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Short Communication

Extreme risk spillovers between China and major international stock markets

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Abstract: We examine the complex dependence structure and risk spillovers between the Chinese stock market and twelve major international markets. To this end, we employ three types of vine copulas and tests for the Granger causality in risk of Hong et al. (2009). The results indicate that the R-vine copula is the optimal model to characterize the high-dimensional dependence structure of the markets after China joined the WTO, which suggests obvious structural differences with varying degrees of mainly positive dependences. Moreover, we identify unilateral extreme risk spillovers from China to the United States, France, and Germany, and either from Japan to China. We also detect bilateral spillovers between China and the United States, Japan, as well as Australia.

Keywords: vine copula, high-dimensional dependence structure, Granger causality in risk, extreme risk spillover

JEL codes: G01, G15, F65

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1. Introduction

The high-dimensional dependence structure of financial markets has garnered enormous attention to its riskiness and spillover. According to Kim and Jung (2016), copulas have the feature of flexibility in distribution1, which is more appropriate in describing the dependence structure of a multi-dimension random variable, and they have become one of the most important tools for handling risk factors in finance, like Value at Risk (VaR). To date, some studies have demonstrated that the R-vine copula is more accurate in modeling high-dimensional distribution than C- and D-vines (Nikoloulopoulos et al. 2012; Koliai 2016). Extant empirical testing of risk spillovers among markets generally tends to, first, focus exclusively on spillovers among mature markets of developed countries (Bae et al. 2003; Bodart and Candelon 2009; Grobys and Klaus 2015) and, second, focus on spillovers between mature markets and emerging markets in the Asia Pacific region (Alotaibi and Mishra 2015). While relatively speaking, less work has focused on the risk spillovers between Chinese and foreign stock markets due to the faultiness of the former until it enters the WTO. Further, there is a growing divergence of opinion surrounding the presence and direction of these risk spillovers. Some scholars find that the Chinese market is largely immune to spillovers from foreign markets or the spillover strength is very weak. However, others argue that these risk spillovers have been increasing with the accelerating financial opening and reform of China. Specifically, international markets mainly influence the Chinese market through the United States and China Hong Kong, while China begins to influence its peripheral markets (Wang and Firth 2004).

Against this backdrop, we aim to shed some light on the high-dimensional dependence structure and extreme risk spillovers between the Chinese stock market and major international markets by contributing to the literature in the following ways. First, unlike most studies that simply specify the same GARCH(1,1)-t model, our marginal model is built on GARCH-type models, in which the standard innovation is to obey five different distributions. Second, we apply vine copulas to characterize the high-dimensional distribution. Third, as for estimating VaR, we use not only different classical approaches but also the Monte-Carlo simulation and out-of-sample forecasting in a rolling time window based on copulas. Finally, we employ tests for the Granger causality in risk of Hong et al. (2009) (hereafter, the Hong method) to examine the extreme risk spillovers among markets because, as a nonlinear test method, it focuses on the transfer of VaR failure information and provides a better fit than the linear measurement methods (e.g., the Granger causality test and GARCH-type models)3. The results reveal that the R-vine copula is the optimal model for our data. Furthermore, we detect that the Chinese market has unilateral or bilateral extreme risk spillovers with the United States, France, Germany, Japan, and Australia.

This paper proceeds as follows. Section 2 presents the data and methods. Section 3 discusses the empirical results. Finally, Section 4 concludes the study.

2. Data and Methods

This paper collects daily closing prices for thirteen representative stock market indices in developed and emerging economies (i.e., China's SSEC, China Hong Kong's HSI, China Taiwan's TWII, the United States SP500, Japan's N225, Korea's KOSPI, Australia's SP200, Britain's FTSE100, France's CAC40, Germany's DAX 30, Brazil's BVSP, Russia's RTS, and India's SSEX30) from Wind Information Inc.4 spanning from December 11, 2001, to December 31, 2018. The returns are computed as the first difference of the natural logarithm of prices multiplied by 100 for a total of 4138 daily observations. Table A.1 in the Online Appendix provides summary statistics on market returns.

We adopt a four-step empirical procedure to perform the Hong method for testing the presence and direction of extreme risk spillovers between the Chinese stock market and major international markets.

Step 1: For each return series, the GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) models with five different marginal specifications (i.e., Gaussian, Student's t, Skew-t, GED, and Skew-GED) are fitted to select the appropriate one5 for depicting the marginal distribution, which assures the validity of subsequent modeling.

Step 2: R-, C-, and D-vine copulas are adopted to determine the optimal model for characterizing the high-dimensional dependence structure of the sampled indices.

Step 3: We forecast the VaR of each index based on the optimal vine copula at 0.005, 0.01, and 0.05 quantiles. (1) We use the Monte-Carlo simulation to obtain $u1$, $u2$, …, uN from the optimal vine copula estimated in Step 2. (2) We calculate the (simulated) standardized residuals according to the inverse functions of the estimated marginals vit = Fit -1(uit), = 1,2, …, N. (3) We get the (simulated) asset returns Rit by using vit and the forecasted means and variances from Step 1. (4) We estimate VaR in a rolling time-window of one year (250 days) with the confidence level α:

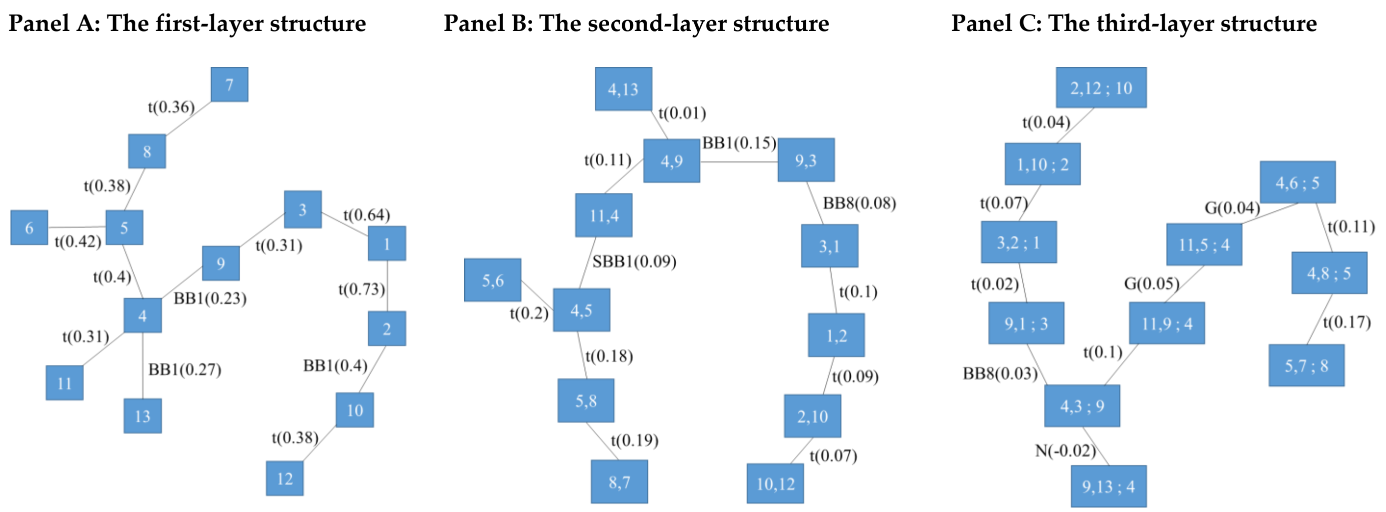
$$\{Rt < -VaR\alpha\} = 1 - \alpha. \quad (1)$$

Step 4: Closely following Hong et al. (2009), we employ the Hong method to test extreme risk spillovers.

3. Results

We demonstrate that R-vine copula is the optimal model to characterize the high-dimensional dependence structure of the sampled indices, whose estimation results of the first three layers are presented in Table A.2 in the Online Appendix. The results suggest obvious structural differences with varying degrees of mainly positive correlation. The corresponding R-vine tree sequence plots are given in Figure 1.

Figure 1. R-vine tree of the first three layer's plots: with copula families and Kendall's τ values.



Note: node abbreviations: 1 <-> CAC40, 2 <-> DAX30, 3 <-> FTSE100, 4 <-> HSI, 5 <-> KOSPI, 6 <-> TWII, 7 <-> SP200, 8 <-> N225, 9 <-> RTS, 10 <-> SP500, 11 <-> SSEX30, 12 <-> BVSP, 13 <-> SSEC.

From the first-layer tree structure, we can intuitively find the selected pair copula family and the unconditional Kendall's τ value. However, the corresponding indices should be eliminated when considering conditional dependence from other layers7. Further, our results reveal that VaR obtained by the Monte-Carlo simulation with out-of-sample forecasting in a rolling time window of one year based on R-vine copula outperforms those of classical approaches, i.e., the historical simulation, variance-covariance, and traditional linear weighted methods, which is consistent with Huang et al. (2009)8. Based on this, we apply the Hong method to examine extreme risk spillovers between Chinese and foreign markets. The results are shown in Table 1.

Table 1. Risk spillovers between stock markets based on R-vine copula

Direction	**M=10**			**M=20**		
	95%	99%	99.5%	95%	99%	99.5%
SSEC->HSI	0.2523	-0.5806	-0.1564	0.6716	-0.5472	-0.3833
SSEC<-HSI	0.4206	-0.7491	-0.4530	1.0619	-0.6921	1.2680
SSEC<->HSI	0.4690	-0.9461	-0.4371	1.2083	-0.8914	0.6087
SSEC->TWII	-0.6588	2.9691***	0.0896	-0.0773	4.4813***	0.2180
SSEC<-TWII	0.6870	0.7534	0.0246	0.7708	1.5856*	0.6857
SSEC<->TWII	0.0135	2.6241***	0.0742	0.4737	4.2688***	0.6222
SSEC->SP500	1.9975**	5.9122***	7.8106***	1.6492**	4.4840***	5.6832***
SSEC<-SP500	0.9932	-0.7110	-0.7416	0.9672	0.1578	3.1324***
SSEC<->SP500	2.1070**	3.6690***	4.9890***	1.8318**	3.2623***	6.2101***
SSEC->N225	0.0328	-0.8814	-0.3993	-0.2297	-1.1626	-0.2699
SSEC<-N225	4.7080***	-0.7183	-1.3000	3.8262***	-0.1049	-0.3125
SSEC<->N225	3.3436***	-1.1369	-1.2073	2.5240***	-0.9113	-0.4274
SSEC->KOSPI	-1.0242	-0.7593	-1.4229	-1.3015	-1.0723	-0.3309
SSEC<-KOSPI	1.1472	0.7845	0.8539	0.8546	0.6286	4.0440***
SSEC<->KOSPI	0.0804	0.0113	-0.4085	-0.3318	-0.3295	2.6064***
SSEC->SP200	2.3847***	1.7932**	6.5811***	2.1561**	4.3365***	9.1613***

SSEC<-SP200	2.0129**	-0.3620	0.5034	2.7720***	4.9785***	3.9300***
SSEC<->SP200	3.1011***	1.0049	4.9998***	3.4645***	6.5628***	9.2300***
SSEC->FTSE100	0.9039	-0.0143	2.2708**	0.4391	1.3457*	1.2458
SSEC<-FTSE100	1.5386*	1.9200**	0.2121	1.0647	8.4940***	4.0545***
SSEC<->FTSE100	1.7196**	1.3402*	1.7481**	1.0460	6.9335***	3.7274***
SSEC->CAC40	1.3005*	7.3403***	2.7218***	1.1034	12.0582***	4.8907***
SSEC<-CAC40	1.6076*	1.6586**	-0.5527	1.1105	13.3399***	4.9747***
SSEC<->CAC40	2.0486**	6.3528***	1.5264*	1.5476*	17.9221***	6.9516***
SSEC->DAX30	2.1785**	5.5197***	3.7458***	1.6744**	7.7219***	3.2661***
SSEC<-DAX30	1.1453	0.6402	-1.3252	0.3523	6.9900***	1.1240
SSEC<->DAX30	2.3423***	4.3465***	1.7041**	1.4153*	10.3746***	3.0845***
SSEC->BVSP	-0.2446	1.3027*	0.9893	-0.0696	1.6351*	5.2428***
SSEC<-BVSP	0.0075	-0.8590	-0.5584	-0.4320	-1.1795	-0.4306
SSEC<->BVSP	-0.1740	0.3071	0.2980	-0.3704	0.3057	3.3826***
SSEC->RTS	-0.7436	2.6219***	-0.0653	-1.0453	5.0732***	-0.3231
SSEC<-RTS	0.0790	3.3327***	1.4950*	0.2712	17.1354***	11.0906***
SSEC<->RTS	-0.4761	4.2014***	1.0038	-0.5629	15.6693***	7.5887***
SSEC->SSEX30	-1.2503	2.7034***	0.0940	-1.5537	3.4356***	0.4056
SSEC<-SSEX30	1.5218*	0.7949	-0.6680	1.2738	0.8897	-0.7543
SSEC<->SSEX30	0.1854	2.4657***	-0.4121	-0.2138	3.0387***	-0.2624

Note: *M* is a smoothing parameter. 95%, 99%, and 99.5% are the confidence levels when estimating *VaR*. "- >" and "<-" represent unilateral tests from the former to the latter and from the latter to the former, respectively, while "<->" represents a bilateral test. ***, **, and * indicate the statistical significance level at 1%, 5%, and 10%, respectively.

As we can clearly see, regardless of whether M equals 10 or 20, there are significantly unilateral extreme risk spillovers of the stock market from China to the United States, France, and Germany, and either from Japan to China. Furthermore, we detect bilateral spillovers between China and the United States, Japan, and Australia.

4. Conclusion

This study measures the high-dimensional dependence structure between thirteen major international markets by the vine copulas and implements the family of GARCH used to reintroduce the heteroskedasticity in the returns, which demonstrates that R-vine copula is superior to C- and Dvines in modeling multivariate distributions. Further, we perform the Hong method based on VaR estimation while detecting significantly unilateral extreme risk spillovers from China to the United States, France, and Germany, and either from Japan to China. Our empirical findings also suggest that there are bilateral spillovers between China and the United States, Japan, as well as Australia. The findings herein preliminarily affirm that the Chinese stock market has influenced foreign markets with the rapid development of the economy in China, although its external spillover intensity is still significantly lower than that from international markets. Future studies may focus on the economic and technical reasons why the above findings manifest.

Supplementary Materials: Online Appendix is available from the authors.

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Conflicts of Interest: The authors declare no conflict of interest

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