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THE MORE CONTAGION EFFECT ON EQUITY MARKETS: THE EVIDENCE OF DCC-GARCH AND ADCC-GARCHMODELS

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Abstract

The purpose of this paper is to test the existence of financial contagion between stock markets of several emerging and developed countries in Asia during the trade wars. As a result of DCC-GARCH and ADCC-GARCH analysis, we find the evidence of contagion during trade wars for most of the developed and emerging countries. Another finding is that emerging markets seem to be the most influenced by the contagion effects during trade wars. Contagion is tested using DCC and ADCC means difference test. Our findings indicate the presence of contagion in the equity markets across all the eight pairs of source-target countries that are considered.

Keywords: Contagion, DCC-GARCH, ADCC-GARCH, Trade War.

I. INTRODUCTION

On 22 January 2018, US President Donald Trump's Administration fired the opening shot of the trade warbetween the US and China by approving global safeguard tariffs on $8.5 billion in imports of solar panelsand $1.8 billion of washing machines from China and some other countries. More than 80 percent of USsolar installations uses imported panels with most coming from Asia. China and South Korea condemned steep import tariffs. Seoul challenged the solar panel and washing machine tariffs through the WTO on May14, 2018 and Beijing filed WTO Dispute Against US Solar Panel Tariffs on August 14, 2018, respectively. On April 4 2018, President Trump administration released its $50 billion list of 1,333 Chinese products under consideration for 25 percent tariffs, setting off a new trade war. And on 16 June 2018, President Trump announced to impose additional tariffs of 25 percent on products worth $50 billion imported fromChina, starting July 6, 2018. China immediately implemented retaliatory tariffs on its $34 billion list ofgoods issued last month, including soybeans, pork and electric vehicles, after the US tariffs went into effect. The tit-for-tat tariffs between the world's two largest economies has an insignificant impact upon China's economy. According to Zhou Xiaochuan, the former governor of People's Bank of China, the directnegative impact is less than half a percent by using the simulation result of econometric model. What's more detrimental is the hit to investor confidence and uncertainty. Maurice Obstfeld, International Monetary Fund's chief economist, said that President Trump intend to use uncertainty as an disincentive to investoutside the U.S. and to destabilize the economies of the countries conducting the unfair trade with the U.S..The mounting costs of doing business for companies are fueling investor fears of the likelihood of a slump in financial markets. The downside risk would be magnified by the rise of artificial AI electronic trading asautomation speeds up financial transactions, allowing them to be conducted across multiple markets at the same time. Chinese stock, in terms of Shanghai A share price index, tumbled more than 25 percent from January 22, 2018 through mid-December. The steep declines were partly because China sold a lot more to the U.S. than it purchased. Many factors, such as declining earnings of manufacturing firms and considerable debt problem, besides tit-for-tat trade wars plausibly affected Chinese share prices. However, stock prices reflected the expected profitability of the companies.

The purpose of this paper is to investigate the measurement of contagion by analyzing 2018 trade war between the U.S. and China in the equity markets of nine Asian countries by using dynamic conditional correlation (DCC) and asymmetric dynamic conditional correlation (ADCC). Forbes and Rigobon (2002) define contagion as a significant increase in correlation coefficient after a shock to one country or group of countries. The advantage of DCC is that Chiang et al. (2007) apply a DCC model to nine Asian daily stock- return data series from 1990 to 2003. They identity two different phases of the Asian crisis. The first, from July 2, 1997 to November 17, 1997, shows an increase in volatility of stock returns (contagion); the second, from November 17, 1997 through 1998, shows a consistently high correlation between stock returns and their volatility (herding). The empirical evidence finds significant contagion effects during the Asian financial crisis. Cho et al. (2008) apply DCC of contagion in the Asian financial crisis in eight countries. They employ t-tests for the mean difference and Wilcoxon z-tests for the median difference to church for the existence of contagion. Taking the Thailand and Hong Kong as source countries, they find the overwhelming evidence of contagion effect in 1997 Asian equities market. Since 2007, DCC has been used to detecting the contagion in several international financial crises. In the literature, some papers test the existence of contagion of various crisis on different financial markets [Stock Markets: (Ahmadd et al. 2013; Baumöhl et al. 2011; Billio 2003; Bonga-Bonga 2018; Caporin et al. 2018; Chiang et al., 2007; Cho and Parhizgari, 2008; Dimitrio 2013; Kazi et al. 2014; Khan and Park, 2009; Hemche et al. 2016; Marçal 2011; Yiu 2010) Foreign Exchange Markets: Celik, 2012, Bond Market: (Min and Hwang 2012; Missio and Watzka 2011)], In addition to papers related to one specific market contagion, studies on cross market contagion also take part in literature: (Cappiello 2016 Kenourgios and Dimitriou 2015).

The paper is organized as follows. Section 2 describes the methodology used. Section 3 defines the dataset and vdiscusses the empirical findings. Section 5 summarizes and concludes.

II. METHODOLOGY

Unlike constant correlation coefficient suggested by CCC GARCH analysis, Dynamic conditional correlation (DCC-GARCH model) detects possible changes in conditional correlations over time, which allows us to detect dynamic investor behavior in response to breaking news. An advantage of Dynamic conditional correlation over the volatility-adjusted cross-market correlations proposed in Forbes and Rigobon (2002), it continuously adjusts the correlation for the time-varying volatility. Another advantage of DCC-GARCH model is that the calculated correlation coefficients account for heteroscedasticity directly (Chiang et al., 2007). We apply DCC-GARCH model of Engle (2002) to test the existence of contagion during trade wars between thus U.S. and China.

The multivariate GARCH dynamic conditional correlation(DCC) estimators proposed by Engle (2002) inthis paper will be employed to examine the existence of contagion effect during the trade war period. Asindicated by Engle (2002), a desirable practical feature of the DCC models is that multivariate andunivariate volatility forecasts are consistent with each other. The dynamic correlation model differs with Bollerslev(1990) constant

conditional correlation(CCC) estimator only in allowing R to be time varying: $H_t = D_t R_t D_t$
The statistical specification of the multivariate DCC-GARCH model can be formulated as follows;

$Y_t = \mu_t + H^{1/2} \varepsilon_t$			(1)
$H_t = D_t R_t D_t$ $D_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2}$		(3)	(2)
$D_t = diag(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots, \sqrt{h_{nn,t}})$	(4)		

where $Y_t = (Y_{1t}, Y_{2t}, \ldots, Y_{nt})$ is the vector of the past observations, H_t is the conditional covariance matrix, $\mu_t = (\mu_{1t}, \mu_{2t}, \ldots, \mu_{nt})$ is the vector of conditional returns, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots \varepsilon_{nt})$ is the vector of the standardized disturbances that has mean zero and variance one, R_t is a $n \times n$ unconditional correlation matrix of standardized residuals and D_t is a diagonal matrix of conditional standard deviations for return series, obtained from estimating a univariate GARCH model. The Y_t can be expressed as conditional returns plus conditional standard deviation times the standardized disturbance.
The evolution of the correlation in the DCC model is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \quad (5)$$

where Q_t is time varying covariance matrix of standardized residuals, $u_{it} = \varepsilon_{it} / \sqrt{h_{it}}$ and nonnegative scalarparameters α and β that satisfy $\alpha + \beta < 1$. The correlation estimator:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$$

In a bivariate case, the correlation estimator can be expressed as:

$$\rho_{12,t} = \frac{(1 - \alpha - \beta)\overline{q_{12}} + \alpha u_{1,t-1} u_{2,t-1} + \beta q_{12,t-1}}{\sqrt{(1 - \alpha - \beta)\overline{q_{11}} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}} \sqrt{(1 - \alpha - \beta)\overline{q_{22}} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}}}$$

As indicated by Engle (2002), the DCC model can be estimated by two-step methods based upon the likelihood function. The log likelihood can be written as the sum of a volatility part and a correlation part. The first step is maximizing the volatility part to find the parameters in D and then taking the estimated parameters as given in the second step. The second step is maximizing the correlation part to find correlationcoefficients.
Cappiello et al. (2006) generalize the DCC GARCH model to allow for series-specific news impact and smoothing parameters and permit conditional asymmetries in correlations. As presented by Cappiello et al. (2006), the correlation evolution equation can be modified as follows:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G) + A'u_{t-1}u'_{t-1}A + G'n_{t-1}n'_{t-1}G + B'Q_{t-1}B \quad (6)$$

where A, B, and G are $k \times k$ parameter matrices, $n_t = I[u_t < 0] \circ u_t$ (I[.] is a $k \times 1$ indicator function which takes on value 1 if the argument is true and 0 otherwise, while "∘" indicates the Hadamard product) and $\bar{N} = E[n_t n'_t]$. Equation (6) is referred by Cappiello et al. (2006) as AG-DCC (the asymmetric generalized DCC) model.

III. DATA AND EMPIRICAL RESULTS

1. Data

We examine the contagion effect between stock markets of China and emerging and developed markets in Asia during the trade war. The dataset includes daily stock market index of China, Hong Kong, Philippine, Indonesia, Japan, Malaysia, Singapore, South Korea, Taiwan, Thailand. The sample period runs from02/28/2017 to 12/12/2018. The data is obtained from Thompson Reuters DATASTREAM.

It is difficult to identify the crisis period. In this paper, we consider news based data for identifying crisis period. We apply the DCC and ADCC models taking into account the 01/19/2018-12/12/2018 as the crisis period and the period before as stable period, based on the fact of tariff imposed by Trump administration. Then, we compare the difference in returns, actual and asymmetric volatilities and correlations between China (considered as the source of contagion) and all other countries for both stable and crisis periods.

The series of interest for the sample period are proven to be nonstationary but stationary in first differences. Following the conventional approach, stock returns are calculated as the first difference of the natural log of each stock-price index, and the returns are expressed as percentages. Given the importance of using stationary series, the first differenced data will be carried out in the empirical analyses of the DCC and ADCC GARCH models.

2. Empirical findings

The summary statistics of stock-index returns of the nine Asian markets in pre-crisis period and crisis periodare presented in Table 1. As expected, the index return series are negatively skewed in crisis period and leptokurtic (with the exception of Philippine). Moreover, the Jarque–Bera test statistic reveals the typical non-normality feature of high frequency financial time series (with the exception of Philippine and Singapore). This finding suggested that for these markets, big shocks of either sign are more likely to be present and that the stock returns series may not be normally distributed. Another noteworthy statistic is that the mean of stock index returns are positive for 9 countries in crisis period. the mean of stock index returnsin the pre-crisis period are greater than those in the crisis periods.

Table 1: Descriptive statistics of stock index returns

pre-crisis period (02/28/2017-01/19/2018)						
	Mean	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness Kurtosis**	**Jarque- Bera**
China	0.000346	0.018376	-0.022931	0.005395	-0.31198 4.824063	36.23618
Hong Kong	0.001303	0.022461	-0.021426	0.00709	-0.120836 3.881747	8.149863
Taiwan	0.000588	0.014061	-0.016365	0.005373	-0.287684 3.229088	3.739409
Japan	0.000964	0.032567	-0.021305	0.00697	0.503878 5.293323	61.18031
Korea	0.000826	0.022987	-0.017293	0.00582	-0.197678 4.681762	29.10013
Malaysia	0.000334	0.012281	-0.008386	0.003443	0.658218 4.087196	28.42126
Phillipine	0.000919	0.020423	-0.020448	0.006966	0.013642 3.393552	1.517369
Singapore	0.000581	0.015997	-0.014125	0.005177	0.078481 3.360649	1.508371
Idndonesia	0.000814	0.025938	-0.018021	0.005256	0.439176 5.479538	67.46622
crisis period (01/22/2018-12/12/2018)						
China	0.001159	0.04092	-0.052242	0.012427	-0.411026 4.961221	44.09103
Hong Kong	0.000796	0.042113	-0.051164	0.012423	-0.296325 4.032532	13.81923
Taiwan	0.000466	0.028975	-0.063125	0.009803	-1.511823 12.1317	902.172
Japan	0.000345	0.026544	-0.047255	0.011116	-0.924867 5.545864	96.55368

Korea	0.000767	0.035338	-0.044395	0.009006	-0.677947 6.001629	105.7702
Malaysia	0.000366	0.015501	-0.03185	0.006679	-0.931595 5.695647	104.6954
Phillipine	0.000637	0.034798	-0.025978	0.011227	0.219661 2.827544	2.171769
Singapore	0.000509	0.023419	-0.026853	0.008394	-0.042197 3.293048	0.906747
Idndonesia	0.000192	0.026681	-0.037559	0.01005	-0.482972 4.095309	20.79431

Figure 1: DCC Coefficient estimates

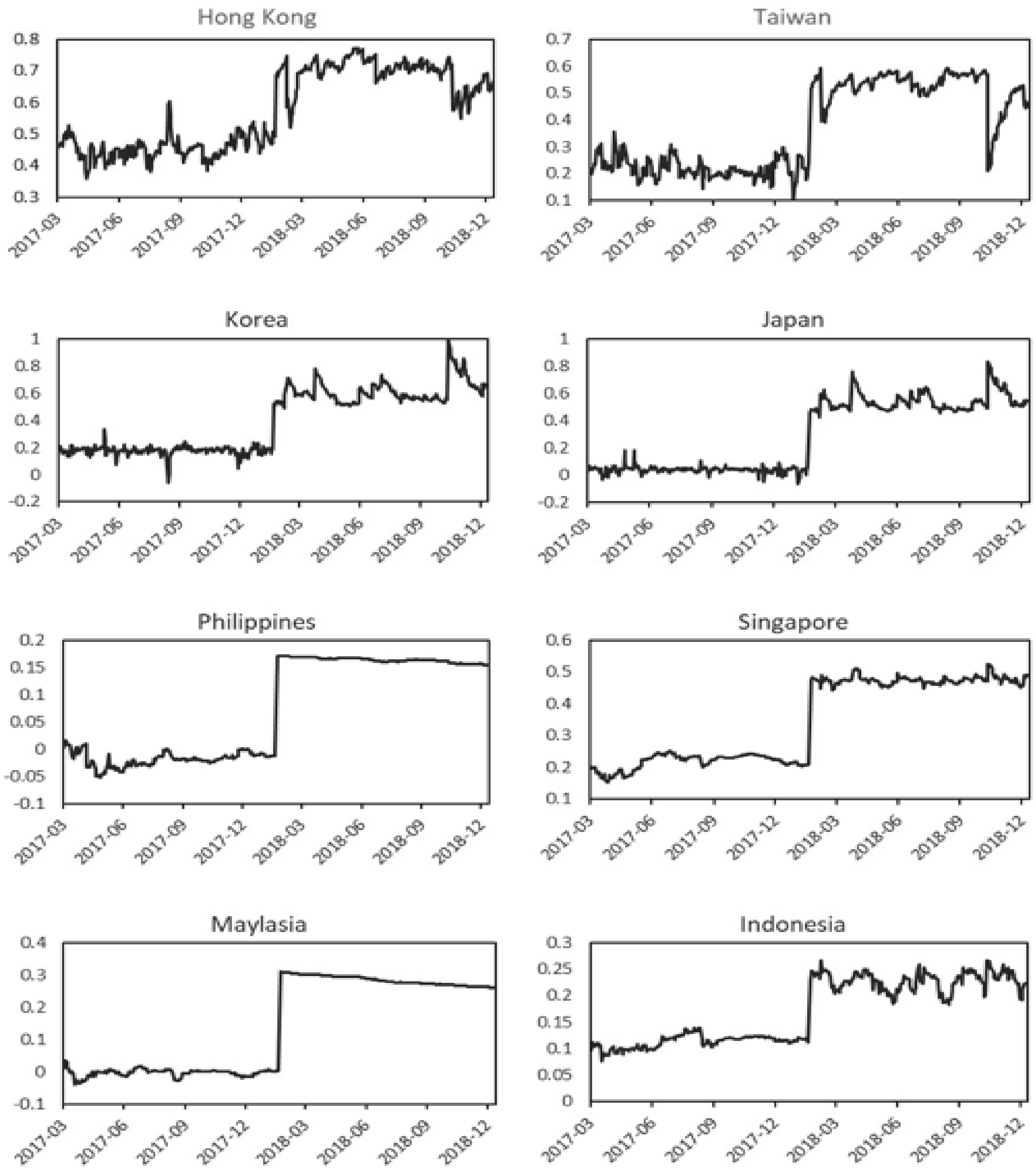
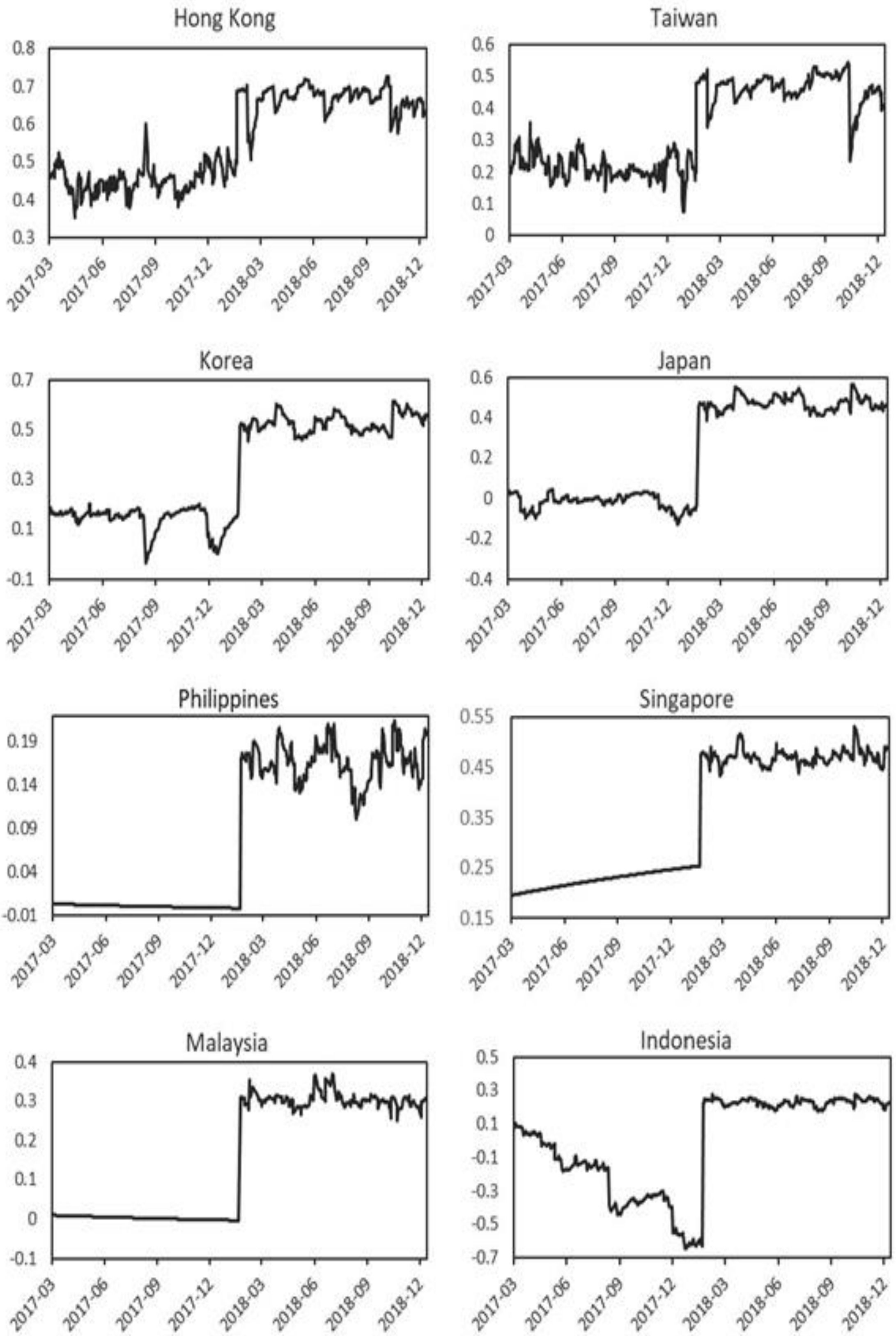


Figure 2: ADCC Coefficient estimates



Computed DCCs, have been graphed them in Figures 1 and 2. Figure 1 provides DCC plots and figure closely related to China stock market in terms of correlation coefficients. Hong Kong is the most important entrepot for trade between China and the rest of the world. And a large number of Taiwan listed companies move their production line to China. Based on the increase in the DCC and ADCC mean values in percentage term, Korea, Japan and Taiwan seem to be the most influenced by the contagion effects from the trade war between U.S. and China.

To examine the existence of stock market contagion, we employ t-tests to test whether the mean difference of DCC and ADCC correlations coefficients are significantly different from zero in pre-crisis and crisis periods or not. The results of contagion effect are summarized in Table 3. All the t statistics indicate that the null hypothesis of the same mean difference of DCC and ADCC in crisis and pre-crisis periods are rejected at one percent significance level. Therefore, we find the strong evidence of contagion effect of trade wars on Asian countries. Furthermore, the pairwise conditional-correlation coefficients between stock returns of these Asian markets were seen to be persistently higher and more volatile in the crisis period than in the pre-crisis period. A higher level of correlation coefficient suggests that the benefit from market-portfolio diversification diminishes, since holding a portfolio with diverse country stocks is subject to systematic risk. Moreover, the higher volatility of correlation coefficients in crisis period implies the presence of either an unstable covariance or an erratic variance, or both.

Table 2: Comparative analysis of *DCC* and ADCC

	DCC			*ADCC*		
Country (Source Country: China)	*Pre-crisis*	*Crisis*	*%difference*	*Pre-crisis*	*Crisis*	*%difference*
Hong Kong	0.45514	0.69388	23.87	0.45461	0.66792	21.33
Taiwan	0.22109	0.51991	29.88	0.21724	0.46277	24.55
Korea	0.17828	0.61713	43.89	0.14132	0.52777	38.65
Japan	0.04075	0.54422	50.35	-0.01653	0.47175	48.33
Singapore	0.21729	0.47514	25.79	0.22676	0.47159	24.48
Malaysia	-0.00347	0.28299	28.65	0.00267	0.30431	30.16
Indonesia	0.11318	0.22826	11.51	-0.25038	0.22963	48.00
Philippines	-0.01838	0.16362	18.20	2.23E-05	0.16674	16.67

Note: Pre-crisis is from 03/01/2017 to 01/19/2018. Crisis period is from 01/22/2018 to 12/12/2018.

Table 3: Contagion effect test

	DCC			ADCC		
	Mean	*Std Dev.*	*t-statistics* $H_0: \mu^{crisis} = \mu^{pre-crisis}$	*Mean*	*Std Dev.*	*t-statistics* $H_0: \mu^{crisis} = \mu^{pre-crisis}$
Hong Kong pre-crisis period	0.45514	0.03697	59.12764 (.0000)	0.45461	0.04029	60.62675 (.0000)
crisis period	0.69388	0.04932		0.66792	0.03551	
Taiwan pre-crisis period	0.22109	0.03826	59.00523 (.0000)	0.21724	0.04251	58.25219 (.0000)
crisis period	0.51991	0.06717		0.46277	0.04829	
Korea pre-crisis period	0.17828	0.0336	71.04854 (.0000)	0.14132	0.05011	94.80031 (.0000)
crisis period	0.61713	0.0881		0.52777	0.03689	
Japan pre-crisis period	0.04075	0.02583	101.866 (.0000)	-0.01653	0.47175	141.512 (.0000)
crisis period	0.54422	0.07088		0.0383	0.03615	
Singapore pre-crisis period	0.21729	0.02343	146.574 (.0000)	0.22676	0.01691	161.677 (.0000)
crisis period	0.47514	0.01313		0.47159	0.01576	
Malaysia pre-crisis period	-0.00347	0.01132	235.058 (.0000)	0.00267	0.00384	235.383 (.0000)
crisis period	0.28299	0.01891		0.30431	0.01918	
Indonesia pre-crisis period	0.11318	0.0119	80.6612 (.0000)	-0.25038	0.20942	34.8004 (.0000)
crisis period	0.22826	0.01824		0.22963	0.02174	
Philippines pre-crisis period	-0.01838	0.00453	197.254 (.0000)	$2.23*10^{-5}$	0.00147	112.706 (.0000)
crisis period	0.16362	0.01527		0.16674	0.02253	

IV SUMMARY AND CONCLUSION

This paper investigates the relationship between the stock returns of China and various Asian countries during the 2018 trade war period. Dynamic conditional correlation and asymmetric dynamic conditional correlation analysis conclude that there is evidence of contagion effects during the trade war, a finding that is consistent with the conclusion reached by Chiang et al. (2007).

The apparent high correlation coefficients during crisis periods seems to imply that the benefit of international diversification their portfolio of stocks form these contagion countries diminishes, since these stock markets are commonly exposed to systematic risk.

Endnotes:

1. This model could include functions of the other variables as predetermined variables or exogenous variables.
2. Results are not reported. The use of the ADF test for the series shows the same conclusion.

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