, \alpha_{2i}, \beta_{2j}, \delta_{2k}\right)$ denote the parameters in the two distinct regimes respectively,$\forall i, j = 1, \cdots, p$. Y_t is the dependent variable (jump event), and Y_{t-i} is the lagged jump. X_{1t-i} and X_{2t-k} are explanatory variables that represent the current and lagged jump events in other systems. ε_{1t} and ε_{2t} are the error terms that follow a white noise process with zero mean and bounded variance. S_t is the transition variable; c denotes the threshold variable, which is determined according to the result of nonlinearity test; and p is the lag order.

As for estimating TAR, it requires the application of the sequential conditional least squares technique as developed by Tong and Lim (1980). The complete estimation process of the TAR model can be summarized as the following three steps: firstly, preset the initial values of parameters c and$d$; secondly, estimate the current TAR model using the least squares technique; finally, search for the optimal parameters c and d and obtain the final TAR model specification.

A nonlinear model must pass a nonlinearity test to identify its specific form. However, the test process of nonlinearity always suffers from the "Davis problem", that is, redundant parameters will appear in the distribution function under the null hypothesis due to the inconsistency of the parameters in both the null and alternative hypothesis (there are unidentifiable parameters in the distribution function of the statistics under the null hypothesis, which makes it difficult to obtain the asymptotic distribution of the test statistics). This leads to a relative lack of test methods in the existing literature. At present, the two most widely used test approaches are Tsay's non-parameter method and Hansen's parameter test, which are based on the principles of the arranged autoregressive model and the nested model, respectively. We mainly introduce the former, which we use as the test method due to its advantages in calculation efficiency.

2.2.2. Threshold specification

The basic idea of the Tsay (1989) test method can be summarized as follows. First, the autoregressive lag order p of the model is determined using the information specification or the partial autocorrelation function, and then the original data is grouped according to the autoregressive dynamic structure. Under the assumption that the delay parameter d is known and a preset threshold variable S_t is given, we can classify the above groups into different regimes according to the value of the threshold variable$c$, and the number of samples contained in each regime is a function of the threshold variable. Note that in the process of data assignment, the autoregressive dynamic relationship between the data remains unchanged, but the original sequence is separated into two subsequences with different regimes. Next, we conduct the regression analysis on the observations evolved in the first regime. If the actual threshold value is greater than the preset threshold value, the error sequence of the model obeys to an asymptotic white noise process. We then add one observation at a time to the first regime by adjusting the threshold value and perform the regression again. We repeat the above implement until the asymptotic white noise nature of the error term is no longer valid. This is a verification that the threshold effect is detected, and the threshold value is at the same time determined. The ordering model that corresponds to model (8) is given as follows:

$$\begin{aligned} Y_{(O)} &= \alpha_{10} + \sum_{i=1}^{p} \alpha_{1i} Y_{(O)t-i} + \sum_{j=1}^{p} \beta_{1j} X_{(O)t-j} + \varepsilon_{1(O)} \text{ for the k first values of } S_0 \\ Y_{(O)} &= \alpha_{20} + \sum_{i=1}^{p} \alpha_{2i} Y_{(O)t-i} + \sum_{j=1}^{p} \beta_{2j} X_{(O)t-j} + \varepsilon_{2(O)} \text{ for the next values of } S_0 \end{aligned} \tag{9}$$

in which O represents the observation ranking according to the value of the threshold variable. The advantage of Tsay's nonlinear test is that it is a non-parametric method and does not refer to the "Davis problem". In addition, all of the data points in a group are depicted by the same linear AR specification and this division does not require the accurate specification of the threshold variable. Since the threshold value is unknown, we employ the recursive technique for each value of d and use the method proposed by Tsay (1989) to test the null hypothesis that the AR structures of the two regimes are equal. The test statistic is given as.

$$Q(p) = \frac{\sum_{t=1}^{T} \widehat{e}_t^2 - \sum_{t=1}^{T} \widehat{u}_t^2}{\sum_{t=1}^{T} \widehat{u}_t^2} \frac{T-k-2p-1}{p+1} \tag{10}$$

where $\widehat{e}_t$ is the estimated standard prediction errorε_t, $\widehat{\mu}_t$ is the residual term and$k = \frac{T}{10} + p$.

Tsay (1989) demonstrate that under the hypothesis of linearity, the statistic $Q(p)$ should be relatively small and should obey a Fisher test$F(p+1, T-k-2p-1)$. If the null hypothesis of linearity is rejected, then a threshold effect is detected, and the optimal value of d is determined by maximizing the statistic$Q(p)$. If there are multiple thresholds in the data, we can search and locate the structural break point of the first k observations according to the method discussed above. We can then use the same principle to search for the next threshold sequentially until the last observation is found.

After determining the threshold variable c and delay parameter$d$, the TAR model expressed in Equation (9) is then estimated by the least squares method.

Table 1

Summary descriptive statistics of the sample data. This table presents the statistic characteristics of each market's realized volatility and their two components over the January 2016-December 2020 period. The realized volatility is calculated by summing the intraday 5-minute interval squared returns. The jump part is calculated by subtracting the bi-power variation from the realized volatility.

Market	Mainland China	Hong Kong	Japan	South Korea	Singapore	Thailand	Taiwan
Panel A: Realized volatility							
Mean	1.498	1.564	1.498	1.354	1.410	1.325	1.398
Median	0.468	0.514	0.526	0.536	0.398	0.298	0.415
Std. Dev	3.315	3.541	4.051	3.987	3.641	3.546	3.368
Skewness	8.065	8.645	9.687	10.451	7.987	7.084	7.978
Kurtosis	90.456	86.548	85.687	86.987	87.684	86.187	80.645
Jarque-Bera	330.51	336.541	340.542	298.548	277.815	408.516	411.135
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Continuous component							
Mean	1.470	1.436	1.453	1.332	1.376	1.173	1.382
Median	0.451	0.499	0.514	0.526	0.381	0.288	0.411
Std. Dev	3.102	3.487	3.948	3.794	3.514	3.526	3.298
Skewness	7.894	6.978	8.521	8.461	8.213	8.064	7.978
Kurtosis	85.461	83.897	81.798	82.687	79.845	78.795	82.465
Jarque-Bera	345.541	336.840	340.879	355.498	362.456	365.456	348.458
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel C: Jump component							
Mean	0.028	0.128	0.045	0.022	0.034	0.152	0.016
Median	0.00	0.01	0.02	0.00	0.01	0.00	0.00
Std. Dev	0.123	0.059	0.214	0.987	1.120	0.251	0.197
Skewness	7.945	8.056	7.897	7.945	7.846	8.121	8.078
Kurtosis	79.845	81.879	105.543	122.942	76.845	79.849	97.865
Jarque-Bera	354.851	368.874	371.181	299.879	286.978	313.854	320.879
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00

3. Empirical research

3.1. Data

We use the jump detection approach discussed in Section 2.1 to derive the jump and the continuous volatility component using 5-minutes high frequency intraday data for seven Asian equity markets, which are the HS300 Composite Index (China), the Hang Seng Index (Hong Kong), the Nikkei 225 Stock Index (Japan), the Korea SE Composite Index (South Korea), the Straits Times Index (Singapore), the SET Index (Thailand), and the Taiwan Weighted Index (Taiwan), respectively. The selected markets' setting enabled us to examine the effect of jump transmission across these markets. The data, which were collected from Bloomberg, cover the period from January 3, 2016 to December 31, 2020. We consider these data convenient to our study for the following reasons: firstly, the sample covers a relatively long observation period, which contains a calm sub-period and a turbulence sub-period caused by the Covid-19 pandemic, so we can investigate the effect of jump contagion during different market phases. Secondly, the selected markets have overlapping intraday trading hours; thus, high-frequency data can be used to study the co-movement behavior among them. The overlapping intraday trading times of the seven markets are 10:00 am to 11:00 am and 02:00 pm to 03:00 pm (Beijing time), so we sample the price series every five minutes from the above periods to smooth the effect of market microstructure noise.

3.2. Preliminary analysis

Tables 2 reports the descriptive statistics results of daily returns and realized volatility, as well as the continuous and jump components of the realized volatility. It can be observed that the difference between the median and the mean level is significant, which indicates that the distribution of returns and volatility is asymmetric. This asymmetry is also apparent in the skewness distribution, in which Mainland China and Thailand are left-skewed, and the rests are right-skewed. All of the samples exhibit leptokurtosis, ranging from 368.67 (Mainland China) to 78.45 (Japan). The null hypotheses of normality are rejected by the J-B test for all the indices.

We use the approach proposed by Andersen et al. (2007) to recover the normality of the return series, and we report the descriptive statistics of the standardized returns in Panel B (Tables 2). After standardization, the normality is no longer rejected for Hong Kong, Japan, South Korea and Singapore. In addition, as the occurrence of jump events can be a cause of normality rejection, we separate the jump part of the volatility and standardized the returns by the unit root of the continuous part. The results are reported in Panel C. We find that in this way, the China and Thailand index enter normality at the significance level of 5%. However, it is still abnormally distributed for the Japan index, even after standardization.

Table 3 gives the number of jumps detected in each market index. We detect the largest number of jumps in the Thailand market, where a total of 143 jumps occurred with an intensity of 11.52%. The Taiwan market has the least active jumping behaviors, with 92

Table 2
Summary descriptive statistics of daily returns. This table presents the statistic characteristics of each market's daily returns and their two forms of standardization.

Market	China	Hong Kong	Japan	South Korea	Singapore	Thailand	Taiwan
Panel A: Daily returns							
Mean	−0.0021	0.0013	0.0001	0.0003	−0.0012	0.0001	−0.0001
Median	−0.0001	0.0002	0.0000	0.0001	−0.0001	0.0003	0.0005
Std. Dev	0.0015	0.0014	0.0013	0.0015	0.0014	0.0015	0.0013
Skewness	−0.1258	0.3212	0.2145	0.3396	0.3215	−0.2145	0.0018
Kurtosis	13.5412	14.8543	16.6551	18.4232	13.5152	10.5164	11.6245
Jarque-Bera	3230.51	3336.42	410.54	263.54	269.51	526.51	309.54
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: returns after standardization (standardized by the square root of realized volatility)							
Mean	0.0021	0.0002	0.0021	0.0033	0.0013	0.0041	0.0052
Median	0.0003	0.0001	0.0001	0.0021	0.0005	0.0022	0.0039
Std. Dev	1.3212	1.5261	1.4321	1.5124	1.2951	1.8424	1.6354
Skewness	0.2251	0.3125	0.1587	0.1215	0.3526	0.2145	1.1358
Kurtosis	2.1212	2.6213	3.5143	5.1541	4.4654	1.6584	6.1254
Jarque-Bera	25.541	2.840	1.879	2.498	2.456	13.456	21.458
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel C: returns after standardization (standardized by the square root of continuous component of realized volatility)							
Mean	0.028	0.128	0.045	0.022	0.034	0.152	0.016
Median	0.0002	0.0001	0.0001	0.0019	0.0002	0.0014	0.0005
Std. Dev	1.3521	1.5212	1.4431	1.4224	1.3151	1.3924	1.5954
Skewness	0.2145	0.1984	0.3216	0.2165	0.1985	0.1864	0.1751
Kurtosis	2.4512	2.6963	3.4943	4.4321	4.1434	1.6379	5.8947
Jarque-Bera	1.1845	2.9784	9.4561	1.8456	1.9587	1.8645	3.879
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3
Number of jumps detected. This table presents the number of jumps detected over the January 2016-December 2020 period. Jump intensity is given by dividing the number of jumps detected by the total number of observation days. We also report the ratio of jumps associated with positive and negative returns, respectively.

Market	China	Hong Kong	Japan	South Korea	Singapore	Thailand	Taiwan
Panel A: Total sample jumps							
number	91	99	102	139	125	143	92
intensity	8.81%	8.98%	9.78%	11.16%	10.42%	11.52%	6.87%
Panel B: Jumps associated with positive returns							
number	41	42	37	58	51	61	38
intensity	40.9%	42.4%	37.1%	41.7%	40.8%	42.7%	41.3%
Panel C: Jumps associated with negative returns							
number	50	57	65	81	74	82	54
intensity	59.1%	57.6%	62.9%	58.3%	59.2%	57.3%	58.7%

detections in total, accounting for 6.87%. This ratio is around 8.81%, 8.98%, 9.78%, 11.16%, and 10.42% for Mainland China, Hong Kong, Japan, South Korea, and Singapore, respectively. Panel B and C show the relationship between jump events and the sign of daily returns. We find that a larger proportion of jumps are accompanied by negative returns compared to positive returns. This further confirms the asymmetry in the jumping dynamics.

Next, we assess the contribution of the jump event to total volatility risk. We report the computing results in Table 4. It can be seen that for all the markets, the proportion of variance that can be accounted for by jumps exceeds 25%, in which the highest and lowest ratios are 33.31% (Hong Kong) and 26.01% (Taiwan) respectively. This further suggests that jump risk is an important component of the total volatility risk. Then, turning to jump size, we examined whether jump size is related to the sign of the daily return on the jump event date. Panels B and C in Table 4 show that jump size associated with negative daily returns are apparently larger than that with positive daily returns. The last two rows in Panel A give the maximum and minimum values of jump size for each index. We can observe that the contribution of jumps to the total volatility varies across a wide range, indicating that higher moments of returns need to be taken into account when describing jump dynamics.

In a nutshell, we can summarize our findings into two points. First, jump risk is an important part of the total volatility risk, and the contribution of jump to variance is asymmetric, as well as corresponding closely to the sign of the returns. Second, jump size and intensity exhibit significant intraday characteristics, needing higher moments to be taken into consideration to better reveal the properties of jump dynamics.

3.3. Linear jump linkages

There is plenty of evidence to prove that the international equity markets are generally connected to the high linkage effect

Table 4
Jump contribution to total realized volatility. This table reports the percentage of realized volatility that can be explained by jumps for each market. We also report the jump contribution associated with positive and negative returns, respectively.

Market	China	Hong Kong	Japan	South Korea	Singapore	Thailand	Taiwan
Panel A: Jump contribution (total sample)							
Mean	27.45%	33.31%	28.89%	29.25%	29.54%	32.12%	26.01%
Median	25.68%	31.64%	26.87%	27.45%	26.84%	28.46%	23.54%
Std. Dev	0.089	0.094	0.154	0.149	0.162	0.125	0.097
MAX	0.672	0.782	0.654	0.662	0.716	0.747	0.668
MIN	0.123	0.094	0.135	0.182	0.219	0.232	0.193
Panel B: Jump contribution (jumps associated with positive returns)							
Mean	28.05%	33.91%	29.49%	29.85%	30.14%	32.72%	26.61%
Median	26.01%	32.12%	27.18%	28.78%	27.84%	30.12%	24.45%
Std. Dev	0.091	0.095	0.156	0.153	0.171	0.132	0.102
MAX	0.683	0.795	0.661	0.665	0.720	0.764	0.697
MIN	0.123	0.093	0.137	0.189	0.221	0.241	0.201
Panel C: Jump contribution (jumps associated with negative returns)							
Mean	27.05%	32.91%	28.49%	28.85%	29.14%	31.72%	25.61%
Median	25.18%	31.14%	26.37%	26.95%	26.34%	27.96%	23.04%
Std. Dev	0.085	0.092	0.147	0.143	0.155	0.122	0.093
MAX	0.651	0.767	0.621	0.632	0.701	0.713	0.623
MIN	0.119	0.089	0.128	0.169	0.201	0.213	0.179

between their returns, volatilities, and higher moments, such as jumps. The research of linkage among jumps is an ongoing topic for a better understanding of risk management, diversification benefit, and contagion. Moreover, it provides us with an insight into whether there is a cause and effect between jump events that are generated in different markets. To this end, we first used a couple of linear specifications to model the linkage of jumps among the seven equity markets.

We first compute the unconditional correlation coefficients between jumps and present the results in Table 5. It can be seen that the correlation between jumps ranges from 0.182 (between South Korea and Thailand) to 0.298 (between Hong Kong and Singapore). This measurement is limited in that it provides only a static measure of the linkages between jumps and fails to capture the dynamic interaction or the lead-lag effects. Moreover, it cannot describe the nonlinear dependence between jumps.

Next, we establish the linear model to capture the lead-lag effect on jumps as follows:

$$Jump\_index_{i,t} = \sigma_1 + \sigma_2 Jump\_index_{i,t-1} + \sigma_3 Jump\_index_{j,t} + \sigma_4 Jump\_index_{j,t-1} + \varepsilon_{i,t} \tag{11}$$

in which $Jump\_index_{i,t}$ denotes the contribution of the jump event detected in the domestic market to the realized volatility at the present period. $Jump\_index_{i,t-1}$ is the jump contribution in the previous period. $Jump\_index_{j,t}$ and $Jump\_index_{j,t-1}$ denote the contribution of jumps to the foreign markets during the present and the previous period, respectively. In the case that there is no jump event for a trading day, the jump contribution is equal to 0.

We first perform the White heteroskedasticity test (White test) and the Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) test for all the jump series to examine the autocorrelation and heteroscedasticity that might exist in the jump series. The results are shown in Table. 6. They suggest that all the jump series are significantly autocorrelated and heteroscedastic at a significance level of at least 5%. An exception is the China market, as we do not detect significant autocorrelation or heteroscedasticity in the China market jump series. We then estimate Eq. (11) by using the least squares technique combined with the Newey-West method to correct the errors from this autocorrelation and heteroscedasticity.

The estimated results of Eq. (11) are presented in Table 7. There is obvious evidence of the contagion effect between jumps in the Asian markets. A positive and significant contemporaneous relationship of jumps can be seen in a majority of the pairwise markets under consideration. This suggests that a specific jump event in one market may be driven by the jumps in other markets. Most market jumps do not exhibit apparent autocorrelation features; only the jumps in the Japan and Singapore markets are affected by the previous jumps in the domestic market and present a reversal effect. It should be noted that the Hong Kong market plays a crucial role in jump interdependency since Hong Kong market jump events in both the current and previous period have a significant impact on the jumps for most of the remaining markets. This may be due to Hong Kong's central position in the Asian financial market.

We also conducted a Granger causality test, and we show the results in Table 8. The results confirm the structure of linear dependency between each pair of indices. It should be noted that the null hypotheses that the Hong Kong market jump does not Granger cause the jump behavior in the China, Japan, South Korea, Singapore and Taiwan markets are all rejected at the level of 1%. This suggests that most of Asian stock market jumps are driven by the Hong Kong market jumps due to its central position in the regional financial markets.

The above analysis shows that there is at least a linear dependence across markets. However, this linear specification may fail to capture the nonlinear interdependency associated with jumps among markets. To provide a deeper insight into the nonlinear dynamics of jumps, we explored how jumps are propagated to the nonlinear framework, while allowing the jump dependency to show its nonlinear and dynamic appearances.

3.4. Linearity and structural break test results

Before performing nonlinear analysis, we need to first conduct a preliminary analysis on the nonlinear and dynamic appearances of the jump series according to the information criteria.

The testing results presented in Table 9 confirm the nonlinearity in jump behaviors, and the null hypothesis of the threshold effect cannot be rejected under the significance level of 1%. Our findings also indicate that a significant structural change occurred in 2020, which suggests that the market turbulence caused by the Covid-19 pandemic has profoundly changed the dynamics of the financial data indices. Moreover, it seems that jumps in the Hong Kong market drive propagation for the other indices under consideration except for the Thailand Index, while the Hong Kong jump is more of a self-incentive process. This evidence supports the findings we obtained in Section 3.3, which also manifest that the Hong Kong market plays a crucial role in the transition of jumps. Overall, it suggests that the dynamics of jump contagion exhibit an obvious threshold effect and are regime-dependent, which requires an

Table 5
This table presents the unconditional correlation between the pairwise markets over the January 2016-December 2020 period.

Market	China	Hong Kong	Japan	South Korea	Singapore	Thailand	Taiwan
China	1.000	0.192	0.201	0.222	0.199	0.235	0.189
Hong Kong		1.000	0.211	0.231	0.298	0.245	0.255
Japan			1.000	0.264	0.271	0.231	0.229
South Korea				1.000	0.269	0.182	0.231
Singapore					1.000	0.255	0.241
Thailand						1.000	0.272
Taiwan							1.000

Table 6
This table reports the results for the White heteroskedasticity test (White test) and the Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) test. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Market	$China_t$	$Hong\ Kong_t$	$Japan_t$	$South\ Korea_t$	$Singapore_t$	$Thailand_t$	$Taiwan_t$
Panel A: White test							
F-statistic	0.425	31.254***	29.645***	28.458***	19.874**	20.774**	15.484**
p-value	0.815	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: LM test							
F-statistic	0.579	33.645***	36.456***	30.145***	28.154***	16.487**	13.584**
p-value	0.794	0.000	0.000	0.000	0.000	0.000	0.000

Table 7
This table reports the estimated results of linear model (11) using the high frequency data collected from the seven major Asian equity markets over the January 2016-December 2020 period. $Market_t$ and $Market_{t-1}$ denote the jump part of realized volatility for the domestic market during the current and previous period, respectively. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Market	$China_t$	$Hong\ Kong_t$	$Japan_t$	$South\ Korea_t$	$Singapore_t$	$Thailand_t$	$Taiwan_t$
Intercept	0.005***	0.011***	0.008**	0.007***	0.002**	0.015***	0.016**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$China_t$	–	0.021	0.016	0.054*	0.031**	0.009	0.011
		(0.181)	(0.222)	(0.001)	(0.098)	(0.081)	(0.079)
$China_{t-1}$	0.316***	0.006	0.008	0.065	−0.049	0.045	0.021
	(0.000)	(0.101)	(0.164)	(0.159)	(0.162)	(0.134)	(0.144)
$Hong\ Kong_t$	0.353***	–	0.265***	0.471**	0.249***	0.103***	0.286*
	(0.014)		(0.012)	(0.002)	(0.000)	(0.001)	(0.009)
$Hong\ Kong_{t-1}$	0.124***	0.126***	0.237**	0.199***	0.214*	0.185	0.226**
	(0.019)	(0.008)	(0.007)	(0.018)	(0.139)	(0.305)	(0.003)
$Japan_t$	0.236*	0.045	–	0.037	0.038	0.106*	0.311***
	(0.002)	(0.516)		(0.465)	(0.501)	(0.014)	(0.001)
$Japan_{t-1}$	−0.003	0.002	−0.015	0.003	0.011	0.008	0.210**
	(0.334)	(0.864)	(0.704)	(0.604)	(0.534)	(0.454)	(0.004)
$South\ Korea_t$	0.032	0.119*	0.322**	–	0.142*	0.003	0.004
	(0.064)	(0.009)	(0.011)		(0.009)	(0.043)	(0.056)
$South\ Korea_{t-1}$	0.004	0.152	0.009	0.312***	0.198*	0.781*	0.069
	(0.078)	(0.311)	(0.302)	(0.001)	(0.021)	(0.031)	(0.123)
$Singapore_t$	0.035	0.037	0.212*	0.255*	–	0.197**	0.005
	(0.812)	(0.625)	(0.031)	(0.033)		(0.074)	(0.302)
$Singapore_{t-1}$	0.003	0.002	0.015	0.013	0.231***	0.009	0.017
	(0.912)	(0.453)	(0.392)	(0.405)	(0.001)	(0.312)	(0.562)
$Thailand_t$	0.004	0.011	0.009	0.010	0.124*	–	0.136*
	(0.454)	(0.348)	(0.321)	(0.415)	(0.006)		(0.012)
$Thailand_{t-1}$	0.013	0.012	0.008	0.009	0.011	0.212*	0.013
	(0.205)	(0.845)	(0.699)	(0.546)	(0.498)	(0.006)	(0.397)
$Taiwan_t$	0.012	0.251**	0.003	0.015	0.016	0.312***	–
	(0.718)	(0.003)	(0.687)	(0.598)	(0.462)	(0.002)	
$Taiwan_{t-1}$	0.009	0.011	0.008	0.013	0.009	0.016	0.292***
	(0.097)	(0.102)	(0.213)	(0.385)	(0.684)	(0.758)	(0.002)

Table 8
This table reports the Granger causality test results for market jumps.

Null hypothesis	Number of markets
Chinese market jump Granger cause other market jump	1
Hong Kong market jump Granger cause other market jump	5
Japan market jump Granger cause other market jump	3
Singapore market jump Granger cause other market jump	3
South Korea market jump Granger cause other market jump	2
Thailand market jump Granger cause other market jump	2
Taiwan market jump Granger cause other market jump	2

appropriate nonlinear framework to deliver further understanding.

We next examine whether the analysis of the jump spread effect can be improved by considering the threshold effect. To this end, we re-estimated model (11) with a structure point by using the LS technique. The results show apparent evidence of breakpoints in jump events, and are very consistent with the linearity test results as reported in Table 9. Overall, these results show that the contagion

Table 9
This table reports the estimated results of the threshold value. We tried different threshold autoregression models while varying the lag order and the regimes using Tsay's method, as described in Section 2.2.2. The best outcomes correspond to a two-regime TAR specification with lag order equal to 1. Column 4 reports the *p*-value of Tsay's nonlinear test. Column 5 presents the time point of the threshold effect detected for each market.

Market	Lag order	Optimal transition variable	*p*-value	Threshold data	Model specification
China	1	Hong Kong	0.00	2020:02:18	TAR
Hong Kong	1	Hong Kong$_{t-1}$	0.03	2020:02:25	TAR
Japan	1	Hong Kong	0.00	2020:03:18	TAR
South Korea	1	Hong Kong	0.00	2020:02:24	TAR
Singapore	1	Hong Kong	0.00	2020:03:06	TAR
Thailand	1	Japan	0.08	2020:03:05	TAR
Taiwan	1	Hong Kong	0.00	2020:02:19	TAR

effects between jumps are asymmetrical and vary under different regimes. Therefore, the jump contagion dynamic can be better characterized by the TAR model.

3.5. TAR model estimation

This section shows how we use the TAR model to investigate the nonlinear dynamics of jump contagion with different regimes. Some meaningful findings are shown in Table 10. Generally, there is strong evidence that jump dynamics are time-varying with endogenous structural breaks for most of the markets under consideration. The results also suggest that the jump dependency structures change significantly across regimes. In the first regime, we note an obvious domestic lagged effect for most of the markets with the exception of the Japan market. In line with the findings of the linear analysis, the Hong Kong market seems to play an active role in the propagation of jumps as we can observe that the dependencies of Hong Kong jumps with respect to all the other markets are all positive and significant at the level of 10%. It is relatively rare to see this sort of dependency in other pairs of markets; only the Japan jumps shows a negative effect on South Korea jumps at the significance level of 10%.

While in the second regime, we observe a much more significant nonlinear interdependent structure and lead-lag effects between market jumps, indicating that the jump contagion effects are apparently strengthened after an abrupt change in market conditions. In this stage, the domestic lagged effects become weaker for the China, Japan, Singapore, and Taiwan markets compared to the first stage, whereas the instantaneous contagion effects increase significantly for most of the markets. For China, it seems to be obviously driven by the instantaneous and lagged Hong Kong market jumps. However, the domestic lagged effect of China market jumps is disappearing. The Hong Kong market still plays a key role in this regime, as the effects of Hong Kong jumps on the South Korea, Singapore, Thailand, and Taiwan markets are all significant at the level of 1%. This is consistent with the findings observed in the first regime with only higher degrees of dependency. As for the Japan market, inconsistent with the findings in the first regime, we find that the Japan market jumps are mostly self-excited within the domestic market. A more special case is the Thailand market, where the jumps are much more independent and are not affected by any other factors. We also test the residual term estimated from the TAR model for each of the individual market jumps, and find that it is white noise distributed, confirming the validity of the model specification.

Overall, our study provides significant evidence of the jump contagion hypothesis across major Asian stock markets. We find that the linkages among the markets vary across regimes in respect to direction, amplitude, and strength. This suggests that the TAR model captures more significant jump contagions compared to the linear model and so meets our research requirements.

4. Conclusion

This paper examines the jump contagion effects across major Asian equity markets over the period 2016–2020. We investigate whether a jump event that occurs in one market has an instantaneous or lead-lag effect on jumps from other markets for high frequency data. To this end, we first identify jumps by using the nonparametric method and then conduct a linear test to show the nonlinearity and threshold effect in jump dynamics. We detect an obviously abrupt change in the market structure, which corresponds exactly to the moment of the Covid-19 outbreak. To accommodate these jump dynamics in the contagion analysis framework, we use the threshold autoregressive model to assess the jump contagion effects for different regimes. Our findings support the existence of jump interdependence across Asian equity markets. Specifically, we show that the Hong Kong market plays a key role in propagating the jump risks for both regimes. Moreover, the interdependence between jumps is significantly strengthened after the abrupt change in the market condition. However, such market linkages vary with respect to direction, time, and strength. These results suggest that the TAR model serves well in capturing more nonlinearity in the analysis of financial contagion effects.

Our research provides some useful insights for market regulators and investors to better control higher order moment risks between stock markets. For the future research, it would be worth broadening the scope of this study by revealing more nonlinearity in the data of financial markets. Extending our "regional contagion" analysis to a more extensive "global contagion" analysis by using some alternative nonlinear specifications should also be of interest.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to

Table 10
This table reports the estimated results of the threshold autoregressive model as given in model (8). ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Market	$China_t$	$Hong\ Kong_t$	$Japan_t$	$South\ Korea_t$	$Singapore_t$	$Thailand_t$	$Taiwan_t$
Regime 1							
Intercept	0.033***	0.021***	0.011**	0.017***	0.029**	0.013***	0.012**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$China_t$	–	0.032	0.021	0.056	0.075	0.011	0.009
		(0.125)	(0.232)	(0.002)	(0.089)	(0.056)	(0.082)
$China_{t-1}$	0.332***	0.005	0.011	−0.071	0.053	0.051	0.019
	(0.001)	(0.132)	(0.224)	(0.172)	(0.202)	(0.204)	(0.224)
$Hong\ Kong_t$	0.413***	–	0.305***	0.511**	0.319***	0.323***	0.316*
	(0.002)		(0.003)	(0.001)	(0.001)	(0.000)	(0.002)
$Hong\ Kong_{t-1}$	0.124	0.126***	0.317*	0.201	0.214*	0.185	0.222
	(0.002)	(0.008)	(0.047)	(0.318)	(0.219)	(0.132)	(0.065)
$Japan_t$	0.236	0.032	–	0.037**	0.039	0.156	0.311
	(0.042)	(0.516)		(0.005)	(0.481)	(0.064)	(0.061)
$Japan_{t-1}$	−0.004	0.012	−0.015***	0.004	0.043	0.007	0.213
	(0.624)	(0.904)	(0.001)	(0.604)	(0.464)	(0.694)	(0.064)
$South\ Korea_t$	0.039	0.119	0.412	–	0.143	0.001	0.003
	(0.164)	(0.009)	(0.013)		(0.011)	(0.039)	(0.046)
$South\ Korea_{t-1}$	0.003	0.142	0.009	0.242***	0.198	0.781	0.069
	(0.069)	(0.221)	(0.302)	(0.001)	(0.021)	(0.031)	(0.123)
$Singapore_t$	0.035	0.331	0.302	0.315	–	0.207	0.005
	(0.812)	(0.585)	(0.087)	(0.053)		(0.068)	(0.292)
$Singapore_{t-1}$	0.002	0.003	0.021	0.013	0.321***	0.008	0.017
	(0.772)	(0.513)	(0.392)	(0.405)	(0.001)	(0.292)	(0.492)
$Thailand_t$	0.004	0.011	0.009	0.010	0.124	–	0.136
	(0.454)	(0.348)	(0.321)	(0.415)	(0.006)		(0.012)
$Thailand_{t-1}$	0.032	0.011	0.009	0.011	0.009	0.362*	0.021
	(0.185)	(0.735)	(0.709)	(0.486)	(0.518)	(0.002)	(0.412)
$Taiwan_t$	0.015	0.331	0.003	0.015	0.016	0.312	–
	(0.698)	(0.052)	(0.687)	(0.598)	(0.462)	(0.002)	
$Taiwan_{t-1}$	0.014	0.051	0.008	0.013	0.009	0.016	0.292***
	(0.078)	(0.332)	(0.213)	(0.385)	(0.684)	(0.758)	(0.002)
Regime 2							
Intercept	0.006***	0.016***	0.006**	0.011***	0.004**	0.012***	0.011**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$China_t$	–	0.022**	0.012*	0.044*	0.029	0.008*	0.011*
		(0.179)	(0.211)	(0.054)	(0.008)	(0.081)	(0.093)
$China_{t-1}$	0.019*	0.007	0.011	0.244*	−0.041	0.024	0.015
	(0.008)	(0.231)	(0.159)	(0.201)	(0.131)	(0.164)	(0.114)
$Hong\ Kong_t$	0.413***	–	0.216**	0.541***	0.367***	0.021	0.306***
	(0.004)		(0.003)	(0.001)	(0.001)	(0.001)	(0.003)
$Hong\ Kong_{t-1}$	0.254***	0.196***	0.281**	0.329***	0.359***	0.295	0.366**
	(0.002)	(0.001)	(0.003)	(0.004)	(0.003)	(0.003)	(0.001)
$Japan_t$	0.316*	0.055*	–	0.027*	0.041**	0.111	0.281**
	(0.002)	(0.316)		(0.454)	(0.801)	(0.009)	(0.005)
$Japan_{t-1}$	−0.002	0.013	0.325**	0.013*	0.011	0.007*	0.330*
	(0.434)	(0.814)	(0.001)	(0.694)	(0.504)	(0.534)	(0.004)
$South\ Korea_t$	0.132**	0.149*	0.382**	–	0.212*	0.004	0.114*
	(0.006)	(0.008)	(0.013)		(0.010)	(0.033)	(0.016)
$South\ Korea_{t-1}$	0.003	0.162*	0.010	0.342**	0.208*	0.391	0.071*
	(0.071)	(0.006)	(0.292)	(0.001)	(0.009)	(0.006)	(0.006)
$Singapore_t$	0.144*	0.201**	0.243**	0.283**	–	0.007	0.005*
	(0.002)	(0.005)	(0.004)	(0.003)		(0.074)	(0.012)
$Singapore_{t-1}$	0.004	0.012	0.032*	0.015	0.008	0.009	0.021
	(0.882)	(0.393)	(0.402)	(0.555)	(0.931)	(0.312)	(0.692)
$Thailand_t$	0.005*	0.013	0.111**	0.311**	0.124	–	0.112*
	(0.504)	(0.398)	(0.021)	(0.005)	(0.316)		(0.021)
$Thailand_{t-1}$	0.011	0.009	0.011	0.109	0.011	0.017	0.192**
	(0.077)	(0.009)	(0.113)	(0.385)	(0.684)	(0.638)	(0.002)
$Taiwan_t$	0.109*	0.111*	0.198**	0.113*	0.239**	0.136	–
	(0.007)	(0.003)	(0.013)	(0.005)	(0.005)	(0.008)	
$Taiwan_{t-1}$	0.011	0.011	0.021	0.015	0.109	0.016	0.106
	(0.089)	(0.114)	(0.205)	(0.415)	(0.594)	(0.698)	(0.051)

influence the work reported in this paper.

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References

Aït-Sahalia, Y., & Xiu, D. (2016). Increased correlation among asset classes: Are volatility or jumps to blame, or both? *Econometrics, 194*(2), 205–219.
Ahelegbey, D. F., Giudici, P., & Hashem, S. Q. (2021). Network VAR models to measure financial contagion. *The North American Journal of Economics and Finance, 55*, 101318. https://doi.org/10.1016/j.najef.2020.101318
Ahlgren, N., & Antell, J. (2010). Stock market linkages and financial contagion: A cobreaking analysis. *The Quarterly Review of Economics and Finance, 50*(2), 157–166.
Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID-19 crisis. *Finance Research Letters, 38*, 101604. https://doi.org/10.1016/j.frl.2020.101604
Anastasopoulos, A. (2018). Testing for financial contagion: New evidence from the Greek crisis and yuan devaluation. *Research in International Business and Finance, 45*, 499–511.
Andersen, T. G., Bollerslev, T., & Dobrev, D. (2007). No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications. *The Journal of Econometrics, 138*(1), 125–180.
Apergis, N., Christou, C., & Kynigakis, I. (2019). Contagion across US and European financial markets: Evidence from the CDS markets. *Journal of International Money and Finance, 96*, 1–12.
Asgharian, H., & Bengtsson, C. (2006). Jump spillover in international equity markets. *Journal of Financial Econometrics, 4*, 167–203.
Asgharian, H., & Nossman, M. (2011). Risk contagion among international stock markets. *Journal of International Money and Finance, 30*(1), 22–38.
Barndorff-Nielsen, O. E., & Shephard, N. (2004). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics, 4*, 1–30.
Baur, D., Saisana, M., & Schulze, N. (2004). Modelling the effects of meteorological variables on ozone concentration-a quantile regression approach. *Atmospheric Environment, 38*(28), 4689–4699.
Baur, D., & Schulze, N. (2005). Coexceedances in financial markets-a quantile regression analysis of contagion. *Emerging Markets Review, 6*(1), 21–43.
Belhassine, O., & Karamti, C. (2021). Contagion and portfolio management in times of COVID-19. *Economic Analysis and Policy, 72*, 73–86.
BenMim, I., & BenSaïda, A. (2019). Financial contagion across major stock markets: A study during crisis episodes. *The North American Journal of Economics and Finance, 48*, 187–201.
BenSaïda, A. (2018). The contagion effect in European sovereign debt markets: A regime-switching vine copula approach. *International Review of Financial Analysis, 58*, 153–165.
Bensaida, A., Bboubaker, S., & Nguren, D. K. (2018). The shifting dependence dynamics between the G7 stock markets. *Quantitative Finance, 18*, 801–1612.
Bianchi, D., Billio, M., Casarin, R., & Guidolin, M. (2019). Modeling systemic risk with Markov Switching Graphical SUR models. *Journal of Econometrics, 210*(1), 58–74.
Bianchi, R. J., Fan, J. H., & Todorova, N. (2020). Financialization and de-financialization of commodity futures: A quantile regression approach. *International Review of Financial Analysis, 68*, 101451. https://doi.org/10.1016/j.irfa.2019.101451
Boubaker, S., Jouini, J., & Lahiani, A. (2015). Financial contagion between the US and selected developed and emerging countries: The case of the subprime crisis. *The Quarterly Review of Economics and Finance, 61*, 14–28.
Caporin, M., Gupta, R., & Ravazzolo, F. (2020). Contagion between real estate and financial markets: A Bayesian quantile-on-quantile approach. *The North American Journal of Economics and Finance, 55*, Article 101347.
Chevapatrakul, T., & Tee, K. H. (2014). The effects of news events on market contagion: Evidence from the 2007–2009 financial crisis. *Research in International Business and Finance, 32*, 83–105.
Choe, K.-il., Choi, P., Nam, K., & Vahid, F. (2012). Testing financial contagion on heteroskedastic asset returns in time-varying conditional correlation. *Pacific-Basin Finance Journal, 20*(2), 271–291.
Choi, S. Y. (2021). Volatility spillovers among Northeast Asia and the US: Evidence from the global financial crisis and the COVID-19 pandemic. *Economic Analysis and Policy, 73*, 179–193.
Corsi, F., Pirino, D., & Renò, R. (2010). Threshold bipower variation and the impact of jumps on volatility forecasting. *Journal of Econometrics, 159*(2), 276–288.
Davidovic, M. (2021). From pandemic to financial contagion: High-frequency risk metrics and Bayesian volatility analysis. *Finance Research Letters, 42*, 101913. https://doi.org/10.1016/j.frl.2020.101913
Deev, O., & Lyócsa, Š. (2020). Connectedness of financial institutions in Europe: A network approach across quantiles. *Physica A: Statistical Mechanics and its Applications, 550*, Article 124035.
Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*(1), 57–66.
Dungey, M., & Fry, R. (2009). More Confusion in Contagion Tests: The Effects of a Crisis Sourced in US Credit Markets. *The Journal of Economic Asymmetries, 6*(3), 41–70.
Dungey, M., & Hvozdyk, L. (2012). Cojumping: Evidence from the US treasury bond and futures markets. *Journal of Bank & Finance, 36*(5), 1563–1575.
Fenech, J. P., & Vosgha, H. (2019). Oil price and gulf corporation council stock indices: New evidence from time-varying copula models. *Economic Modelling, 77*, 81–91.
Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance, 57*(5), 2223–2261.
Fry, R., Martin, V. L., & Tang, C. (2010). A new class of tests of contagion with applications. *Journal of Business & Economic Statistics, 28*(3), 423–437.
Evgenidis, A., & Tsagkanos, A. (2017). Asymmetric effects of the international transmission of us financial stress: A threshold-var approach. *International Review of Financial Analysis, 51*, 69–81.
Fur, E. L., Ameur, H. B., Braune, E., & Faye, B. (2016). Financial market contagion and fine wines: The evidence of the ADCC GARCH model. *International Journal of Entrepreneurship and Small Business, 29*(4), 583. https://doi.org/10.1504/IJESB.2016.079967
Guidolin, M., & Tam, Y. M. (2013). A yield spread perspective on the great financial crisis: Break-point test evidence. *International Review of Financial Analysis, 26*, 18–39.
Guo, Y., Li, P., & Li, A. (2021). Tail risk contagion between international financial markets during COVID-19 pandemic. *International Review of Financial Analysis, 73*, 101649. https://doi.org/10.1016/j.irfa.2020.101649
Heiny, J., & Podolskij, M. (2021). On estimation of quadratic variation for multivariate pure jump semimartingales. *Stochastic Processes and their Applications, 138*, 234–254.
Hoesli, M., & Reka, K. (2015). Contagion channels between real estate and financial markets. *Real Estate Ecoaomios, 43*(1), 101–138.
Huang, X., & Tauchen, G. (2005). The relative contribution of jumps to total price variance. *Journal of Financial Economics, 3*, 456–499.
Inci, A. C., Li, H. C., & McCarthy, J. (2011). Financial contagion: A local correlation analysis. *Research in International Business and Finance, 25*(1), 11–25.
Iwanicz-Drozdowska, M., Rogowicz, K., Kurowski, Ł., & Smaga, P. (2021). Two decades of contagion effect on stock markets: Which events are more contagious? *Journal of Financial Stability, 55*, 100907. https://doi.org/10.1016/j.jfs.2021.100907

Hohamed, A., & Jawadi, F. (2011). Do on/off time series models reproduce emerging stock market comovements? *Economic Bulletin, 31*, 960–968.
Jawadi, F., Louhichi, W., & Idi Cheffou, A. (2015). Testing and modeling jump contagion across international stock markets: A nonparametric intraday approach. *Journal of Financial Markets, 26*, 64–84.
Jayech, S. (2016). The contagion channels of July-August-2011 stock market crash: A DAG-copula based approach. *European Journal of Operational Research, 249*(2), 631–646.
Johansson, A. C., & Ljungwall, C. (2009). Spillover effects among the greater china stock markets. *World Development, 37*(4), 839–851.
Kang, S. H., McIver, R., & Yoon, S.-M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics, 62*, 19–32.
Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money, 21*(1), 92–106.
Laborda, R., & Olmo, J. (2021). Volatility spillover between economic sectors in financial crisis prediction: Evidence spanning the great financial crisis and Covid-19 pandemic. *Research in International Business and Finance, 57*, 101402. https://doi.org/10.1016/j.ribaf.2021.101402
Lai, Y., & Hu, Y. (2021). A study of systemic risk of global stock markets under COVID-19 based on complex financial networks. *Physica A: Statistical Mechanics and its Applications, 566*, Article 125613.
Lee, S. S., & Mykland, P. A. (2008). Jumps in financial markets: A new nonparametric test and jump dynamics. *The Review of Financial Studies, 21*(6), 2535–2563.
Li, F., & Zhu, H. (2014). Testing for financial contagion based on a nonparametric measure of the cross-market correlation. *Review of Financial Economics, 23*(3), 141–147.
Li, W. (2021). COVID-19 and asymmetric volatility spillovers across global stock markets. *The North American Journal of Economics and Finance, 58*, 101474. https://doi.org/10.1016/j.najef.2021.101474
Li, Y., Zhuang, X., & Wang, J. (2021). Analysis of the cross-region risk contagion effect in stock market based on volatility spillover networks: Evidence from China. *The North American Journal of Economics and Finance, 56*, 101359. https://doi.org/10.1016/j.najef.2020.101359
Luo, C., Liu, L., & Wang, D. (2021). Multiscale financial risk contagion between international stock markets: Evidence from EMD-Copula-CoVaR analysis. *The North American Journal of Economics and Finance, 58*, 101512. https://doi.org/10.1016/j.najef.2021.101512
Mandilaras, A., & Bird, G. (2010). A Markov switching analysis of contagion in the EMS. *Journal of International Money and Finance, 29*(6), 1062–1075.
Mollah, S., Quoreshi, A. M. M. S., & Zafirov, G. (2016). Equity market contagion during global financial and Eurozone crises: Evidence from a dynamic correlation analysis. *Journal of International Financial Markets, Institutions and Money, 41*, 151–167.
Namaki, A., Shirazi, A. H., Raei, R., & Jafari, G. R. (2011). Network analysis of a financial market based on genuine correlation and threshold method. *Physica A: statistical Mechanics and Its Applications, 390*(21-22), 3835–3841.
Nitoi, M., & Pochea, M. M. (2020). Time-varying dependence in European equity markets: A contagion and investor sentiment driven analysis. *Economic Modelling, 86*, 133–147.
Pericoli, M., & Sbracia, M. (2003). A primer on financial contagion. *Journal of Economic Survey, 17*(4), 571–608.
Pragidis, I. C., Aielli, G. P., Chionis, D., & Schizas, P. (2015). Contagion effects during financial crisis: Evidence from the Greek sovereign bonds market. *Journal of Financial Stability, 18*, 127–138.
Pukthuanthong, K., & Roll, R. (2015). Internationally correlated jumps. *The Review of Asset Pricing Studies*, 5, 92-111.
Rao, P., Goyal, N., Kumar, S., Hassan, M. K., & Shahimi, S. (2021). Vulnerability of financial markets in India: The contagious effect of COVID-19. *Research in International Business and Finance*, 101462.
Reboredo, J. C., Rivera-Castro, M. A., & Ugolini, A. (2016). Downside and upside risk spillovers between exchange rates and stock prices. *Journal of Banking & Finance, 62*, 76–96.
Rejeb, A. B., & Arfaoui, M. (2016). Financial market interdependencies: A quantile regression analysis of volatility spillover. *Research in International Business and Finance, 36*, 140–157.
Soylu, P. K., & Güloğlu, B. (2019). Financial contagion and flight to quality between emerging markets and U.S. bond market. *The North American Journal of Economics and Finance, 50*, 100992. https://doi.org/10.1016/j.najef.2019.100992
Støve, B., Tjøstheim, D., Hufthammer, K., & O. (2014). Using local Gaussian correlation in a nonlinear re-examination of financial contagion. *Journal of Empirical Finance, 25*, 62–82.
Sugimoto, K., Matsuki, T., & Yoshida, Y. (2014). The global financial crisis: An analysis of the spillover effects on African stock markets. *Emerging Markets Review, 21*, 201–233.
Tsay, R. (1989). Testing and modelling threshold autoregressive processes. *The Journal of the American Statistical Association, 84*, 231–240.
Thomas, C., Chiang, T. C., Jeon, B. N., & Li, H. M. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance, 26*, 1206–1228.
Tong, H., & Lim, K. S. (1980). Threshold autoregression, limit cycles and cyclical data. *The Journal of the Royal Statistical Society, 42*, 245–292.
Tsagkanos, A., Evgenidis, A., & Vartholomatou, K. (2017). Financial and monetary stability across Euro-zone and BRICS: An exogenous threshold VAR approach. *Research in International Business and Finance, 44*, 386–393.
Vo, X. V., & Tran, T. T. A. (2020). Modelling volatility spillovers from the US equity market to ASEAN stock markets. *Pacific-Basin Finance Journal, 59*, 101246. https://doi.org/10.1016/j.pacfin.2019.101246
Wen, F., Gong, X., & Cai, S. (2016). Forecasting the volatility of crude oil futures using HAR-type models with structural breaks. *Energy Economics, 59*, 400–413.
Yang, L. I., Luo, J., & Jiang, Y. (2021). Policy uncertainty spillovers and financial risk contagion in the Asia-Pacific network. *Pacific-Basin Finance Journal, 67*, Article 101554.
Ye, W., Luo, K., & Liu, X. (2017). Time-varying quantile association regression model with applications to financial contagion and VaR. *European Journal of Operational Research, 256*(3), 1015–1028.
Ye, W., Zhu, Y., Wu, Y., & Miao, B. (2016). Markov regime-switching quantile regression models and financial contagion detection. *Insurance: Mathematics and Economics, 67*, 21–26.
Yiu, M. S., Alex Ho, W.-Y., & Choi, D. F. (2010). Dynamic correlation analysis of financial contagion in Asian markets in global financial turmoil. *Applied Financial Economics, 20*(4), 345–354.
Zainudin, A. D., & Mohamad, A. (2021). Financial contagion in the futures markets amidst global geo-economic events. *The Quarterly Review of Economics and Finance, 81*, 288–308.
Zorgati, I., & Garfatta, R. (2021). Spatial financial contagion during the COVID-19 outbreak: Local correlation approach. *The Journal of Economic Asymmetries, 24*, e00223. https://doi.org/10.1016/j.jeca.2021.e00223
Zorgati, I., & Lakhal, F. (2020). Spatial contagion in the subprime crisis context: Adjusted correlation versus local correlation approaches. *Economic Modelling, 92*, 162–169.