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If worst comes to worst: Co-movement of global stock markets in the US-China trade war

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Abstract

This paper investigates the co-movement characteristics of global stock markets in the context of the US-China trade war. By applying a set of different trivariate Copulas, our results suggest that markets co-move symmetrically in the pre-trade war period, but exhibit negative downside movements and heavy tails during the trade war. Furthermore, we find evidence for left-tail dependency structures during that period. Most importantly, this study finds that the trade war poses a systematic risk on global markets, which potentially can trigger simultaneous market downside trends. Our results are robust across different European equity market indices.

Keywords: trade war; co-movement; Copulas; market reaction
JEL Classification Codes: B17, C46, G15

1. Introduction

The world is experiencing one of the most severe trade wars of the last decades. With China and the US being the two largest economies in terms of trade, foreign direct investment and capital flows, the trade war did not only damage international trade relationships but also continuously damage international financial markets performances. In 2018, stock markets had their worst year in a decade when the S&P 500 fell more than 6% and the Hang Seng index and the Shanghai index fell 13% and 25%, respectively. Since then, investors' attention to the trade war spiked as indicated by Google search volume (Figure 1).

Our motivation to take a closer look at the trade war is threefold. During the financial crisis, negative shocks often were triggered by bad news from the banking sector. We believe that one of the major differences this time is that information are continuously released and sometimes

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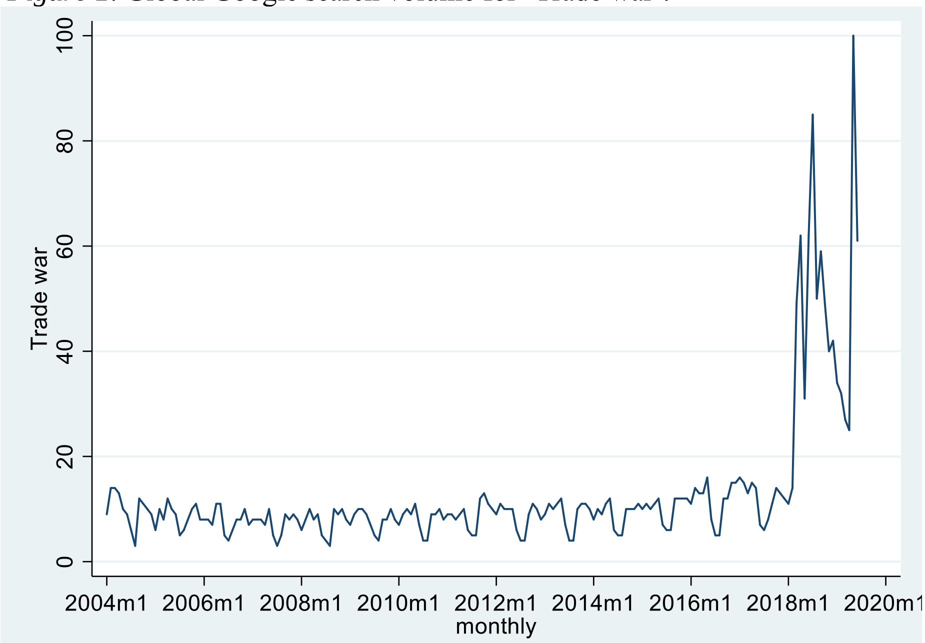
even 'leaked' by White House officials via social media, potentially leading to more stochastic and volatile equity markets (Burggraf et al., 2019). In addition, we believe that advancement in globalization and the interconnectedness of the US and Chinese economies with the rest of the world are potential sources for spillover effects in the context of ongoing trade war tensions. The impact of military war on financial markets was studied by Brune et al. (2015) and to the best of our knowledge, this is the first study to examine the new kind of 'war' in the fourth industrial revolution on financial markets. In this study, we investigate downside co-movements among the US, China and the G7 equity markets based on market return distributions. We use Copula estimates including Clayton (left tail), Gumbel (right tail), Gaussian (normal distribution) and Student-t Copula (heavy-tail) to evaluate contemporaneous multivariate tail dependencies. To ensure the robustness of our results and because four out of seven G7 countries are European, this paper also examines co-movement characteristics between US-China and the EURO STOXX 50 index.

The rest of this study is structured as follows. Section 2 briefly reviews the existing literature on co-movement and contagion phenomenons. Section 3 introduces our methodology and data. In section 4, we discusses our empirical results. Section 5 concludes.

Figure 1. Global Google search volume for 'Trade war'.



Note. The figures displays Global Search volume for the keyword 'trade war' over the period January 2004 – June 2019. Search queries are normalized on a 0-100 scale.

2. Related literature

Risk-averse investors typically hold internationally diversified assets in their portfolios to avoid negative (idiosyncratic) market downturns (Arouri 2019). Lahaye et al. (2010) show that stock market co-movement is strongly associated with macroeconomic news announcements. Apparently, in the context of the US-China trade war, bad (good) news are continuously disclosed by the competing governments. As a result, news (Appendix A.3.) lead to lower (higher) analyst forecasts, which in turn trigger stock prices to rise or fall. Aside from news, when the actual trade war takes place, for example in the form of tariffs, the effects of the trade war directly influence global economic output and indirectly global supply chain networks. As a result, a "crowding-out" phenomenon is taking place: When two governments escalate the trade-war, manufacturing companies are afraid of the uncertainty surrounding the economy's future, thereby reducing their output. Thus, not only financial market but also the rest of the market is negatively impacted, which has deteriorating effects on the entire market. Hendricks and Singhal (2005) show that this can have significant negative impact on stock price performance. They find that the average abnormal stock return of firms that experience supply chain disruptions is nearly -40%. Therefore, our study contributes to the literature investigating the linkage between supply-chain disruptions and financial markets (Houston et al. 2016; Hertzel et al. 2008).

While there is a large body of literature investigating the impact of the 2008 financial crisis on co-movement characteristics in global financial markets, such as Sakemoto (2018).who examine financial distances of spillover effects; or Dimitrios Asteriou (2016). investigating macroeconomic uncertainties on stock and bond markets. In addition, Jin (2016) who applies the Hurst exponential approach; and Baumöhl & Shahzad (2019) employing quantile coherency networks for many international equity markets contribute to the ongoing literature of co-movements and spillover effects on capital markets. To the best of our knowledge, this is the first study to examine the impact of the US-China trade war on stock markets' co-movement. Furthermore, our study attempts to uncover directional volatility frequencies by using daily data, which tend to better explain market behaviors under trade war tensions.

In line with the above discussion, we pose the following three research questions to be answered:

1. In which tail (direction) do global stock markets represented by G7 economies move during the trade war period? Do they move differently compared to the non-trade war period?
2. Does the trade war pose a systematic risk to global economies?
3. Which economic framework can reasonably explain that co-movement behavior?

To answer these questions, we refer to the Copula methodology, which allows us to capture tail-dependencies for multiple variables. In contrast to previous studies; this study employs multivariate Copulas, which cover three variables moving at the same time, specifically the US, China and one G7 stock market. Our study contributes to the literature by focusing on the performance of equity markets during the trade war period, but more importantly, we emphasize on the trivariate copula to estimate the co-movements in terms of trade war tension. To the best of our knowledge, trivariate copulas are rarely applied in the finance literature and the trade war poses one of the most alarming threats on international relations of our time.

3. Data and methodology

We focus on G7 economies, which represent almost 50% of the global Gross Domestic Product. Financial market data denominated in USD are retrieved from Refinitiv and are proxied by the following total return indices: S&P500 for the US, MSCI China for China, Nikkei for Japan, DAX for Germany, FTSE for UK, TSX for Canada, CAC for France and MIB for Italy. The sample (7,038 observations) covers the period June 13, 2016 to June 10, 2019 and is split into two equally large sub-samples (before and after the trade war). Descriptive statistics are presented in Table A.1. in the Appendix.

Copulas are joint distributions with uniform marginals, representing the dependence structure in the joint distribution. Copulas were first introduced by Sklar's theorem (1959). To account for asymptotically large losses, Nguyen & Huynh (2019), Boako et al. (2018) and Rivieccio & De Luca (2016) demonstrated how to define dependence structure through the family of heavy tail and stochastic copula. To begin with, we denote u, v and z are three random and continuous variables defined between 0 and 1. Table 1 summarizes various copula-modeling approaches in terms of symmetric and asymmetric dependence structures between three variables (trivariate). In the scope of this paper, we extend the bivariate framework to a multivariate, three-dimensional model.

Table 1. Summary of Copula modeling approaches.

Copula	Parameter estimation	Eq.
Gaussian	$C(u,v,z) = -\frac{1}{\theta}\ln\left(1 + \frac{(\exp(-\theta u)-1)(\exp(-\theta v)-1)(\exp(-\theta z)-1)}{\exp(-\theta)-1}\right.$	(1)
Clayton	$C(u,v,z) = (u^{-\theta} + v^{-\theta} + z^{-\theta} - 1)^{-\frac{1}{\theta}}$	(2)
Gumbel	$C(u,v,z) = exp\left\{-[(-lnu)^{\theta} + (-lnv)^{\theta} + (-lnz)^{\theta}]^{\frac{1}{\theta}}\right\}$	(3)
Student-t	$C(u,v,z) = \int_{-\infty}^{t_v^{-1}(u)} \int_{-\infty}^{t_v^{-1}(v)} \int_{-\infty}^{t_v^{-1}(z)} \frac{1}{2\pi\sqrt{1-\theta^2}} (1 + \frac{s^2 - 2\theta st + t^2}{v(1-\theta^2)})^{-\frac{v+2}{2}} dsdt$	(4)

Notes. θ denotes the linear correlation coefficient. $t_v^{-1}(u)$ denotes the inverse of the cumulative distribution function of standard univariate Student-t distribution with v being the degree of freedom. Gaussian copula: normal distribution; Student-t Copula: extreme dependence; Clayton: negative tail (left-tail) dependence; Gumbel: positive tail (right-tail) dependence. The Gaussian parameter estimation formula can be rewritten as $C(u,v,z) = \Phi_{\mathbb{R}}(\Phi^{-1}(u), \Phi^{-1}(v), \Phi^{-1}(z))$, where $\mathbb{R}$ is the correlation matrix used for the intended joint distribution and Φ is the standard normal cumulative distribution function of random and continuous variables defined between 0 and 1. The rest of Copulas can be written in numerical forms as Gaussian Copulas (Smith, 2013), (Zimmer and Trivedi, 2006).

4. Results

Table 2 summarizes our Copula estimates, dependence parameters and Maximized Loglikelihood values. Based on the highest value of Maximized Loglikelihood, all multivariate variables (US-China and G7 economies) fall into a specific Student-t Copula family. In addition, the BB1 Copulas (known as Clayton-Gumbel Copulas) and BB7 (Joe-Clayton Copulas) are estimated to support our result that the considered financial markets show strong co-movement dependence structures in the left-tail of the distribution[1]. The results are presented in Table A.3. (Appendix). Therefore, the data are characterized by extreme co-movement and heavy tails between US-China and G7 countries.

Table 2. Dependence parameter estimation by different Copulas.

Sub-sample 1: Before Trade war (From 13th June 2016 to 1st January 2018)				
	Gaussian	**Clayton**	**Gumbel**	**Student-t**
US-China-Japan	**0.26**	0.35	1.20	**0.26**
	[36.93]	[35.18]	[40.25]	**[46.17]**
US-China-Germany	**0.41**	0.52	1.32	**0.41**
	[89.84]	[73.37]	[78.78]	**[98.19]**
US-China-UK	**0.38**	0.48	1.28	**0.37**
	[75.94]	[63.19]	[66.89]	**[88.86]**
US-China-Canada	**0.41**	0.52	1.30	**0.40**
	[88.6]	[69.11]	[75.77]	**[98.65]**
US-China-France	**0.41**	0.54	1.33	**0.40**
	[89.09]	[74.68]	[83.22]	**[98.18]**
US-China-Italy	**0.36**	0.48	1.28	**0.36**
	[70.20]	[62.85]	[65.91]	**[81.29]**

[1] We thank an anonymous reviewer for suggesting these kinds of Copulas to support our main findings.

Table 2. Dependence parameter estimation by different Copulas (cont.).

	Gaussian	Clayton	Gumbel	Student-t
Sub-sample 2: During Trade war (From 1st January 2018 to 10th June 2019)				
US-China-Japan	**0.38**	0.55	1.32	**0.40**
	[73.18]	[70.73]	[65.06]	**[86.40]**
US-China-Germany	0.46	**0.70**	1.40	**0.48**
	[108.30]	**[108.30]**	[91.87]	**[120.40]**
US-China-UK	0.43	**0.63**	1.36	**0.45**
	[92.90]	**[93.06]**	[81.31]	**[101.30]**
US-China-Canada	0.36	**0.63**	1.27	**0.37**
	[64.38]	**[90.11]**	[41.26]	**[70.50]**
US-China-France	0.33	**0.57**	1.25	**0.34**
	[52.87]	**[78.47]**	[35.89]	**[62.05]**
US-China-Italy	0.28	**0.43**	1.20	**0.29**
	[40.42]	**[51.91]**	[25.35]	**[43.75]**
Full sample (From 13th June 2016 to 10th June 2019)				
US-China-Japan	**0.34**	0.47	1.27	**0.35**
	[121.00]	[121.00]	[111.50]	**[147.70]**
US-China-Germany	**0.44**	0.65	1.36	**0.45**
	[208.90]	[202.40]	[175.70]	**[236.40]**
US-China-UK	**0.41**	0.58	1.33	**0.42**
	[178.90]	[173.10]	[151.80]	**[203.90]**
US-China-Canada	**0.47**	0.67	1.37	**0.47**
	[235.50]	[211.20]	[185.90]	**[256.60]**
US-China-France	**0.45**	0.67	1.38	**0.46**
	[218.80]	[212.70]	[190.70]	**[243.90]**
US-China-Italy	**0.39**	0.53	1.31	**0.40**
	[163.30]	[153.30]	[140.10]	**[182.30]**

Notes. The table displays the estimated Copula dependence parameters (θ) for the Gaussian, Clayton, Gumbel and Student's t-Copulas. The parameter range depends on the specific Copula, for example, the Gaussian parameter is restricted to the interval (-1,1), while Gumbel Copula is an asymmetric copula with higher probability concentration in the right tail from 1 to infinity (1; +∞). The parameters measure the magnitude of dependence. Maximized Loglikelihoods are in square brackets. Rodriguez (2007) and Huynh (2019) suggested to employ maximized log likelihood to choose the most appropriate copula model. In this study, we consider two types of fitting copula: (i) between Gaussian and Student-t to examine whether heavy tails exist or not; (ii) among Gaussian, Clayton, Gumbel to check whether the co-movement either lies in both, the left-tail or the right-tail, respectively. The degrees of freedom of the Student's t-Copulas and AIC estimates (for model selection) are available upon request.

During the pre-trade war period (June 13, 2016 – January 1, 2018), all co-movements fall into the Gaussian Copula – they are symmetric and have no tail dependence. Therefore, they co-move in the entire distribution and not only in some specific tails. During the trade war period (January 1, 2018 – June 10, 2019), all G7 economies except Japan exhibit heavy left tails and negative co-movements. The inverse relationship from Gaussian Copula to Clayton Copula in times of financial turmoil is consistent with the literature (Aloui, 2011; Yarovaya, and Lau, 2016) and can be explained by the contagion hypothesis, stating that co-movement across markets increases during periods of financial turbulence. We argue that measures in the context of the trade war, such as tariffs, have comparable effects as military conflicts on stock prices – They trigger a reduction in global trade volume, therefore reduce future cash flows and equity valuations that lead to falling stock prices (Brune et al., 2015) that impact companies across markets and countries and ultimately yield the observed strong stock market correlation and left-tail dependence. Therefore, our study finds evidence that the trade war constitutes a source of *systematic risk*, whose early detection is of interest for policy makers and investors alike. For policymakers who attempt to prevent the recurrence of another global crisis, and for investors who try to diversify their investments across economies during difficult times. Because Japan is the only country which has the same symmetric distribution across both periods, it likely plays a special role in the trade war. It has the least open and responsive economy among our G7 sample, therefore constitutes a more passive role in transmitting and sending negative information. This result is consistent with previous studies of Malliaris & Urrutia (1992) which examine the international crash of October 1987. Finally, to ensure the robustness of our results, we perform the same analysis for the EURO STOXX 50 index. We find that the results are consistent, indicating that US, Chinese and European indices have the same heavy tail and left tail co-movement characteristics as a result of a negative (trade war) shock. The results of our robustness check are presented in Table A.2. (Appendix).

5. Conclusion

In this study, we investigate contemporaneous co-movements between the US, China and G7 equity market indices. In line with the current literature, our empirical results indicate that these markets are heavy-tailed but symmetrically distributed in the pre-trade war period. However, during the trade war, all G7 countries but Japan share fat-tail and left-tail dependence structures with the US and China. This study contributes to the current literature on market co-movements by examining a novel negative shock to financial markets, confirming the findings from previous studies which investigate financial market co-movement characteristics in the financial crisis context. Finally, we find evidence that the trade war represents a systematic risk, posing a threat to international investors who attempt to hedge against downside risks by diversifying across economies. While this study focused on the impact of cross-country stock market co-movements, future research might investigate the impact on the industry level in order to test whether diversification across industries might provide better diversification benefits and therefore a hedge against market downturns. Lastly, it might be of interest to compare the trade war with past political turmoil, for example Hillier and Loncan (2019) examining political uncertainty and stock market reaction in Brazil.

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Appendix A

Table A1. Descriptive statistics.

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
US	0.0004	0.0078	-0.6697	9.1816	1302***
China	0.0004	0.0109	-0.2417	3.7251	24.72***
Japan	0.0003	0.0107	-0.9059	11.7169	2580***
Germany	0.0002	0.0090	-0.6596	8.5475	1058***
UK	0.0002	0.0072	-0.0488	5.5699	215.2***
Canada	0.0003	0.0057	-0.4379	5.3950	211.6***
France	0.0002	0.0087	-1.0797	14.9148	4771***
Italy	0.0002	0.0118	-1.7274	23.6823	1400***
Europe	0.0001	0.0087	-1.3472	18.0481	7605***

Notes. This table reports the summary statistics including mean, standard deviation (Std. Dev.), skewness, excess kurtosis, and Jarque-Bera (J-B) test. The symbols *, ** , and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

Table A.2. Robustness test with EURO STOXX.

	Full sample			
	Gaussian	**Clayton**	**Gumbel**	**Student-t**
US-China-Europe	**0.45**	0.67	1.37	**0.46**
	[215.60]	[210.70]	[183.90]	**[239.60]**
	During Trade war (From Jan 1st, 2018 to Jun 10th, 2019)			
US-China-Europe	0.47	**0.74**	1.41	**0.49**
	[114.40]	**[117.40]**	[97.61]	**[126.80]**
	Before Trade war (From Jun 13th, 2016 to Jan 1st, 2018)			
US-China-Europe	**0.41**	0.54	1.32	**0.41**
	[90.47]	[75.02]	[82.61]	**[99.29]**

Notes: Maximized loglikelihoods of the corresponding parameters are in square brackets.

Table A3. Some example of key news regarding Trade War in 2018.

No	**Date**	**Event**
1	January 2018	Trump imposed steep tariffs on imported solar panels and washing machines.
2	March 1st 2018	Trump imposed Sweeping Steel and Aluminum Tariffs.
3	March 8th 2018	Donald Trump signs order for metals tariff plan.
4	March 22nd 2018	Presidential memorandum in reference to Section 301 of the Investigation of China's Laws, Policies, Practices, or Actions was issued to response China's alleged theft of US intellectual property.
5	March 23rd 2018	Chinese government declared to impose 15-25% tariffs on aluminum scraps, airplanes, automobiles, pork products, and soybeans (subject to a 25% tariff) as well as nuts, fruits, and steel piping (subject to a 15% tariff).
6	April 2nd 2018	Approval of the proposal on March 23rd by China's Ministry of Commerce.
7	April 3rd 2018	US declared the list 1,300 Chinese products would be subject to new duties in retaliation to "the forced transfer of American technology and intellectual property."
8	April 4th 2018	Chinese government revenged by imposing 25% on 106 list of products.
9	April 5th 2018	US declared to impose $100 billion tariff because China's unfair retaliation.
10	April 16th 2018	US Commerce Department banned the American companies to sell parts, software, and components to China's ZTE Corporation.
11	May 20th 2018	US announced to have a pause in Trade War.
12	May 29th 2018	Trump office announced to impose 25% tariffs on the $50 billion worth of imports from China.
13	June 15th 2018	Official imposition of May 29th 2018. US warned that they will impose more if China retaliated.
14	June 18th 2018	Trump requested United States Trade Representative to identify $200 billion of Chinese products for additional tariff.
15	July 6th 2018	Tariffs on $34 billion Chinese products were imposed.
16	July 10th 2018	The new list of Chinese products was threatened to more tariff imposed.
17	August 8th 2018	US announced the list of 279 Chinese goods to be subject to a 25% tariff from August 23rd. China retaliated to impose 25% tariffs on August 23rd 2018.
18	August 14th 2018	China complained to World Trade Organization (WTO) that US treated unfairly to cause the legally commercial market distortion.
19	August 22nd 2018	US and China tried to reopen negotiation.
20	September 17th 2018	US announced to impose 10% tariff on Chinese products and immediately Chinese government retaliated in the following working days.
21	November 10th 2018	Trump signed article 32.10 of the agreement (called the revised U.S.–Mexico–Canada Agreement), which aims at preventing any non-market economy, especially China, from taking advantage.
22	December 1st 2018	The tariff was delayed.

Table A4. BB1 and BB7 Copulas dependence parameter estimation.

Parameters	US-China-Japan	US-China-Germany	US-China-UK	US-China-Canada	US-China-France	US-China-Italy
BB1 Copulas - Sub-sample 1: Before Trade war (From 13th June 2016 to 1st January 2018)						
$\boldsymbol{k_1}$	1.22	1.35	1.19	1.02	1.16	1.00
$\boldsymbol{k_2}$	0.00	0.29	0.03	0.10	0.00	0.24
$\boldsymbol{\tau}$	0.18	0.35	0.17	0.07	0.14	0.11
AIC	-103.91	-231.54	-194.81	-274.15	-239.12	-184.54
BB1 Copulas - Sub-sample 2: During Trade war (From 1st January 2018 to 10th June 2019)						
$\boldsymbol{k_1}$	1.24	1.18	1.19	1.02	1.00	1.00
$\boldsymbol{k_2}$	0.05	0.00	0.00	0.07	0.37	0.26
$\boldsymbol{\tau}$	0.21	0.15	0.16	0.05	0.16	0.11
AIC	-317.86	**-497.36**	**-422.35**	**-645.61**	**-521.88**	**-373.44**
BB1 Copulas - Full sample (From 13th June 2016 to 10th June 2019)						
$\boldsymbol{k_1}$	1.24	1.28	1.19	1.02	1.00	1.00
$\boldsymbol{k_2}$	0.04	0.00	0.00	0.07	0.37	0.26
$\boldsymbol{\tau}$	0.21	0.27	0.16	0.05	0.16	0.11
AIC	**-318.43**	-496.90	-422.01	-644.74	-521.75	-373.80
BB7 Copulas - Sub-sample 1: Before Trade war (From 13th June 2016 to 1st January 2018)						
$\boldsymbol{k_1}$	1.23	1.00	1.00	1.00	1.28	1.28
$\boldsymbol{k_2}$	0.39	0.41	0.39	0.13	0.00	0.42
$\boldsymbol{\tau}$	0.25	0.17	0.16	0.06	0.14	0.27
AIC	-188.52	-247.03	-213.48	-235.08	-187.92	-139.08
BB7 Copulas - Sub-sample 2: During Trade war (From 1st January 2018 to 10th June 2019)						
$\boldsymbol{k_1}$	1.23	1.00	1.00	1.00	1.28	1.28
$\boldsymbol{k_2}$	0.39	0.41	0.39	0.13	0.00	0.42
$\boldsymbol{\tau}$	0.24	0.17	0.16	0.06	0.14	0.27
AIC	-187.99	-246.74	**212.94**	-235.44	-187.82	-139.13
BB7 Copulas - Full sample (From 13th June 2016 to 10th June 2019)						
$\boldsymbol{k_1}$	1.30	1.18	1.47	1.02	1.23	1.17
$\boldsymbol{k_2}$	0.08	0.10	0.44	0.11	0.03	0.00
$\boldsymbol{\tau}$	0.17	0.13	0.32	0.06	0.12	0.09
AIC	-104.06	-231.65	-195.02	-273.31	-239.29	-184.60

Notes. BB1 Copulas (known as Clayton-Gumbel) function is constructed by the formula $C_{BB1}(u;v;z;\underline{k}) = \left(1+[((u)^{-k_2}-1)^{k_1}+((v)^{-k_2}-1)^{k_1}+((z)^{-k_2}-1)^{k_1}]^{-\frac{1}{k_1}}\right)^{\frac{1}{k_2}}$ where $k_1 \geq 1$ and $k_2 \geq 0$. Therefore, the BB1 Copulas only capture for positive dependence only. This Copulas was mentioned in a study of Joe (1997) and applied in Patton (2006). The BB7 Copulas is called Joe-Clayton Copulas, which shares the similar structure with BB1. However, BB7 Copulas strictly follows the constraints with $k_1 \geq 0$ and $k_2 \geq 1$. (Hurd et al., 2007). The results of flexible function of Copulas are presented in the table with parameter and model selection based on AIC (Akaike Information Criterion). Due to the fit of Copulas is based on the combination of two kinds of Copulas, we refer to AIC for model selection. The maximum likelihood estimation will be available upon request.