



A new view of risk contagion by decomposition of dependence structure: Empirical analysis of Sino-US stock markets

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ARTICLE INFO

JEL classification:

C58

G11

Keywords:

Risk contagion

Dependence structure

Patched Bivariate Fréchet copula

Comonotonicity

ABSTRACT

With the fragile recovery of world economy and increasing financial uncertainty, global capital allocations and risk management become more sensitive to the risk spillover and contagion among financial markets, especially in extreme conditions. We propose a new view to detect risk contagion by the local comonotonicity and counter-monotonicity decomposed from dependence structure. It allows us to distinguish risk spillover, portfolio diversification risk, mild, moderate and severe contagions in the uniform framework. We apply it to analyze the identifications and degrees of risk contagion between Sino-US stock markets, and then find that they experience higher frequencies of portfolio diversification risk and moderate contagions while fewer proportions of mild and severe contagions. Impact factors from United States play the main role in increasing the odd ratio of risk spillover and moderate contagion between Sino-US stock markets. Our results can help global investors to develop sophisticated risk strategies by revealing structure information of dependence.

1. Introduction

Recently, the outbreak of global COVID-19 epidemic and volatility of global capital markets have raised heated discussions on the financial risk contagion from all walks of life (Chopra & Mehta, 2022; Jebabli et al., 2022; Levy et al., 2022; Nguyen et al., 2022; Zhu et al., 2021, etc.). World Bank summarizes definitions of risk contagion in three levels. In a broad sense, risk contagion refers to transnational transmission of shocks or general transnational spillover effects (see Eichengreen et al., 1996; Mantegna, 1999; Ramchand & Susmel, 1998, etc.); In a narrow sense, contagion refers to the dependence of crisis transmission to other countries beyond common impact of any economic fundamentals, also called excessive linkage or 'pure contagion' (see Bekaert et al., 2014; BenSaïda, 2018; Forbes & Rigobon, 2002; Gray, 2009; Pesaran & Pick, 2007, etc.); Risk contagion in a very strict sense refers to the significant increase of volatility dependence between financial markets in a crisis period, relative to a stable market (see Barberis et al., 2005; Diebold & Yilmaz, 2009, 2012, 2014). Following these classical definitions, Bradley and Taqqu (2004) focused on the discrepancies between the probability mass concentrated in the tail and central sets of the probability distributions of target financial time series, referred as the 'spatial contagion' (see further discussions in Durante et al., 2014; Durante & Jaworski, 2010; Jaworski & Pitera, 2014; Zorgati & Lakhal, 2020). As we can see, most of the literature detects risk contagion on

the premise of dependence even with the disunity of its definitions. However, few studies in the literature further differentiate the level of risk contagion, which is also meaningful for investors to balance the benefits and costs of handling risk contagion. We make stress on decomposition of dependence structure in the probability way to detect different levels of contagion.

Dependence structure includes more information than single dependence coefficients, where two maximum and minimum structures, i.e., comonotonicity and counter-monotonicity obtain more and more interest in the fields of actuary and risk contagion (see Bedoui et al., 2018; Dai et al., 2020, etc.). Comonotonicity (or counter-comonotonicity) gives the upper-bound (or lower bound) of dependence caused by the common underline factor which is closer to the characteristics of risk contagion. Artzner et al. (1999) first studied the comonotonic structure in the field of financial mathematics, and Dhaene et al. (2002) introduced this concept into the field of actuary where it is popular to use comonotonicity to determine the upper limit of capital requirements of portfolio (see also Denuit & Lambert, 2005; Koch-Medina et al., 2018, etc.). As comonotonicity between financial markets was not common or even non-existent at an early stage, it is rarely mentioned in the field of risk contagion until Global Finance Crisis (GFC for short) in 2008. However, the increased market correlation severely undermined the international diversification during GFC crisis. Investors must accurately assess the degree of risk spillover and

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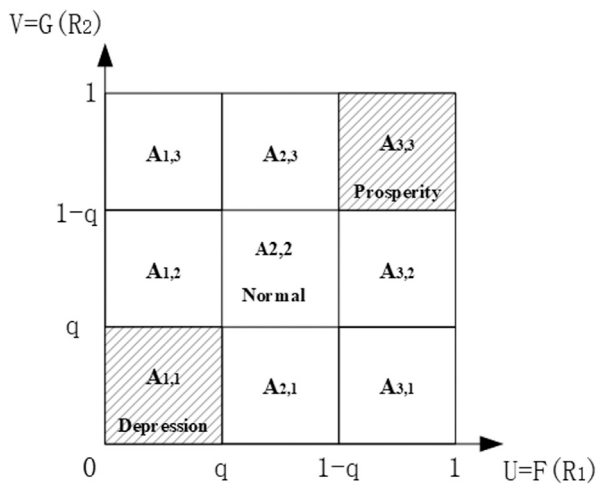


Fig. 1. Segmentations of market conditions.¹

contagion between global markets to ensure portfolio returns and risks. Meanwhile, academics detected local comonotonicity in extreme market especially when more and more assets witnessed larger risk loss along with some underlining system factor, and then applied comonotonicity and counter-monotonicity to measure risk contagion (Cherubini & Mulinacci, 2014; Cheung, 2009; Sass & Thörs, 2021; Zhang & Duan, 2013). But there is still a gap on how to identify and forecast risk contagion by them. Under a unified framework of decomposition of dependence structure, we argue that it is workable to identify contagion by comonotonicity and distinguish levels of contagion by counter-monotonicity.

Mixed copula is one efficient way to model complex dependence structure being independent of marginal distributions. Yang et al. (2006) proved that any dependence structure is decomposed uniquely as a convex combination of comonotonicity, independence, counter-monotonicity and an undecomposable part. Zheng et al. (2011) constructed Patched Bivariate Fréchet (PBF) copula family to approximate any bivariate copula and proved the convergency (see further discussions in Durante et al., 2015, 2013). In the sense of probability, the change of dependence is a comprehensive expression of changes of comonotonic and counter-monotonic structures. Based on these findings, the present work is to apply PBF copulas to analyze risk contagion and its levels in extreme market condition, by defining risk contagion as abnormal increasing of the local comonotonic structure and further measuring the local counter-monotonic structure's offsetting effect to distinguish the levels of contagion. As an empirical application of our model, we concentrate on one of the most concerned bilateral relations, i.e., Sino-US stock markets whose relationship witnesses enormous changes and dependence structure becomes more complex. In addition to identification and classification of risk contagion in the new framework, we also analyze their annual contagion dominance and influence factors of different channels. It is meaningful for global investors to form accurate judgment on dealing with the possible risk contagion between Sino-US stock markets.

Our contributions are concluded as following. Firstly, we provide a new way to classify and identify the risk contagion under the unified framework of decomposition of dependence structure. With the

inspiration of comonotonicity and counter-monotonicity with intuitive probabilistic structures, investors experiencing risk shocks in extreme markets may develop more definite decisions rather than aggressively avoiding or reducing risk exposures of some certain assets or markets. Secondly, we illustrate the structural characteristics of risk contagion between Sino-US stock markets, i.e. their asymmetry of identification and symmetry of dominance of risk contagion, which enrich the in-depth insight into the interdependence between the capital markets of the two major global economies. Finally, we provide complete details of model specifications, algorithms, empirical analysis, and robustness of the decomposition of dependence structure, which is a solid foundation for this new framework to further apply in the network analysis of multi-financial assets or markets.

The paper is structured as follows. Section 2 reviews related literatures. Section 3 provides how to realize the decomposition of dependence structure and the identifications of contagion. Then, Section 4 offers the empirical results on identification, degrees, dominance and influence factors of risk contagion between Sino-US stock markets and discusses the robustness. Finally, Section 5 represents the conclusions. The algorithms and robust results are presented in Appendix.

2. Literature reviews

Dependence is one efficient way to detect risk contagion, as it is usually experienced with a significant increase when contagion occurs, but the reverse is not necessarily true. Extensive research investigated risk contagion by focusing on conditional correlations (Eichengreen et al., 1996; Mantegna, 1999; Ramchand & Susmel, 1998; Yousfi et al., 2021), but it is easy to ignore the difference between dependence and contagion. Isolating contagion from dependence gradually attracted the attention of academics. Forbes and Rigobon (2002) first recommended a heteroskedasticity bias test to detect evidence of contagion regardless of any other effect due to interdependence or market volatility. Then more researchers argued that increased dependence does not necessarily mean contagion (Bekaert et al., 2014; BenSaïda, 2018; Gray, 2009; Pesaran & Pick, 2007). However, most of the above identification models of risk contagion are driven by crisis events and have to face the problem of inconsistent identifications caused by insufficient crisis observations. To avoid prior specification of crisis/non-crisis periods, Bradley and Taqqu (2004) used the joint probability distributions to identify the relationship between local dependence coefficients and the 'spatial contagion'. Durante et al. (2014) used copulas to extend the identification of spatial contagion to non-linear dependence. Note that copula function defines not only the degree of dependence, but also the structure of dependence. Baur (2013) illustrated that contagion is a phenomenon that leads to changes both in the degree and the structure of dependence including changes in the lower and upper tails of the distribution. Therefore, we go forward to study the degree of contagion from the view of dependence structure.

With frequent occurrence of financial crises in recent decades, dependence structure under extreme markets has become increasingly monotonous, especially for large asset portfolios. Cheung (2009) first defined the upper comonotonicity to accurately describe this phenomenon, and then Zhang and Duan (2013) defined the lower tail and center comonotonicity for supplementary, which provides more theoretical support for applications of comonotonicity in the field of risk contagion. From the perspective of distortion risk and systematic risk measurement, Cherubini and Mulinacci (2014) calculated the explicit relationships between comonotonicity and typical measurements of systemic risk, such as CoVaR and marginal expected loss (MES), and constructed the distortion risk measurement of contagion, being applied to measure the distortion risk of Bank Solvency in European debt crisis. On the other hand, counter-monotonic structure plays an important role in hedging and diversification effects for portfolio optimization. Baur and Lucey (2009) believed that in the early stage of crisis, investors always pursue higher quality and safe assets (i.e., flight

¹ As previous literature divides market conditions into bullish, normal, and bearish, we also divide it into three cases, including two extreme sub-spaces $A_{1,1}$ and $A_{3,3}$ and the rest normal subspace, although we obtain nine sub-spaces by PBF copulas. It is not the most effective way to divide market conditions equally in this paper. However, we still observe the structure information of dependence by decomposition. We continue research on the contagion analysis under the unequal division of market conditions.

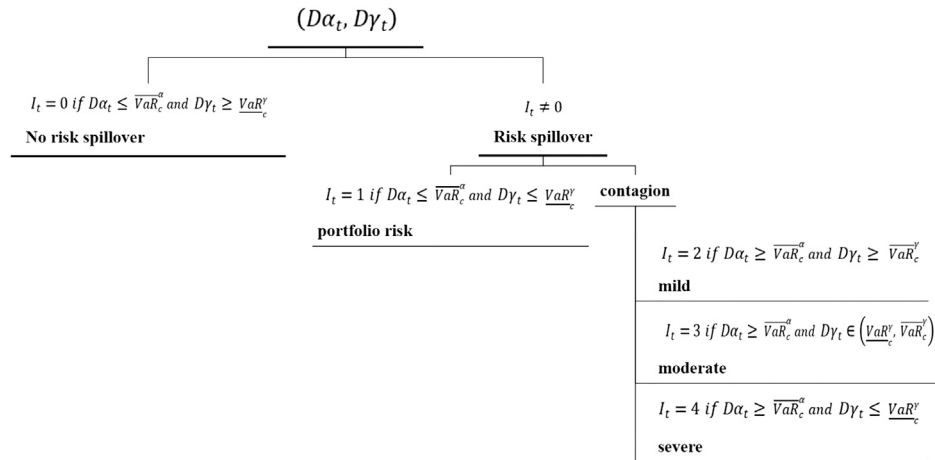


Fig. 2. Identification of risk contagion.

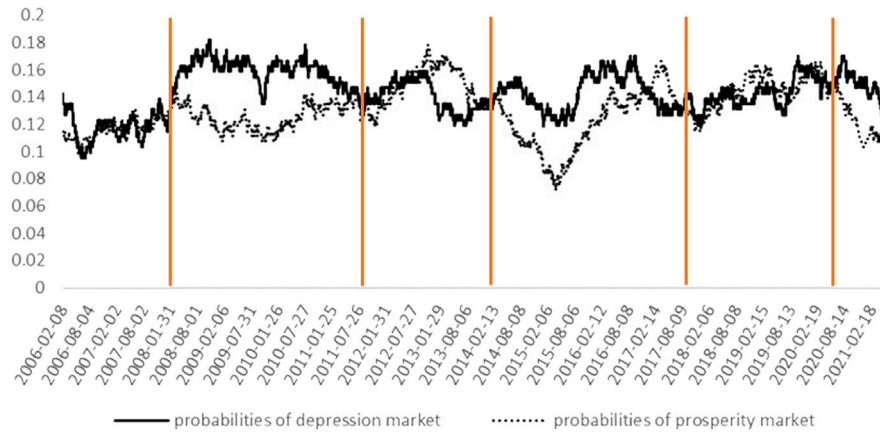


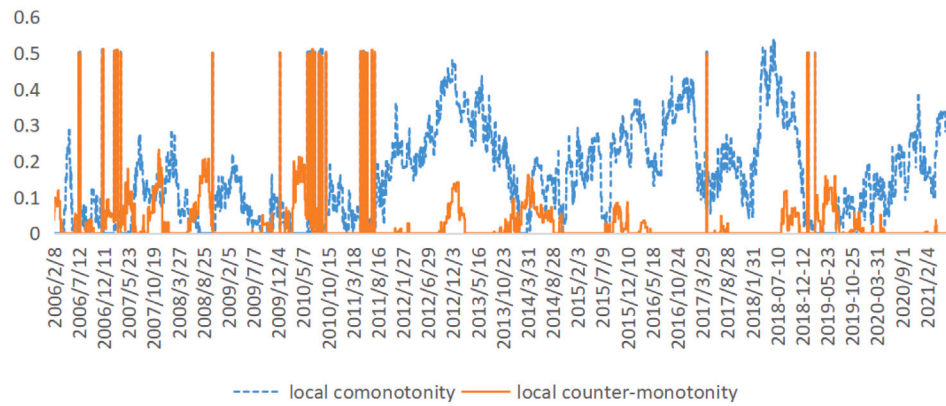
Fig. 3. Dynamic probabilities of depression and prosperity markets.

Table 1

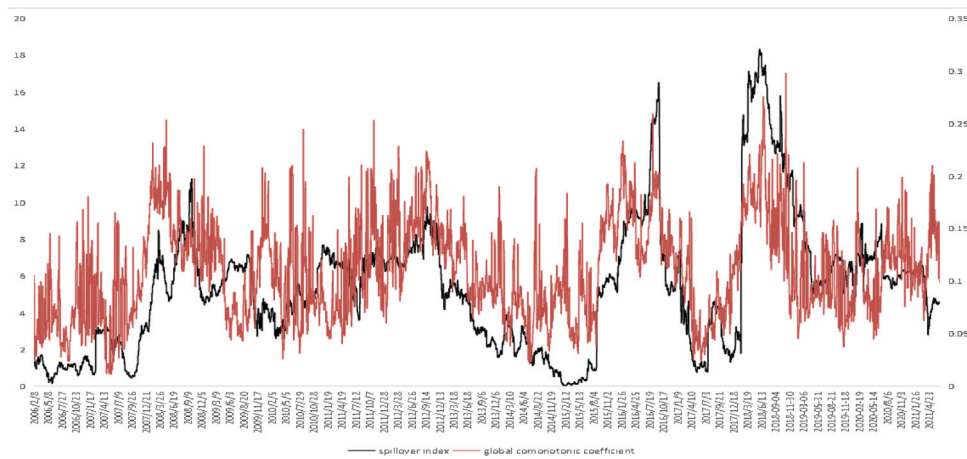
Impact factors on identification and classification of risk contagion.

Channels	Abbreviation	Full name	Frequency
Finance	Ar0	Federal Funds Rate	Daily
	Ar10	TNOTE(The US 10-year Treasury note)	Daily
	Libor	LIBOR	Daily
	Shibor	Shanghai InterBank Offered Rate	Daily
	Cr7	Interbank lending rate(7 days)	Daily
Trade	Import	China from US	Monthly
	Export	China to US	Monthly
	Rex	Midpoint: USD to RMB	Daily
EU: economics uncertainty	WTI	West Texas Intermediate	Daily
	Gold	COMEX Gold	Daily
	VIX	CBOE Volatility Index	Daily
EPU: economics policy uncertainty	AEPUS	US EPU (US Daily News Index)	Monthly
	APEU2	US EPU (US Historical News-Based Policy Index)	Monthly
	CEPU	News_Based_Policy_Uncert_Index	Monthly
	GEPU	Global Economic Policy Uncertainty Index (based on current-price GDP)	Monthly
	GEPU2	Global Economic Policy Uncertainty Index (based on PPP-adjusted GDP)	Monthly
Consumer confidence	Sentix	USA: Sentix Investor Confidence	Monthly
	CS-C	Consumer Confidence Index(China)	Monthly
	CS-A	USA: Michigan University Consumer Sentiment Index	Monthly

Note: Continuous variables are standardized by Z-score, and outliers with more than three times variance are subject to tailing. We directly use the monthly data as its daily data of this month when performing logistic regression.



(a) Local comonotonic versus counter-monotonic coefficients in the depression market



(b) Global comonotonic coefficients versus spillover index

Fig. 4. Comparisons of the target dynamic coefficients between Sino-US stock markets.

to quality), and their trading behavior weakens the dependence between markets with different risk levels, generating risk diversification. Soyulu and Güloğlu (2019) pointed out that categorizing risk spillovers as interdependence, contagion, and flights could provide important insights for investors who want to diversify or reduce risks. Inspired by the above literature, we aim to identify risk contagion by comonotonicity and analyze its degree by counter-monotonicity in depression markets.

As the two largest economies in the world, risk spillover and contagion between stock markets of United States and China have attracted popular attention of industry and academia (Bhuyan et al., 2016; Chien et al., 2015; Jennifer et al., 2021; Selmi et al., 2019; Shan et al., 2022; Shu et al., 2018; Wan et al., 2021). Most of literature on the relationship between Sino-US stock markets focuses on three aspects: comparisons of risk characteristics, risk spillover from US stocks markets and their dependence (Guidi et al., 2016; Guo et al., 2021; Li & Lu, 2017; Shi et al., 2021; Wan et al., 2021; Yang et al., 2018; Zhang et al., 2019; Zhang & Li, 2014, etc.). Part of literature illustrates that US stock market shows robust and significant risk spillover on Chinese stock market, and owns significant predictability on Chinese stock market's return and volatility. While part of literature uses more structured models to show that a bidirectional impact has been detected in recent years, illustrating Chinese stock market can not only reflect the market information of US stock market, but also has the ability to affect the US stock market. For example, Wan et al. (2021) illustrated that the dynamic linkage between Sino-US stock markets strengthened since 2004 in general, whereas risk contagion spread heterogeneously during the global financial crisis; Pan et al. (2021) investigated the dynamic

Table 2
Descriptive statistics.

	Size	min	max	mean	std	Skewness	Kurtosis
SCI	3880	-0.009	0.009	0.00027	0.0016	-0.540	7.624
S&P500	3880	-0.128	0.110	0.00033	0.0013	-0.545	16.910
ρ^{pe}				0.168***			
ρ^{pea}				0.181***			
τ				0.114***			
Ar10	2800	0.520	3.980	2.323	0.734	-0.137	-0.201
Ar0	2800	0.040	2.450	0.534	0.712	1.537	0.905
Libor	2800	0.050	2.400	0.554	0.699	1.514	0.841
Shibor	2800	0.600	13.440	2.296	0.946	1.997	12.298
Cr7	2800	0.920	12.250	3.031	1.087	1.320	5.581
Rex	2800	6.090	7.130	6.562	0.291	-0.026	-1.267
Import	150	49.545	172.904	112.469	25.659	-0.182	-0.231
Export	150	104.889	519.766	318.716	79.115	-0.270	-0.124
WTI	2800	10.010	112.860	68.511	22.148	0.160	-1.117
Gold	2800	811.600	2075.200	1368.735	249.380	0.493	-0.379
VIX	2800	9.140	82.690	19.186	8.429	2.152	7.004
AEPV	150	63.877	503.963	158.225	71.241	2.092	5.804
APEU2	150	71.262	350.460	140.578	47.140	1.488	3.151
CEPU	150	26.144	970.830	323.932	255.243	1.011	-0.111
GEPU	150	86.302	430.177	169.015	69.070	1.293	1.339
GEPU2	150	84.971	437.172	172.264	72.064	1.254	1.104
Sentix	150	-50.500	40.100	8.944	18.884	-1.029	0.846
CS-C	150	97.000	127.000	109.709	8.897	0.585	-1.133
CS-A	150	55.700	101.400	83.539	11.800	-0.268	-0.983

Note: ρ^{pe} represents the Spearman's rho; ρ^{pea} represents the Pearson's rho; τ represents Kendall's rho, respectively. *** represent the statistical significance at the 1% level.

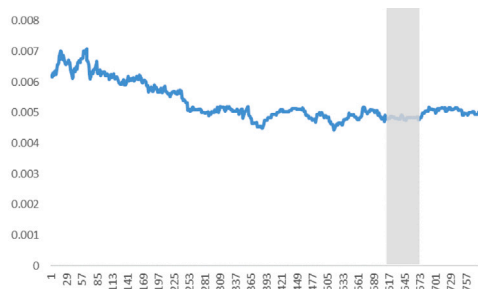
Table 3
Comparisons of goodness-of-fit tests for copulas.

Basic copula models									
Copulas		Parameter	Spearman	Kendall	Upper-tail	Lower-tail	MSE		
Gaussian		0.1806	0.1727	0.1156	0.0000	0.0000	1.25 * 10 ⁻⁴		
T-copula		0.1850 7.2381	0.1743	0.1185	1.9060	1.9060	1.09 * 10 ⁻⁴		
Clayton		0.2550	0.1689	0.1131	0.0000	0.0660	1.59 * 10 ⁻⁴		
Gumbel		1.1089	0.1463	0.0982	0.1316	0.0000	1.66 * 10 ⁻⁴		
Frank		1.1022	0.1808	0.1210	0.0000	0.0000	1.18 * 10 ⁻⁴		
PBF copula model									
Local comonotonic matrix			Local counter-comonotonic matrix			Probabilities of market conditions			MSE
0.0000	0.0000	0.0468	0.0116	0.0138	0.0000	0.0861	0.1183	0.1289	1.55 * 10 ⁻⁵
0.0000	0.0122	0.0057	0.0096	0.0154	0.0360	0.1036	0.1196	0.1101	
0.2373	0.0223	0.0000	0.0000	0.0000	0.0040	0.1436	0.0954	0.0944	

Table 4
Annual proportions of contagion identifications.

Year T	c = 0.9					c = 0.95				
	$I_t = 0$	$I_t = 1$	$I_t = 2$	$I_t = 3$	$I_t = 4$	$I_t = 0$	$I_t = 1$	$I_t = 2$	$I_t = 3$	$I_t = 4$
2009	87.71%	5.51%	1.27%	4.66%	0.85%	94.49%	1.27%	1.27%	2.97%	0.00%
2010	70.46%	24.05%	2.11%	3.38%	0.00%	75.95%	18.99%	2.11%	2.95%	0.00%
2011	77.64%	5.91%	3.38%	12.66%	0.42%	85.65%	4.64%	3.38%	6.33%	0.00%
2012	82.83%	8.15%	0.86%	7.30%	0.86%	93.56%	3.00%	0.43%	2.58%	0.43%
2013	79.91%	10.04%	1.31%	7.86%	0.87%	93.01%	3.06%	0.44%	3.49%	0.00%
2014	77.54%	15.25%	1.27%	5.08%	0.85%	87.71%	8.47%	0.42%	2.97%	0.42%
2015	77.64%	11.39%	0.42%	9.70%	0.84%	89.87%	3.80%	0.00%	6.33%	0.00%
2016	85.11%	4.68%	0.00%	10.21%	0.00%	94.04%	1.28%	0.00%	4.68%	0.00%
2017	85.59%	1.69%	2.12%	9.75%	0.85%	94.07%	0.42%	0.42%	4.66%	0.42%
2018	75.64%	9.83%	0.85%	13.68%	0.00%	88.46%	4.70%	0.00%	6.84%	0.00%
2019	77.54%	17.80%	0.85%	3.39%	0.42%	87.71%	9.75%	0.85%	1.69%	0.00%
2020	84.68%	2.13%	0.00%	11.91%	1.28%	94.04%	0.43%	0.00%	5.53%	0.00%
2021	93.04%	0.00%	0.87%	5.22%	0.87%	98.26%	0.87%	0.00%	0.87%	0.00%
mean	81.18%	8.96%	1.18%	8.06%	0.62%	90.53%	4.67%	0.72%	3.99%	0.10%
std	5.76%	6.64%	0.89%	3.40%	0.40%	5.44%	5.00%	0.97%	1.81%	0.18%

Note: $\{I_t \neq 0\}$ means risk spillover. $\{I_t = 1\}$ represents portfolio diversification risk; $\{I_t = 2, 3, 4\}$ represents mild, moderate and severe contagion.



(a) MSE of forecast local comonotonicities



(b) MSE of forecast local counter-monotonicities

Fig. 5. Mean square errors with different forecast windows.

conditional correlations (DCC) with leverage and volatility spillover effects between Sino-US stock markets during the Sino-US trade friction and found bidirectional spillovers in the mean and volatility. In the new view of risk contagion, we make empirical analysis on the dependence structure between Sino-US stock markets to investigate their risk contagion's characters and influence factors in terms of identification and degree.

3. Methodology

Let R_1 and R_2 represent the logarithm return rates of target random variables. The marginal distributions are $F(\cdot)$ and $G(\cdot)$, and $H(\cdot, \cdot)$ is their joint distribution function. According to Sklar's theorem (Sklar

(1959)), for the joint distribution $H(\cdot, \cdot)$, there is a copula $C(\cdot, \cdot)$ such that,

$$H(\cdot, \cdot) = C(F(x), G(y)), \forall x, y \in (-\infty, +\infty). \quad (1)$$

For any copula $C(u, v)$, it is known that,

$$W(u, v) \leq C(u, v) \leq M(u, v), \quad (2)$$

where $M(u, v) = P(U \leq u, U \leq v) = \min\{u, v\}$, $W(u, v) = P(U \leq u, 1 - U \leq v) = \max\{u + v - 1, 0\}$ are comonotonicity and counter-monotonicity. Another basic copula $\Pi(u, v) = uv$ is independent structure, and their linear convex combinations give the family of Bivariate Fréchet (BF) copulas, i.e.,

$$C(u, v) = \alpha * M(u, v) + \beta * \Pi(u, v) + \gamma * W(u, v). \quad (3)$$

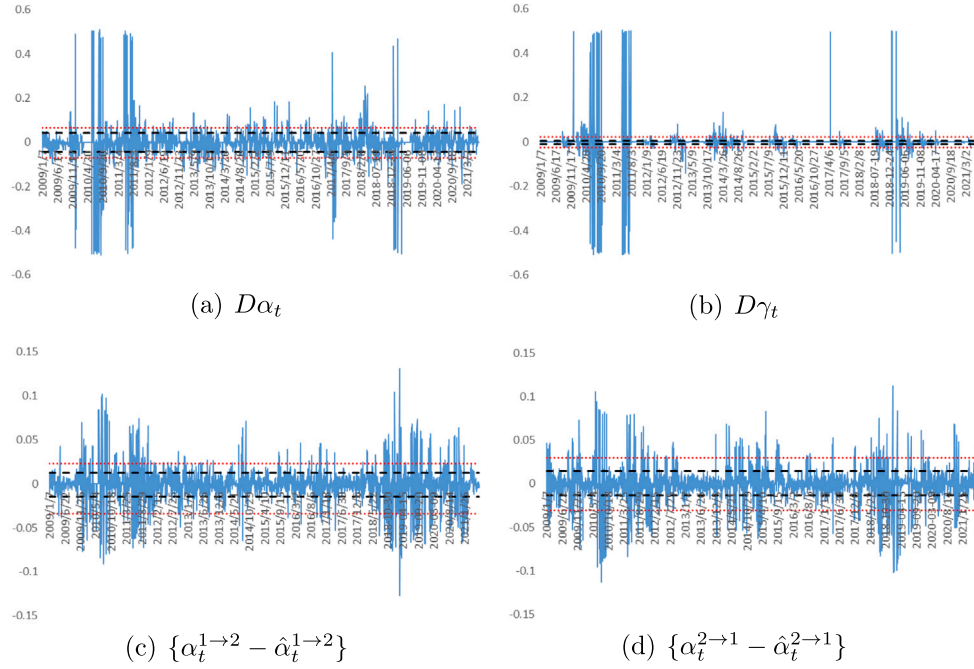


Fig. 6. Deviation from the true value to the forecast.

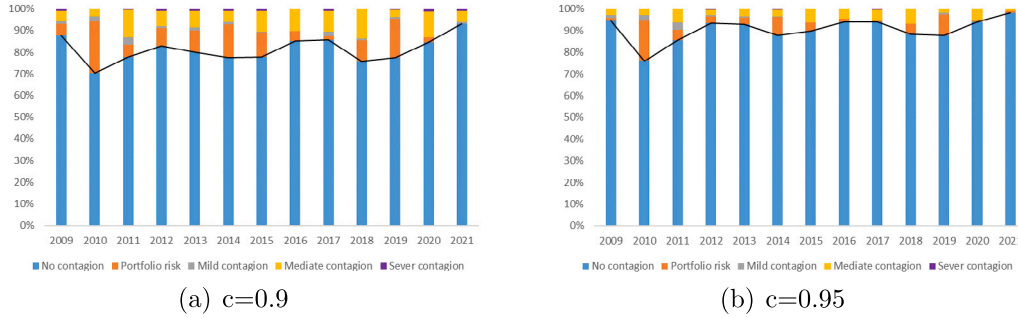


Fig. 7. Annual proportions of contagion identifications.

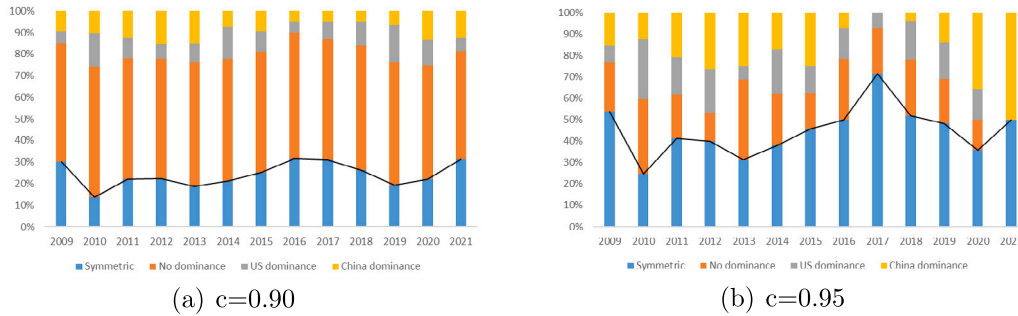


Fig. 8. Annual proportions of contagion dominance.

Although dependence structure of BF copula is intuitive and easy to understand, it performs poorly in empirical fitness, limiting its application in finance. To improve the goodness-of-fit, Zheng et al. (2011) provides Patched Bivariate Fréchet (PBF) copulas, which makes use of Bivariate Fréchet copula to approximate the local dependence structures with the conditional margins in each sub-space unchanged.

That is, we can rewrite the original copula C as

$$C(u, v) = \sum_{i=1}^3 \sum_{j=1}^3 P(A_{i,j}) C^{i,j}(F_{i,j}(u), G_{i,j}(v)). \quad (4)$$

By keeping the $P(A_{i,j})$, $F_{i,j}(u)$ and $G_{i,j}(v)$ unchanged, we chose the best BF copula $C_{a_{i,j}^*}^{F_{i,j}^*}(F_{i,j}(u), G_{i,j}(v))$ to approximate the complex copula $C^{i,j}$

Table 5
Annual proportions of contagion dominance.

Year T	c = 0.90				c = 0.95			
	No dominance	US	China	Symmetric	No dominance	US	China	Symmetric
2009	54.72%	5.66%	9.43%	30.19%	23.08%	7.69%	15.38%	53.85%
2010	60.34%	15.52%	10.34%	13.79%	35.09%	28.07%	12.28%	24.56%
2011	55.79%	9.47%	12.63%	22.11%	20.59%	17.65%	20.59%	41.18%
2012	55.56%	6.94%	15.28%	22.22%	13.33%	20.00%	26.67%	40.00%
2013	57.50%	8.75%	15.00%	18.75%	37.50%	6.25%	25.00%	31.25%
2014	56.38%	14.89%	7.45%	21.28%	24.14%	20.69%	17.24%	37.93%
2015	55.79%	9.47%	9.47%	25.26%	16.67%	12.50%	25.00%	45.83%
2016	58.33%	5.00%	5.00%	31.67%	28.57%	14.29%	7.14%	50.00%
2017	55.74%	8.20%	4.92%	31.15%	21.43%	7.14%	0.00%	71.43%
2018	57.58%	11.11%	5.05%	26.26%	25.93%	18.52%	3.70%	51.85%
2019	56.99%	17.20%	6.45%	19.35%	20.69%	17.24%	13.79%	48.28%
2020	52.94%	11.76%	13.24%	22.06%	14.29%	14.29%	35.71%	35.71%
2021	50.00%	6.25%	12.50%	31.25%	0.00%	0.00%	50.00%	50.00%
mean	55.97%	10.02%	9.75%	24.26%	21.64%	14.18%	19.42%	44.76%
std	2.44%	3.75%	3.63%	5.39%	9.30%	7.17%	13.00%	11.32%

Table 6
Factor analysis on identification of risk spillover and contagion since 2009.

Factors	Identifications of risk spillover							
	Univariate analysis				Multivariate analysis			
	B	P-value	exp(B)	F-score	B	P-value	exp(B)	F-score
Ar0	0.149	0.119	1.160	0.800				
Ar10	0.195***	0.003	1.216	0.728	0.195***	0.003	1.216	0.728
Libor	0.160	0.109	1.173	0.800				
Shibor	0.089*	0.077	1.093	0.798				
Cr7	0.08	0.113	1.084	0.806				
Rex	−0.067	0.531	0.935	0.893				
Import	−0.144**	0.031	0.866	0.769				
Export	0.067	0.296	1.069	0.826				
WTI	0.135***	0.006	1.144	0.720				
Gold	−0.064	0.227	0.938	0.825				
VIX	0.025	0.663	1.025	0.873				
AEPu	−0.136***	0.009	0.873	0.667				
APEU2	−0.095*	0.061	0.909	0.719				
CEPU	−0.094**	0.043	0.910	0.674				
GEPU	−0.084	0.117	0.920	0.738				
GEPU2	−0.094*	0.077	0.910	0.702				
Sentix	0.019	0.690	1.020	0.894				
CS-C	−0.018	0.725	0.982	0.894				
CS-A	−0.015	0.776	0.985	0.894				
Classifications of portfolio diversification risk and moderate contagion								
Ar0	−0.343*	0.053	0.71	0.352				
Ar10	−0.950***	0.000	0.387	0.640				
Libor	−0.371**	0.046	0.69	0.352				
Shibor	0.170	0.096	1.185	0.598	0.452***	0.001	1.572	0.709
Cr7	0.155	0.139	1.168	0.562				
Rex	−0.511**	0.012	0.600	0.561				
Import	0.608***	0.000	1.837	0.582	0.846***	0.000	2.331	
Export	0.384***	0.006	1.468	0.546				
WTI	−0.314***	0.001	0.731	0.592	−0.711***	0.000	0.491	
Gold	0.290*	0.057	1.336	0.560	−1.181***	0.000	0.307	
VIX	0.158	0.165	1.171	0.591				
AEPu	0.374***	0.001	1.453	0.599				
APEU2	0.268**	0.015	1.307	0.545				
CEPU	0.052	0.539	1.054	0.620				
GEPU	−0.164	0.664	0.849	0.513				
GEPU2	0.000	1.000	1.000	0.695				
Sentix	0.040	0.706	1.041	0.603				
CS-C	0.073	0.461	1.075	0.639				
CS-A	0.129	0.189	1.137	0.593				

Note: From Table 4 in Section 4.3, the total proportions of risk (i.e., risk spillover is identified) between Sino-US stock markets account for about 20%, thus we set 0.2 as class-weight threshold to ensure a better classification forecast rate. As the proportion of portfolio risk (i.e. P_1^T) and moderate contagion (i.e. P_3^T) is roughly the same, we use the default class-weight threshold 0.5.

Table 7

Factor analysis on identification of risk spillover and contagion in 2010–2012.

Factors	Identifications for risk spillover							
	Univariate analysis				Multivariate analysis			
	B	P-value	exp(B)	F-score	B	P-value	exp(B)	F-score
Ar0	2.163	0.495	8.700	0.640				
Ar10	−0.144	0.424	0.866	0.711				
Libor	4.218	0.146	67.893	0.603				
Shibor	−0.089	0.326	0.915	0.572				
Cr7	−0.074	0.391	0.929	0.618				
Rex	0.785**	0.048	2.192	0.647				
Import	−0.897***	0.000	0.408	0.647				
Export	0.27	0.342	1.309	0.685				
WTI	−0.926***	0.000	0.396	0.648				
Gold	−0.155	0.251	0.856	0.706				
VIX	0.504***	0.000	1.655	0.740	0.517***	0.001	1.677	0.764
AEPV	−0.159	0.373	0.853	0.663				
APEU2	−0.315	0.110	0.730	0.663	−0.604***	0.003	0.546	
CEPU	0.002	0.994	1.002	0.848				
GEPU	0.341	0.130	1.406	0.739				
GEPU2	0.244	0.276	1.276	0.745				
Sentix	−0.475**	0.011	0.622	0.589	−0.374***	0.067	0.688	
CS-C	1.282***	0.000	3.603	0.645	0.730***	0.014	2.076	
CS-A	−0.154	0.525	0.857	0.765				
Classifications of portfolio diversification risk and moderate contagion								
Ar0	−31.438***	0.000	0.000	0.750				
Ar10	−2.429***	0.000	0.088	0.791				
Libor	−22.164***	0.000	0.000	0.750				
Shibor	0.778***	0.001	2.176	0.818				
Cr7	0.705***	0.001	2.025	0.831				
Rex	−5.594***	0.000	0.004	0.842	−4.137***	0.002	0.016	0.764
Import	3.960***	0.000	52.439	0.847				
Export	3.309***	0.000	27.370	0.650				
WTI	2.368***	0.000	10.677	0.833				
Gold	3.973*	0.068	53.126	0.692				
VIX	0.641**	0.017	1.898	0.737				
AEPV	2.229***	0.000	9.287	0.836				
APEU2	3.375***	0.000	29.226	0.845	1.429***	0.003	4.173	
CEPU	4.919***	0.000	136.882	0.853				
GEPU	−12.691***	0.004	0.000	0.694				
GEPU2	−5.745***	0.000	0.003	0.694				
Sentix	−1.365***	0.001	0.255	0.756				
CS-C	−4.509***	0.000	0.011	0.781				
CS-A	−2.317***	0.000	0.099	0.752				

by minimizing MSE (mean square errors), i.e.,

$$C^*(u, v) = \sum_{i=1}^3 \sum_{j=1}^3 P(A_{i,j}) C_{\alpha_{i,j}^*, \gamma_{i,j}^*}^F(F_{i,j}(u), G_{i,j}(v)), \quad (5)$$

where

$$C_{\alpha_{i,j}^*, \gamma_{i,j}^*}^F = \alpha_{i,j}^* * M(u, v) + (1 - \alpha_{i,j}^* - \gamma_{i,j}^*) * \Pi(u, v) + \gamma_{i,j}^* * W(u, v). \quad (6)$$

And $\{A_{i,j}, i, j = 1, 2, 3\}$ in the uniform square $[0, 1] \times [0, 1]$ is shown in Fig. 1. The sub-space $A_{1,1}$ represents the depression market, whose probability is $P(A_{1,1}) = P(0 \leq U \leq q, 0 \leq V \leq q)$ for given $q \in (0, 1)$, and $A_{3,3}$ represents the prosperity market, whose probability is $P(A_{3,3}) = P(1 - q \leq U \leq 1, 1 - q \leq V \leq 1)$. The remaining sub-spaces with probability $1 - P(A_{1,1}) - P(A_{3,3})$ represent the normal market.

3.1. Identification and classification of risk contagion

Suppose that investors usually form their reasonable expectations of the local dependence structure by historical information, where we use the decision tree model to determine the optimal historical window with minimal global forecast error. It becomes risky if the local dependence structures with common underlining factor witness any abnormal change. Let $\hat{\alpha}_t$ be the reasonable expectation of local comonotonicity, and $D\hat{\alpha}_t$ be the forecast error of the local comonotonicity at time t . Given the confidential level c , we regard the extreme quartiles $\overline{VaR}_c^\alpha$ and $\underline{VaR}_c^\alpha$ as the upper and lower bounds of abnormal diagnosis.

Similarly, we define $\hat{\gamma}_t$, $D\hat{\gamma}_t$, $\overline{VaR}_c^\gamma$ and $\underline{VaR}_c^\gamma$ as the reasonable expectation, forecast error, upper and lower bounds for diagnosis of the local counter-monotonicity respectively. Denote $I_t \in \{0, 1, 2, 3, 4\}$ as our identification and classification of risk contagion. Fig. 2 illustrates our idea in detail.²

Once risk spillover ($I_t \neq 0$) is identified, portfolio managers could select the optimal strategy to decrease portfolio's risk exposures, based on further classifications of risk spillover. Take portfolios with two asset for example, assuming that $r_p = x r_a + (1 - x) r_b$, where r_a owns higher risk than r_b , and the total scale of portfolio is W_0 . Roughly, contagion grading means different portfolio strategies. We suggest to reduce the total scale W_0 (or proportion x for higher risk asset) when the abnormal increase (or decrease) of the local comonotonicity (or counter-monotonicity) structure occurs in extreme markets. In detail, if portfolio risk ($I_t = 1$) is identified, it is reasonable to make internal 'flight to quality' by decreasing x but keeping W_0 ; if mild contagion ($I_t = 2$) is identified, it is better to reduce W_0 while increasing x ; if moderate contagion ($I_t = 3$) is identified, it is suggested to reduce W_0 while keep x unchanged; if severe contagion ($I_t = 4$) is identified, it is optimal to reduce both W_0 and x .

Diebold and Yilmaz model (2009, 2012, 2014) (DY model for short) is also a classical model based on decomposition perspective. We compare DY model with the decomposition model of dependence structure (PBF model for short) from three aspects: definitions of risk

² We offer the detail steps in Algorithms C.1–C.3 in Appendix C.

Table 8
Factor analysis on identification of risk spillover and contagion in 2017–2019.

Factors	Identifications for risk spillover							
	Univariate analysis				Multivariate analysis			
	B	P-value	exp(B)	F-score	B	P-value	exp(B)	F-score
Ar0	0.041	0.931	1.042	0.870				
Ar10	−0.082	0.716	0.921	0.787				
Libor	0.024	0.962	1.024	0.870				
Shibor	−0.109	0.656	0.897	0.810				
Cr7	−0.257	0.536	0.773	0.789				
Rex	−0.009	0.977	0.991	0.870				
Import	0.17	0.394	1.186	0.730				
Export	0.281	0.228	1.325	0.741				
WTI	0.087	0.825	1.090	0.868				
Gold	0.145	0.632	1.156	0.775				
VIX	0.689***	0.001	1.992	0.762	0.689***	0.001	1.992	0.762
AEPV	−0.213	0.238	0.808	0.691				
APEU2	−0.272	0.204	0.762	0.691				
CEPU	−0.019	0.863	0.981	0.870				
GEPU	0.148	0.377	1.159	0.711				
GEPU2	0.129	0.418	1.138	0.715				
Sentix	0.217	0.338	1.242	0.703				
CS-C	−0.225	0.612	0.799	0.782				
CS-A	0.551	0.299	1.735	0.736				
Classifications of portfolio diversification risk and moderate contagion								
Ar0	−6.025***	0.000	0.002	0.793				
Ar10	0.608	0.155	1.837	0.653				
Libor	−6.341***	0.000	0.002	0.793				
Shibor	1.593**	0.014	4.917	0.632				
Cr7	1.618*	0.091	5.044	0.667				
Rex	−4.561***	0.000	0.010	0.862	−2.676***	0.007	0.069	0.935
Import	2.955***	0.000	19.195	0.829	3.299***	0.000	27.087	
Export	−1.920***	0.001	0.147	0.679				
WTI	2.770***	0.003	15.961	0.754				
Gold	−4.479***	0.000	0.011	0.768				
VIX	0.774*	0.092	2.168	0.684				
AEPV	0.016	0.965	1.016	0.677				
APEU2	−0.217	0.626	0.805	0.561	1.649***	0.008	5.204	
CEPU	−1.558***	0.000	0.211	0.800				
GEPU	0.687	0.783	1.988	0.591				
GEPU2	1.396	0.573	4.040	0.591				
Sentix	1.744***	0.001	5.719	0.722				
CS-C	−0.471	0.589	0.624	0.613				
CS-A	1.012	0.286	2.751	0.557				

spillover, model principles, and empirical performance. Specifically, both DY and PBF model identify risk spillover by decomposing second-order moment features between random variables. In the framework of simple (or generalized) VAR model which includes all information of margins and dependence, DY model defined risk spillover as the ratio of cross variance shares to total forecast error variation. While in the framework of mixed copula model which includes only dependent information and is independent of marginal distributions. PBF model defines risk spillover as the abnormal changes in either comonotonicity or counter-monotonicity, emphasizing the nonlinear dependence of variables in extreme market conditions and how decomposition of dependence structure helps to differentiate the risk spillover's classification. In the empirical analysis of Sino-US stock markets in Section 4.2, even with consistence in average trend under the same sample and rolling window, global comonotonic coefficients by PBF model perform more volatile than spillover indexes by DY model and may have the opposite judgment in specific events (see more details in Fig. 4(b) and its discussions).

3.2. Analysis of factors on the identification of contagion

From Section 3.1, our identification of risk contagion is related to the comprehensive judgments of the local comonotonicity and local counter-monotonicity. It is interesting to analyze and compare what kind of factors affect the identification of contagion and further the levels of contagion. Specifically, we regard the identification of risk

contagion I_t as a target variable and use a non-linear logistic regression model as I_t is a qualitative variable.

4. Empirical study

4.1. Data and description statistics

It is ideal to use stock market indexes with more coverage, market attention and time span to calculate the dependence between Sino-US stock markets (Liu & Shehzad, 2023; O'Neill et al., 2016; Ozdemir, 2022; Xu et al., 2019). Thus, we select Shanghai Composite Index (SCI), the first flag ship index in Shanghai, as the symbol of Chinese stock market.¹ For the representative of US stock market, we choose S&P500 index which is sufficient to reflect the overall strengths or weaknesses of the economy, including no much noise.² We collect their closed prices from January 3, 2005 to June 30, 2021 by Wind Database.

¹ SCI is the largest index in terms of stock market value and trading volume in China, covering large-cap, mid-cap, and small-cap stocks. We select SCI as the proxy of Chinese stock market for convenient comparison with other literature in the field of risk contagion.

² S&P500 index weighted by liquid market value includes many stocks in major American exchanges, such as the NYSE and NASDAQ. Compared with the Dow Jones index, its risk is more diversified and will exclude illiquid stocks to maintain industry neutrality, which can better represent the liquidity of the US stock market.

Table 9
Rankings of impact factors' Shapley Lorenz with $c = 0.9$.

Factors	2009–2021-01		2009–2021-13		2010–2012-01	
	slv	cra	slv	cra	slv	cra
Shibor			0.088	7.1%		
Ar10	0.122	100.0%				
Import			0.240	19.5%		
WTI			0.420	34.0%		
Rex						
VIX					0.272	30.0%
AEPUS2					0.264	29.2%
Gold			0.486	39.4%		
CS-C					0.193	21.3%
Sentix					0.176	19.4%
Factors	2010–2012-13		2017–2019-01		2017–2019-13	
	slv	cra	slv	cra	slv	cra
Shibor						
Ar10						
Import					1.009	57.0%
WTI						
Rex	0.647	53.8%			0.468	26.4%
VIX			0.234	100.0%		
AEPUS2	0.555	46.2%			0.293	16.6%
Gold						
CS-C						
Sentix						

Note: For example, “2009–2021-01” refers to risk spillover identification with a 90% confidence level from 2009 to 2021. “2009–2021-13” refers to classifications of portfolio diversification risk and moderate contagion with a 90% confidence level from 2009 to 2021. “slv” represents the Shapley Lorenz value; and “cra” calculates relative contribution ratios of each factor's Shapley Lorenz value.

Firstly, due to S&P500's trading time being on average 8 h later than SCI's, we lag the close prices of SCI one day to match with that of S&P500, and then delete all the non-overlapping holiday samples to obtain $N = 3880$ close prices for each index. Next, we unify pricing two indices in RMB to reduce the possible impact of bilateral exchange rates on the prices of cross-border indices, and then calculate their logarithmic returns with sample size $N = 3879$. Finally, drawing on the method to process cross-border data in Diebold and Yilmaz's (2009), we convert these daily log returns from nominal to real terms using monthly consumer price index of each country.³

The determinants of risk spillover and risk contagion receive a great deal of interest, which is helpful to explain the occurrence and intensity of contagions between financial markets in relation to the various crisis episodes and recessions (see Gravelle et al., 2006; Jiang et al., 2022; Luchtenberg & Vu, 2015; Wang et al., 2021; Yarovaya et al., 2022). We use the joint probability space to divide the market status and identify the risk contagion in a non-parametric way, which belongs to the data-driven contagion model. Thus, it is interesting to study how the influence factors mentioned in the crisis-driven contagion model affect the identification of risk contagion by a data-driven model. Referring to predecessor's research, Table 1 gives a description of 19 impact factors selected from five risk transmission channels, including finance, trade linkage, economic uncertainty, economic policy uncertainty and consumer confidence.

Table 2 includes the descriptive statistics for all the data. It finds that both returns of the stock indexes defy the normal distribution. Chinese stock market owns less mean and more volatility than US stock market. The sample dependence of Sino-US stock markets is low during the whole period. US financial system owns higher liquidity than that of China during our sample period.

³ By comparing the sample correlation coefficients before and after data processing, we find that the impact of denomination currency and inflation rate on the dependence between Sino-US stock markets is limited.

For the impact factors in the trade channel in Table 2, the scale of exports from China to United States is larger than that of imports, and China's trade surplus supports the exchange rate of USD/CNY of which the mode is greater than its mean value. During the sample period, global economic uncertainty and economic policy uncertainty of US are relatively smaller but have more extreme values. Higher uncertainty usually reduces information efficiency and thus increase the dependence of stock markets. As for the investment sentiment channel, Chinese consumer confidence is slightly stronger than that of United States.

4.2. Decomposition of dependence structure between sino-US stock markets

To avoid possible problems in misspecification in the dependence structure, we use the cubic-spline interpolation method to increase the robustness of marginal distributions in the probability integral transformation. Both series after non-parametric standardization pass the Kolmogorov–Smirnov test. For comparison, we fit not only PBF copula, but also common copulas, including Gaussian copula without tail, T-copula with thick tail and two parameters, Clayton copula with lower tail, Gumbel copula with upper tail and Frank copula with symmetric tail.⁴

Table 3 compares the goodness-of-fit tests of five classical copulas and PBF copula by Mean Square Errors (MSE). From the perspective of MSE and parameter estimations of classical copulas without decomposition of dependence structure, T-copula performs better, followed by Frank copula, Gaussian copula, Clayton copula and Gumbel copula respectively, indicating that dependence structure between Sino-US stock markets in the sample period tends to be symmetric and thick tails. As PBF copula decomposes the local dependence structure with maintaining all the conditional margin information in each sub-space, it performs the best in the goodness-of-fit test.

It is also interesting to find that the symmetric character fitted by T-copula seems to be caused by the symmetric probabilities of extreme markets. However, if conditioning on extreme markets, the local comonotonic structure in depression market is higher than that in prosperity market, showing obviously asymmetry, which cannot be found by classical copulas without decomposition of dependence structure.

Next, we use the rolling window with 252 days width and one-day step to investigate the dynamic performance of dependence structure between Sino-US stock markets. Fig. 3 gives the dynamic probabilities of depression and prosperity markets and illustrates that probabilities of two extreme markets are usually symmetric except during the global finance crisis (GFC), Sino-US trade friction and COVID-19. Fig. 4(a) further gives the dynamic characters of the local comonotonic and counter-monotonic structures in the depression markets. In the depression market, the local dependence structure between Sino-US stock markets undergoes significant changes after Euro-debt crisis. Specifically, the local comonotonic structure is strengthened and more volatile, and the local counter-monotonic structure is weakened but still play a key role of offsetting during special crisis, showing the effectiveness of diversified strategies of markets to shocks. It is worth noting that fluctuations of local comonotonic and counter-monotonic structures are not synchronized, signifying the difference of degrees of risk contagion in different periods. It seems to be meaningful for investors to evaluate their strategies of risk management by investigating of the counter-monotonic structure by the decomposition of dependence structure.

Fig. 4(b) dynamically compares the global comonotonic coefficients (i.e. $\sum_{i,j=1}^3 P(A_{i,j}) \times \alpha_{i,j}^*$) in the decomposition model of dependence structure with the spillover index in the Diebold and Yilmaz (2012) under the same sample and rolling window. We find that: (1) the average

⁴ Their expressions are given in Appendix B.

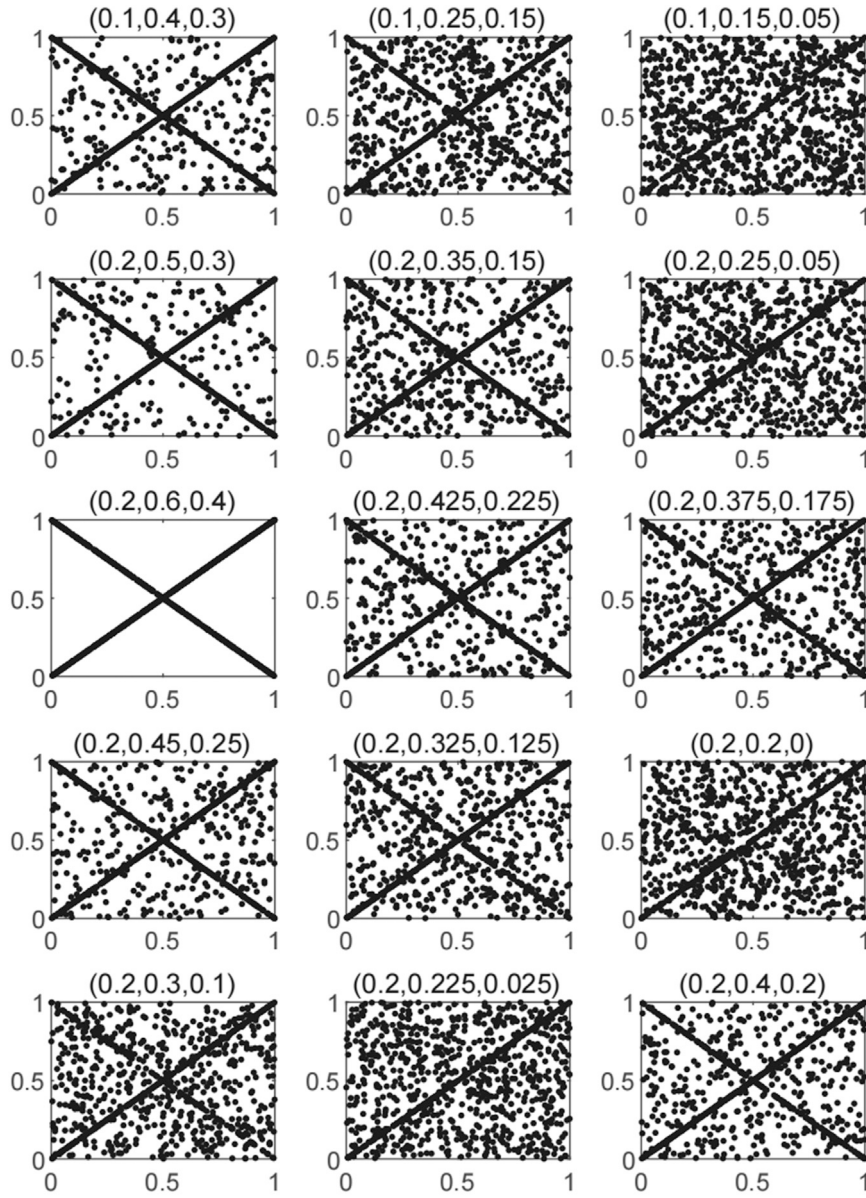


Fig. A.1. Spearman's rho versus Dependence structures, i.e., (ρ, α, γ) . Three different dependence structures with $\rho = 0.1$ are shown in the first row, and we also draw 12 different dependence structures with $\rho = 0.2$ to illustrate the relationship and difference between dependence ρ and dependence structure (α, γ) .

correlation between the two series is 0.6, indicating their certain degree of consistency on tracking risk spillover between Sino-US stock markets during the sample period; (2) unlike the spillover indexes, the global comonotonic coefficients are more volatile and behave differently during subprime crisis, European debt crisis and COVID-19 pandemic; (3) In addition to global tracking of risk spillover, decomposition model of dependence structure can further analyze risk spillover and contagion's identification locally in extreme market conditions.

4.3. Risk contagion between sino-US stock markets

Fig. 5 gives the MSE errors under different forecast windows. The larger the forecast window W is, the smaller the forecast error of the outside sample is, but the fewer the outside sample is, when we use limited historical samples to train the model of decision tree. Thus, in order to ensure the sufficient capacity for the outside sample, we set three years as the upper limit of window W and choose the optimal

forecast window as $W^* = 662$, where the optimal MSE of the local comonotonic and counter-monotonic structures are obtained.

Fig. 6 offers the forecast errors $\{D\alpha_t, D\gamma_t; t = 1, 2, \dots, N\}$ of local comonotonicity and counter-monotonicity, and also the difference sequences $\{\alpha_t^{1 \rightarrow 2} - \hat{\alpha}_t^{1 \rightarrow 2}, \alpha_t^{2 \rightarrow 1} - \hat{\alpha}_t^{2 \rightarrow 1}; t = 1, 2, \dots, N\}$ of conditional comonotonicity. And then we obtain the identification series of risk contagion between Sino-US stock markets $\{I_t | I_t = 0, 1, 2, 3, 4; t = 1, 2, \dots, N\}$, according to the steps in Fig. 2.

For each natural year T , we are also interested in the proportion structures of identification of risk contagion. Then we have

$$P_i^T = \frac{\sum_{t=1}^N I_{\{I_t=i\}}}{\sum_{t=1}^N I_{\{t \in [T, T+1]\}}}, i = 0, 1, 2, 3, 4. \quad (7)$$

From the results in Table 4 and Fig. 7, we find that the risk spillover between Sino-US stock markets is weak, and once risk spillover is identified, portfolio diversification and moderate contagion are the main components and almost equal, while proportions of mild and

Table D.1Linearity tests for logistic regression with $c = 0.9$ for the overall sample.

Overall sample	Identification of risk spillover			Identification of contagion		
	Co-linearity		Logistic linearity	Co-linearity		Logistic linearity
Factors	Tolerance	VIF	P-value	Tolerance	VIF	P-value
Ar0						
Ar10	0.112	8.989	0.831	0.223	4.474	
Libor	0.112	8.962	0.364	0.135	7.426	
Shibor	0.141	7.104	0.419	0.507	1.972	0.107
Cr7	0.142	7.065	0.679			
Rex	0.178	5.626	0.130	0.230	4.343	0.941
Import	0.360	2.776	0.844	0.441	2.265	0.906
Export	0.335	2.982	0.169	0.325	3.080	0.109
WTI	0.114	8.748	0.618	0.202	4.956	0.022
Gold	0.110	9.117	0.853	0.653	1.532	0.306
VIX	0.327	3.059	0.605	0.488	2.048	0.013
AEPu						
APEU2	0.250	3.996		0.263	3.804	0.921
CEPU	0.116	8.629	0.329	0.142	7.029	0.199
GEPU						
GEPU2	0.139	7.176		0.410	2.442	0.867
Sentix	0.159	6.299		0.196	5.104	
CS-C	0.263	3.796		0.318	3.144	
CS-A	0.141	7.102	0.935	0.126	7.940	

Note: We use the Box–Tidwell method to test logistic linearity, and P-value corresponds to the interaction terms of $X \times \ln(X)$, where X represents one impact factor. We keep X whose p-value exceeds Bonferroni correction of 0.05.

Table D.2Linearity tests for logistic regression with $c = 0.9$ during Euro-debt crisis.

2010–2012	Identification of risk spillover			Identification of contagion		
	Co-linearity		Logistic linearity	Co-linearity		Logistic linearity
Factors	Tolerance	VIF	P-value	Tolerance	VIF	P-value
Ar0						
Ar10	0.108	9.246	0.081	0.108	9.246	0.939
Libor	0.206	4.857	0.947	0.193	5.184	0.130
Shibor	0.108	9.242	0.085			
Cr7	0.117	8.560	0.284			
Rex				0.135	7.407	0.827
Import	0.247	4.044	0.972	0.628	1.593	0.346
Export	0.151	6.625	0.765	0.174	5.739	0.309
WTI						
Gold	0.105	9.491	0.453	0.241	4.148	0.146
VIX	0.300	3.336	0.830	0.240	4.162	0.315
AEPu						
APEU2	0.460	2.172	0.656	0.441	2.267	0.203
CEPU						
GEPU						
GEPU2				0.187	5.336	0.657
Sentix	0.191	5.241	0.019			
CS-C	0.401	2.493	0.028			
CS-A	0.119	8.430	0.293			

severe contagion are less. During the periods of Euro-debt crisis, it is more likely to identify portfolio diversification risk first and then the moderate contagion after, while moderate contagion is identified first and then portfolio risk after during Sino-US trade friction.

Table 5 and Fig. 8 illustrate the annual proportion structure of contagion dominance at confidence of 90% and 95%. Interestingly, once risk contagion is identified between Sino-US stock markets, the dominance of US stock market is not confirmed frequently, but no dominance and symmetric dominance are the main features, which is in line with Pan et al. (2021).

4.4. Analysis of factors on identification of contagion

In this section, we regard the identification series $\{I_t\}$ as our dependent variable, and use logistic classification regression model as $\{I_t\}$ belongs to discrete qualitative variable. Because the annual proportions

of mild contagion (i.e. $\{I_t = 2\}$) and severe contagion (i.e. $\{I_t = 4\}$) are relatively small, illustrating the imbalance of our classification samples, the parallelism test of ordinal polysemous logistic regression model is rejected, and then the disordered multi-classification regression model almost has no forecast rate. Therefore, we decide to use the stepwise binary logistic regression model.

Specifically, we analyze which impact factors lead to risk spillover between Sino-US stock markets, i.e., the dependent variable in first step is $\{I_t = 0, I_t \neq 0\}$, and then observe which channel factors lead to portfolio diversification risk or moderate contagion, i.e., binary logistic regression analysis on the classification subset $\{I_t = 1, I_t = 3\}$.

Note that in order to obtain original impressions on the significance, sign symbol and forecast ability of impact factors, we make single-factor regressions first and then consider multi-factors regressions in each binary logistic regression step. We use the back-step method to delete factors with no logistic linearity, and then keep as many factors

Table D.3Linearity tests for logistic regression with $c = 0.9$ during Sino-US trade friction.

2017–2019	Identification of risk spillover			Identification of contagion		
	Co-linearity		Logistic linearity	Co-linearity		Logistic linearity
	Tolerance	VIF	P-value	Tolerance	VIF	P-value
Ar0						
Ar10	0.172	5.804	0.165			
Libor	0.150	6.688	0.226			
Shibor	0.662	1.510	0.050			
Cr7	0.744	1.344				
Rex	0.150	6.650	0.118	0.200	4.990	0.122
Import	0.148	6.746	0.118	0.348	2.870	0.997
Export	0.307	3.261	0.865			
WTI						
Gold	0.170	5.899	0.342			
VIX	0.638	1.569	0.476			
APEU						
APEU2				0.833	1.200	0.995
CEPU				0.128	7.806	0.991
GEPU						
GEPU2	0.128	7.822	0.653	0.717	1.395	0.993
Sentix				0.292	3.419	0.992
CS-C						
CS-A						

Table D.4Linearity tests for logistic regression with $c = 0.95$.

Overall sample	Identification of risk spillover			Identification of contagion		
	Co-linearity		Logistic linearity	Co-linearity		Logistic linearity
	Tolerance	VIF	P-value	Tolerance	VIF	P-value
Ar10	0.254	3.940	0.070			
Shibor	0.640	1.563		0.753	1.328	0.451
Import	0.886	1.129	0.326	0.903	1.107	0.243
WTI	0.316	3.169	0.296	0.801	1.248	
Gold	0.449	2.229	0.039	0.870	1.150	0.545
2010–2012						
Factors	Identification of risk spillover			Identification of contagion		
	Co-linearity		Logistic linearity	Co-linearity		Logistic linearity
	Tolerance	VIF	P-value	Tolerance	VIF	P-value
Libor	0.269	3.720		0.161	6.204	0.087
Rex	0.230	4.341		0.210	4.761	0.081
VIX	0.500	1.998	0.421	0.574	1.743	
APEU2	0.545	1.833	0.015	0.472	2.120	0.312
Sentix	0.423	2.362	0.299	0.329	3.039	
CS-C	0.656	1.524	0.036	0.637	1.571	
2017–2019						
Factors	Identification of risk spillover			Identification of contagion		
	Co-linearity		Logistic linearity	Co-linearity		Logistic linearity
	Tolerance	VIF	P-value	Tolerance	VIF	P-value
Rex	0.234	4.281	0.789	0.410	2.442	0.123
Import	0.226	4.427	0.692	0.289	3.455	0.781
VIX	0.760	1.315	0.626	0.679	1.472	0.952
APEU2	0.746	1.340	0.471	0.758	1.320	0.326
CEPU	0.115	8.653	0.372			
Sentix	0.264	3.787	0.952	0.310	3.226	0.374

as possible when testing the co-linearity. Choice of factors for multi-factor regression at confidence levels of 90% and 95% can be found in [Tables D.1–D.4](#) respectively. Based on preliminary screening and single regression, we continue to carry on multi-factor regression of all variables, variables with significance and variables with positive significance in turn, and keep the multivariate regression results with the highest forecast rate.

For the whole sample period, [Table 6](#) shows the main factors that affect the odd ratios of risk spillover and contagion between Sino-US stock markets at confidence level of 90% in the long term (similar discussions at confidence level 95% are given in [Tables D.1–D.4](#)). From [Table 6](#), it is found that 10-year US government bond rate in financial channel increases the odds ratio of risk spillover between Sino-US stock markets over total sample period. Once risk spillover is identified, China's imports from US in the trade channel will increase the odd ratio of moderate contagion.

For specific risk events, we also investigate impact factors that affected the odd ratios of identifications of risk spillover and contagion between Sino-US stock markets in the short term. By the annual proportion of identifications listed in [Table 4](#) in [Section 4.3](#), it is not conducive to obtain consistent and robust conclusions by too few samples. Thus, we tend to focus on Euro-debt crisis and Sino-US trade frictions, and select three years as the event window period (consistent with our choice of rolling windows). [Tables 7](#) and [8](#) offer the impact factors on the odd ratios of risk identifications during Euro-debt crisis (2010–2012) and Sino-US trade friction (2017–2019) at a confidence level of 90%. We find that impact factors of identifications in short term are different from those in the long term.

During specific risk events, investment sentiment factor is prone to increase the odd ratio of risk spillover between Sino-US stock markets, so it is important to strengthen the management of investor expectations in the early stage of risk event. Once risk spillover identified,

Table D.5
Robustness of factor analysis with $c = 0.95$ since 2009.

Factors	Identifications of risk spillover							
	Univariate analysis				Multivariate analysis			
	B	P-value	exp(B)	F-score	B	P-value	exp(B)	F-score
Ar0	0.107	0.396	1.113	0.826	0.418***	0.000	1.519	0.717
Ar10	0.418***	0.000	1.519	0.717				
Libor	0.132	0.316	1.141	0.826				
Shibor	0.055	0.409	1.057	0.727				
Cr7	0.000	0.995	1.000	0.948				
Rex	0.054	0.704	1.055	0.733				
Import	−0.335***	0.000	0.715	0.719				
Export	−0.089	0.286	0.915	0.747				
WTI	0.166**	0.011	1.180	0.719				
Gold	−0.127*	0.073	0.881	0.586				
VIX	0.107	0.135	1.113	0.783				
AEPu	−0.221***	0.003	0.802	0.606				
APEU2	−0.092	0.175	0.912	0.631				
CEPU	−0.218***	0.001	0.804	0.582				
GEPU	−0.226***	0.003	0.798	0.576				
GEPU2	−0.255***	0.001	0.775	0.579				
Sentix	−0.080	0.199	0.923	0.776				
CS-C	−0.018	0.792	0.983	0.789				
CS-A	−0.121*	0.072	0.886	0.697				
Covid	−1.077***	0.000	0.341	0.227				
Trade	−0.030	0.844	0.971	0.940				
Classifications of portfolio diversification risk and moderate contagion								
Ar0	−0.272	0.267	0.762	0.330	0.577***	0.008	1.781	0.713
Ar10	−1.070***	0.000	0.343	0.685				
Libor	−0.314	0.224	0.730	0.330				
Shibor	0.117	0.434	1.124	0.606				
Cr7	0.118	0.431	1.125	0.556				
Rex	−1.096***	0.000	0.334	0.621				
Import	0.597***	0.002	1.817	0.614				
Export	0.492**	0.018	1.636	0.593				
WTI	−0.446***	0.003	0.640	0.639				
Gold	0.533***	0.002	1.704	0.645				
VIX	−0.037	0.813	0.964	0.578				
AEPu	0.327*	0.066	1.387	0.619				
APEU2	0.125	0.467	1.134	0.557				
CEPU	0.017	0.886	1.017	0.615				
GEPU	0.133	0.376	1.142	0.637				
GEPU2	0.110	0.456	1.117	0.642				
Sentix	0.185	0.254	1.203	0.595				
CS-C	0.026	0.853	1.026	0.641				
CS-A	0.300**	0.028	1.349	0.626				
Covid	1.963**	0.012	7.118	0.717				
Trade	0.008	0.978	1.008	0.703				

it is American Economic Policy Uncertainty that plays an important role in increasing the odd ratio of moderate contagion between the two stock markets. It is also interesting to note that exchange rate of USD to RMB has a significant negative effect on the odd ratio of moderate contagion, indicating that it tends to increase portfolio diversification risk only. During Sino-US trade friction, China's imports from US in trade channel also increase the odd ratio of moderate contagion. Although no dominance or symmetric contagion dominance accounts for larger proportion annually on average in Table 5 in Section 4.3, factors from United States still have the main impact on the odd ratios of risk spillovers and contagion between Sino-US stock markets either in the long-run or short-run.

Following the final results of multi-logistical regression, we keep on calculating their respective Shapley Lorenz values by the way in Giudici and Raffinetti (2021).⁵ Table 9 lists the rankings of impact factors' Shapley Lorenz values for the whole sample, European debt crisis, and Sino-US trade friction respectively at the confidence level of 0.9, where we confirm the consistence with their regression coefficients

during the whole sample and Sino-US trade friction (similar results at the confidence level of 0.95 are given in Table D.8). But there still exists a certain difference in the classification results of the European debt crisis, which we think may be due to its small and unbalanced sub-samples.

Finally, we tested the robustness of the above factors and channels at the confidence level of 95%. To avoid problems caused by sample size reduction at higher confidence level 95%, we only focus on testing the robustness of selected impact factors in the above main channels at confidence level of 95%, including co-linearity, logistic linearity, significance, sign symbol and forecast rate. Tables D.5–D.8 in Appendix D illustrate that our results at a confidence level of 95% are robust.

5. Conclusions

This paper provides a new framework to identify risk contagion and classify the degree of contagion by the local comonotonicity and counter-monotonicity decomposed from dependence structure. In the view of intuitive understanding of probability, we strengthen the harmful change of dependence structure caused by common underlying random factor as the signal of risk transmission. Specifically, risk spillover refers to the situation that at least one of the local comonotonic

⁵ Shapley Lorenz value based on logistic regression describes the marginal contribution of independent variables to the accuracy of classification.

Table D.6
Robustness of factor analysis with $c = 0.95$ in 2010–2012.

Factors	Identifications for risk spillover							
	Univariate analysis				Multivariate analysis			
	B	P-value	exp(B)	F-score	B	P-value	exp(B)	F-score
Ar0	6.501*	0.067	665.973	0.639				
Ar10	−0.045	0.820	0.956	0.666				
Libor	7.908**	0.014	2718.542	0.642				
Shibor	−0.08	0.425	0.923	0.522				
Cr7	−0.106	0.274	0.899	0.581				
Rex	1.260***	0.005	3.527	0.666				
Import	−1.178***	0.000	0.308	0.677				
Export	0.295	0.349	1.343	0.589				
WTI	−1.267***	0.000	0.282	0.670				
Gold	−0.306**	0.046	0.736	0.643				
VIX	0.420***	0.006	1.523	0.731	0.356**	0.036	1.428	0.743
AEPu	−0.271	0.187	0.763	0.563				
APEU2	−0.465**	0.042	0.628	0.637				
CEPU	−0.682	0.101	0.506	0.585				
GEPU	0.002	0.995	1.002	0.724				
GEPU2	−0.138	0.592	0.871	0.429				
Sentix	−0.333	0.102	0.717	0.558	−0.466**	0.041	0.628	
CS-C	1.871***	0.000	6.495	0.671	1.863***	0.000	6.444	
CS-A	0.117	0.670	1.125	0.553				
Classifications of portfolio diversification risk and moderate contagion								
Ar0	−24.031***	0.002	0.000	0.757				
Ar10	−3.084***	0.000	0.046	0.819				
Libor	−18.125***	0.006	0.000	0.781	43.914**	0.027	1.179 * 10 ¹⁹	0.919
Shibor	0.528**	0.027	1.696	0.811				
Cr7	0.416*	0.061	1.515	0.808				
Rex	−5.138***	0.000	0.006	0.833	−7.671***	0.002	0.000	
Import	4.256***	0.000	70.544	0.862				
Export	3.962***	0.003	52.579	0.660				
WTI	1.726***	0.007	5.616	0.784				
Gold	2.150***	0.000	8.583	0.841				
VIX	0.617**	0.048	1.854	0.738				
AEPu	3.028***	0.000	20.663	0.885				
APEU2	4.228***	0.000	68.585	0.909	3.930***	0.000	50.883	
CEPU	6.310***	0.000	550.121	0.819				
GEPU	3.688***	0.000	39.951	0.815				
GEPU2	3.911***	0.000	49.971	0.815				
Sentix	−1.934***	0.001	0.145	0.743				
CS-C	−5.613***	0.000	0.004	0.835				
CS-A	−2.376***	0.000	0.093	0.842				

or counter-monotonic structures witnesses abnormal adverse change; Portfolio diversification risk emphasizes the abnormal adverse change of the local counter-monotonic structure; Risk contagion emphasizes the abnormal adverse change of the local comonotonic structure. We also distinguish the degree of contagion into mild, moderate and severe at the same time as risk contagion is confirmed. It is meaningful for investors to make judgment on their risk countermeasures by the local counter-monotonic structure. When we apply the new method in the identification of risk contagion between Sino-US stock markets, especially in extreme market conditions, our findings are concluded as follows. Annual proportions of identifications for risk spillover and risk contagion between Sino-US stock markets are average low but they have obvious structural characteristics, i.e., the average annual proportions of portfolio diversification risk and moderate contagion are symmetric and larger than that of mild and severe contagion. No dominance and symmetric dominance of risk contagion between Sino-US stock markets get larger proportions of confirmation.

As for impact factors from channels of economic, finance, trade, and sentiment, we conclude that (1) in the long run, 10-year US government bond rate in the finance channel tends to induce risk spillover and import trade volume in trade channel increases the odd ratio of moderate contagion, but it is not the case in short run; (2) for specific risk events in short-run, VIX in global economic channel always increases

the odd ratio of risk spillover and US economic policy uncertainty usually increases the odd ratio of moderate contagion between Sino-US stock markets; (3) it is necessary to make separate research on impact factors of special events, because of obvious differences of the factors affecting structures of risk contagion in different events. Our results are robust for the main influence factors.

In the future, it is meaningful to decompose the dependence structure among global markets, as well as discuss their network topology characteristics and influence channels. Global markets with dense interconnections can amplify financial market risk and the complex dependence structures pose great challenges to international investors' risk management. It can be helpful if our native decomposition of dependence structure among global markets exists not only in time series but also in panel data and network. [Ahelegbey and Giudici \(2022\)](#) used Bayesian graphical VAR model to estimate the weighted adjacency matrix for constructing a network volatility index (NetVIX) via market interconnections and volatilities. Comparatively, this paper focus on the non-linear dependence structure which is independent of marginal information including volatility. For next research in the global market perspective, it is interesting and feasible to combine the decomposed comonotonic (or counter-monotonic) structure with the appropriate volatilities by the network way provided by [Ahelegbey and Giudici \(2022\)](#).

Table D.7
Robustness of factor analysis with $c = 0.95$ in 2017–2019.

Factors	Identifications for risk spillover							
	Univariate analysis				Multivariate analysis			
	B	P-value	exp(B)	F-score	B	P-value	exp(B)	F-score
Ar0	0.069	0.912	1.071	0.651				
Ar10	−0.094	0.749	0.91	0.737				
Libor	0.088	0.894	1.092	0.651				
Shibor	0.564	0.134	1.757	0.567				
Cr7	0.136	0.792	1.146	0.690				
Rex	−0.389	0.304	0.678	0.736				
Import	0.09	0.727	1.095	0.753				
Export	−0.201	0.491	0.818	0.687				
WTI	−0.152	0.764	0.859	0.633				
Gold	0.234	0.547	1.264	0.765				
VIX	0.790***	0.001	2.203	0.766	0.790***	0.001	2.203	0.766
AEPu	−0.01	0.964	0.99	0.717				
APEU2	−0.001	0.996	0.999	0.936				
CEPU	−0.034	0.813	0.967	0.683				
GEPU	−0.024	0.911	0.976	0.693				
GEPU2	−0.055	0.790	0.947	0.651				
Sentix	0.169	0.565	1.184	0.646				
CS-C	0.296	0.616	1.344	0.617				
CS-A	0.127	0.849	1.136	0.552				
Classifications of portfolio diversification risk and moderate contagion								
Ar0	−7.215***	0.000	0.001	0.793				
Ar10	0.858	0.179	2.358	0.654				
Libor	−7.631***	0.000	0.000	0.839				
Shibor	0.515	0.501	1.674	0.522				
Cr7	0.405	0.740	1.500	0.581				
Rex	−4.805***	0.000	0.008	0.925	−0.343**	0.012	0.000	0.921
Import	2.483***	0.001	11.976	0.800	2.809**	0.020	16.594	
Export	−2.307***	0.007	0.100	0.742				
WTI	2.68**	0.035	14.587	0.746				
Gold	0.593	0.434	1.809	0.585				
VIX	1.088*	0.083	2.969	0.689				
AEPu	−0.262	0.598	0.770	0.643				
APEU2	−0.564	0.348	0.569	0.690	1.212**	0.016	3.362	
CEPU	−1.595***	0.000	0.203	0.875				
GEPU	−1.923***	0.001	0.146	0.767				
GEPU2	−1.965***	0.000	0.140	0.767				
Sentix	2.328***	0.001	10.260	0.780				
CS-C	0.285	0.819	1.330	0.464				
CS-A	2.145	0.119	8.539	0.577				

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yanting Zheng reports was provided by National Natural Science Foundation of China.

Data availability

Data will be made available on request.

Acknowledgments

We are very grateful to the editors and referees for their insightful comments. The paper is supported by the National Natural Science Foundation of China (Grant No. 71971004).

Appendix A. Intuitiveness of decomposition of dependence

It is helpful to understand dependence structures intuitively by Spearman's rho of Bivariate Fréchet copula in Eq. (3), which owns simple expression as following

$$\rho = \alpha - \gamma. \quad (\text{A.1})$$

Comonotonicity $M(u, v)$ (or counter-monotonicity $W(u, v)$) refers to the maximum (or minimum) dependence caused by the same common factor U , and Spearman's rho in Eq. (A.1) means the net dependence determined by them. In fact, not all kinds of dependence structures are risky, even though the corresponding dependence increases, especially in the extreme markets. Higher comonotonicity always means higher loss risk, while counter-monotonicity can diversify portfolio risk in finance. Fig. A.1 illustrates that dependence structures with the same Spearman's rho can be very different, and own abundant situations when Spearman's rho is increasing, which is the basis for our new view to identify risk contagion and its degree. Let (α, γ) represent the dependence structure. Take $\rho = 0.1$ increasing to $\rho = 0.2$ for example, it corresponds to a number of different dependence structural changes. Comparing with the situation of dependence structure changing from (0.4, 0.3) to (0.5, 0.3), it is more dangerous to change from (0.4, 0.3) to (0.45, 0.25) which means comonotonicity increases but counter-monotonicity decreases at the same time.

Appendix B. Common copulas in risk management

(1) Gaussian Copula without tail

$$C_G(u, v, \theta_g) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta_g^2}} \exp\left(\frac{-(x^2 + y^2 - 2\theta_g xy)}{2(1-\theta_g^2)}\right) dx dy, \quad (\text{B.1})$$

Table D.8
Robustness of factors' Shapley Lorenz values with $c = 0.95$.

Factors	2009–2021-01		2009–2021-13		2010–2012-01	
	slv	cra	slv	cra	slv	cra
Ar10	0.269	100.0%				
Libor						
Import			0.287	48.9%		
Rex						
VIX					0.170	19.5%
AEP2						
Gold			0.299	51.1%		
CS-C					0.464	53.4%
Sentix					0.236	27.1%
Factors	2010–2012-13		2017–2019-01		2017–2019-13	
	slv	cra	slv	cra	slv	cra
Ar10						
Libor	2.138×10^{-4}	0.0%				
Import					0.619	54.2%
Rex	0.507	38.4%			0.464	40.7%
VIX			0.278	100.0%		
AEP2	0.811	61.5%			0.058	5.1%
Gold						
CS-C						
Sentix						

Note: For example, “2009–2021-01” refers to risk spillover identification with a 95% confidence level from 2009 to 2021. “2009–2021-13” refers to classifications of portfolio diversification risk and moderate contagion with a 95% confidence level from 2009 to 2021. “slv” represents the Shapley Lorenz value; and “cra” calculates relative contribution ratios of each factor's Shapley Lorenz value.

where $\theta_g \in (-1, 1)$, $\Phi^{-1}(\cdot)$ is the inverse function of a normal distribution function $\Phi(\cdot)$.

(2) T-copula with thick tail

$$C_T(u, v, \theta_t, \nu_t) = \int_{-\infty}^{T_{\nu_t}^{-1}(u)} \int_{-\infty}^{T_{\nu_t}^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta_t^2}} \times [1 + \frac{x^2 + y^2 - 2\theta_t xy}{\nu_t(1-\theta_t^2)}]^{-\frac{\nu_t+2}{2}} dx dy, \quad (B.2)$$

where $\theta_t \in (-1, 1)$, $T_{\nu_t}^{-1}(\cdot)$ is the inverse function of a t-distribution function $T_{\nu_t}(\cdot)$ with ν_t degrees of freedom.

(3) Clayton Copula with lower tail

$$C_{Cl}(u, v, \theta_{cl}) = (u^{-\theta_{cl}} + v^{-\theta_{cl}} - 1)^{-\frac{1}{\theta_{cl}}}, \quad (B.3)$$

where $\theta_{cl} \in (0, \infty)$.

(4) Gumbel Copula with upper tail

$$C_{Gu}(u, v, \theta_{gu}) = \exp(-[(-\ln u)^{\frac{1}{\theta_{gu}}} + (-\ln v)^{\frac{1}{\theta_{gu}}}]^{\theta_{gu}}), \quad (B.4)$$

where $\theta_{gu} \in (0, 1]$.

(5) Frank Copula with symmetric tail

$$C_{Fr}(u, v, \theta_{fr}) = -\frac{1}{\theta_{fr}} \ln(1 + \frac{(e^{-\theta_{fr}u} - 1)(e^{-\theta_{fr}v} - 1)}{e^{-\theta_{fr}} - 1}). \quad (B.5)$$

where $\theta_{fr} \neq 0$.

Appendix C. Algorithms for identification of risk contagion

Algorithm C.1. Selection of the optimal forecast window by decision tree, and take α_t for example:

- (1) Denote the local comonotonicities in $A_{1,1}$ as $\{\alpha_t, t = 1, \dots, T\}$;
- (2) Given the original forecast window $W \in \{7, 8, \dots, N, N < T\}$, we regard $\{\alpha_t | t = 1, \dots, W\}$ as independent variables and α_{W+1} as dependent variable;
- (3) Using sub-sample $\{\alpha_t | t = 1, 2, \dots, 30\}$ to train the prediction function using a decision tree with rolling window W ;
- (4) Forecast the local comonotonicities $\{\hat{\alpha}_{W+30+k} | k = 1, 2, \dots, T - W - 30\}$ by decision tree model in step 3);
- (5) Calculate the mean square errors (MSE):

$$MSE(W) = \sum_{t=W+31}^T (\alpha_t - \hat{\alpha}_t)^2; \quad (C.1)$$

(6) Obtain the optimal forecast window:

$$W^* = \inf\{W | \arg \min_W MSE(W)\}. \quad (C.2)$$

Algorithm C.2. Identification of risk contagion at time t :

- (1) Calculate the forecast errors of local comonotonicity and counter-monotonicity, i.e., $D\alpha_t = \alpha_t - \hat{\alpha}_t$ and $D\gamma_t = \gamma_t - \hat{\gamma}_t$;
- (2) Given the confidential level $c = 0.90$ or 0.95 , the upper and lower bounds of abnormal diagnosis are determined by the extreme quartiles $\overline{VaR}_c^\alpha$ and $\underline{VaR}_c^\alpha$ of the sequence $D\alpha_t$;
- (3) If $D\alpha_t = \alpha_t - \hat{\alpha}_t$ exceeds its upper (or lower) boundary $\overline{VaR}_c^\alpha$ (or $\underline{VaR}_c^\alpha$), the true value is abnormally large (or small);
- (4) At the abnormal time t of α_t , further diagnose whether $D\gamma_t = \gamma_t - \hat{\gamma}_t$ exceeds its upper (or lower) boundary $\overline{VaR}_c^\gamma$ (or $\underline{VaR}_c^\gamma$);
- (5) Denote I_t as the identification results at time t , and Fig. 3 shows the steps in detail.

Algorithm C.3. At time t with risk contagion, to determine the contagion dominance:

- (1) Calculate the real and forecast values of conditional comonotonicity when R_1 is in depression, i.e., $\alpha_t^{1 \rightarrow 2} = \sum_{i=1}^3 P(A_{1,i})\alpha_t^{1,i}$ and $\hat{\alpha}_t^{1 \rightarrow 2} = \sum_{i=1}^3 P(A_{1,i})\hat{\alpha}_t^{1,i}$;
- (2) Calculate the real and forecast values of conditional comonotonicity when R_2 is in depression, i.e., $\alpha_t^{2 \rightarrow 1} = \sum_{i=1}^3 P(A_{i,1})\alpha_t^{i,1}$ and $\hat{\alpha}_t^{2 \rightarrow 1} = \sum_{i=1}^3 P(A_{i,1})\hat{\alpha}_t^{i,1}$;
- (3) If $\alpha_t^{1 \rightarrow 2} > \hat{\alpha}_t^{1 \rightarrow 2}$ and $\alpha_t^{2 \rightarrow 1} > \hat{\alpha}_t^{2 \rightarrow 1}$, i.e., both the conditional comonotonicities of R_1 and R_2 have exceeded their forecast values, it is symmetric risk contagion;
- (4) If only $\alpha_t^{1 \rightarrow 2} > \hat{\alpha}_t^{1 \rightarrow 2}$, i.e., the conditional comonotonicity of R_1 exceeds its forecast value, it is R_1 that is dominant in risk contagion;
- (5) If only $\alpha_t^{2 \rightarrow 1} > \hat{\alpha}_t^{2 \rightarrow 1}$, i.e., the conditional comonotonicity of R_2 exceeds its forecast value, it is R_2 that is dominant in risk contagion.

Appendix D. Tests for collinearity and robustness

See Tables D.1–D.8.

References

- Ahelegbey, D. F., & Giudici, P. (2022). NetVIX - A network volatility index of financial markets. *Physica A-Statistical Mechanics and its Applications*, 594, Article 127017.
- Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent measures of risk. *Mathematical Finance*, 9, 203–228.
- Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, [ISSN: 0304-405X] 75(2), 283–317.
- Baur, D. G. (2013). The structure and degree of dependence: A quantile regression approach. *Journal of Banking & Finance*, [ISSN: 0378-4266] 37(3), 786–798.
- Baur, D. G., & Lucey, B. M. (2009). Flights and contagion-an empirical analysis of stock-bond correlations. *Journal of Financial Stability*, 5(4), 339–352.
- Bedoui, R., Braeik, S., Goutte, S., & Guesmi, k. (2018). On the study of conditional dependence structure between oil gold and usd exchange rates. *International Review of Financial Analysis*, 59, 134–146.

- Bekaert, G., Michael, E., Marcel, F., & Arnaud, M. (2014). The global crisis and equity market contagion. *The Journal of Finance*, 69(6), 2597–2649.
- 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.
- Bhuyan, R., Robbani, M. G., & Jain, A. (2016). Information transmission and dynamics of stock price movements: An empirical analysis of BRICS and US stock markets. *International Review of Economics & Finance*, 46, 180–195.
- Bradley, B., & Taqqu, M. S. (2004). Framework for analyzing spatial contagion between financial markets. *Finance Letters*, 2(6), 8–15.
- Cherubini, U., & Mulinacci, S. (2014). Contagion-based distortion risk measures. *Applied Mathematics Letters*, 27(27), 85–89.
- Cheung, K. C. (2009). Upper comonotonicity. *Insurance Mathematics and Economics*, 45(1), 35–40.
- Chien, M., Lee, C., & Hu, H. (2015). Dynamic Asian stock market convergence: Evidence from dynamic cointegration analysis among China and ASEAN-5. *Economic Modelling*, 51, 84–98.
- Chopra, M., & Mehta, C. (2022). Is the COVID-19 pandemic more contagious for the Asian stock markets? A comparison with the Asian financial, the US subprime and the eurozone debt crisis. *Journal of Asian Economics*, 79, 1–21.
- Dai, X. Y., Wang, Q. W., Zha, D. L., & Zhou, D. Q. (2020). Multi-scale dependence structure and risk contagion between oil, gold, and US exchange rate: A wavelet-based vine-copula approach. *Energy Economics*, 88, Article 104774.
- Denuit, M., & Lambert, P. (2005). Constraints on concordance measures in bivariate discrete data. *Journal of Multivariate Analysis*, 93(1), 40–57.
- Dhaene, J., Denuit, M., Goovaerts, M. J., Kaas, R., & Vyncke, D. (2002). The concept of comonotonicity in actuarial science and finance: theory. *Insurance: Mathematics & Economics*, 31, 3–33.
- Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119, 158–171.
- Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28, 57–66.
- Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182, 119–134.
- Durante, F., Fernández-Sánchez, J., Quesada-Molina, J. J., & Beda-Flores, M. (2015). Convergence results for patchwork copulas. *European Journal of Operational Research*, 247(2), 525–531.
- Durante, F., Fernández-Sánchez, J., & Sempi, C. (2013). Multivariate patchwork copulas: A unified approach with applications to partial comonotonicity. *Insurance: Mathematics & Economics*, 53(3), 897–905.
- Durante, F., Foscolo, E., Jaworski, P., & Wang, H. (2014). A spatial contagion measure for financial time series. *Expert Systems with Applications*, 41(8), 4023–4034.
- Durante, F., & Jaworski, P. (2010). Spatial contagion between financial markets: A copula-based approach. *Applied Stochastic Models in Business and Industry*, 26, 551–564.
- Eichengreen, B., Rose, A. K., & Wyplosz, C. (1996). Contagious currency crises. In *NBER Working Papers*, 155.
- Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance*, 57(5), 2223–2261.
- Giudici, P., & Raffinetti, E. (2021). Shapley-lorenz explainable artificial intelligence. *Expert Systems with Applications*, 167, Article 114104.
- Gravelle, T., Kichian, M., & Morley, J. (2006). Detecting shift-contagion in currency and bond markets. *Journal of International Economics*, 68(2), 409–423.
- Gray, D. (2009). Financial contagion among members of the EU-8: A cointegration and granger causality approach. *International Journal of Emerging Markets*, 4(7), 199–214.
- Guidi, F., Savva, C. S., & Ugur, M. (2016). Dynamic co-movements and diversification benefits: The case of the greater China region, the UK and the US equity markets. *Journal of Multinational Financial Management*, 35, 59–78.
- Guo, Y., Li, J., & You, W. (2021). The roles of political risk and crude oil in stock market based on quantile cointegration approach: A comparative study in China and US. *Energy Economics*, 97, 1–24.
- Jaworski, P., & Pitera, M. (2014). On spatial contagion and multivariate GARCH models. *Applied Stochastic Models in Business and Industry*, [ISSN: 1524-1904] 30(3), 303–327.
- Jebabli, I., Kouaissah, N., & Aroui, M. (2022). Volatility spillovers between stock and energy markets during crises: A comparative assessment between the 2008 global financial crisis and the Covid-19 pandemic crisis. *Finance Research Letters*, 46, 1–12.
- Jennifer, N. C., Fangzhou, L., & Robert, F. W. (2021). The real value of china's stock market. *Journal of Financial Economics*, 139, 679–696.
- Jiang, H., Tang, S., Li, L., Xu, F., & Di, Q. (2022). Re-examining the contagion channels of global financial crises: Evidence from the twelve years since the US subprime crisis. *Research in International Business and Finance*, 60, 1–13.
- Koch-Medina, P., Munari, C., & Svindland, G. (2018). Which eligible assets are compatible with comonotonic capital requirements? *Insurance: Mathematics & Economics*, 81, 18–26.
- Levy, D., Mayer, T., & Raviv, A. (2022). Economists in the 2008 financial crisis: Slow to see, fast to act. *Journal of Financial Stability*, 60, 1–25.
- Li, X. M., & Lu, P. (2017). US economic policy uncertainty and co-movements between Chinese and US stock markets. *Economic Modelling*, 61, 27–39.
- Liu, X. X., & Shehzad, K. (2023). Analyzing time-different connectedness among systemic financial markets during the financial crisis and conventional era: New evidence from the VARX-DCC-MEGARCH model. *Journal of Applied Economics*, 26(1), Article 2212455.
- Luchtenberg, K. F., & Vu, Q. V. (2015). The 2008 financial crisis: Stock market contagion and its determinants. *Research in International Business and Finance*, 33, 178–203.
- Mantegna, R. (1999). Hierarchical structure in financial markets. *The European Physical Journal B*, 11(1), 193–197.
- Nguyen, T. C., Castro, V., & Wood, J. (2022). A new comprehensive database of financial crises: Identification, frequency, and duration. *Economic Modelling*, 108, 1–17.
- O'Neill, M., Wang, K., & Liu, Z. X. (2016). A state-price volatility index for China's stock market. *Accounting and Finance*, 56(3), 607–626.
- Ozdemir, O. (2022). Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. *Financial Innovation*, 8(1), 12.
- Pan, Q., Mei, X., & Gao, T. (2021). Modeling dynamic conditional correlations with leverage effects and volatility spillover effects: Evidence from the Chinese and US stock markets affected by the recent trade friction. *The North American Journal of Economics and Finance*, 59, 1–18.
- Pesaran, H., & Pick, A. (2007). Econometric issues in the analysis of contagion. *Journal of Economic Dynamics and Control*, 31(4), 1245–1277.
- Ramchand, L., & Susmel, R. (1998). Volatility and cross correlation across major stock markets. *Journal of Empirical Finance*, 5(4), 397–416.
- Sass, J., & Thös, A. K. (2021). Risk reduction and portfolio optimization using clustering methods. *Econometrics and Statistics*, in press.
- Selmi, R., Bouoiyour, J., & Miftah, A. (2019). China's new normal: Will China's growth slowdown derail the BRICS stock markets? *International Economics*, 159, 121–139.
- Shan, C., Tang, D. Y., Wang, S. Q., & Zhang, C. (2022). The diversification benefits and policy risks of accessing Chinese stock market. *Journal of Empirical Finance*, 66, 155–175.
- Shi, Y., Wang, L., & Ke, J. (2021). Does the US-China trade war affect co-movements between US and Chinese stock markets? *Research in International Business and Finance*, 58, 1–16.
- Shu, C., He, D., & Wang, H. (2018). Regional pull vs global push factors: China and US influence on Asian financial markets. *Journal of International Money and Finance*, 87, 112–132.
- Sklar, M. J. (1959). Fonctions de repartition a n dimensions et leurs marges. <https://api.semanticscholar.org/CorpusID:127105744>.
- 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, 1–33.
- Wan, L., Han, L. Y., Xu, Y., & Matousek, R. (2021). Dynamic linkage between the Chinese and global stock markets: A normal mixture approach. *Emerging Markets Review*, 49, 1–22.
- Wang, H., Yuan, Y., Li, Y., & Wang, X. (2021). Financial contagion and contagion channels in the forex market: A new approach via the dynamic mixture copula-extreme value theory. *Economic Modelling*, 94, 401–414.
- Xu, W. J., Ma, F., Chen, W., & Zhang, B. (2019). Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States. *Energy Economics*, 80, 310–320.
- Yang, J. P., Cheng, S. H., & Zhang, L. H. (2006). Bivariate copula decomposition in terms of comonotonicity, counter-monotonicity and independence. *Insurance: Mathematics & Economics*, 39(2), 267–284.
- Yang, L., Tian, S., & Hamori, S. (2018). Dependence structures between Chinese stock markets and the international financial market: Evidence from a wavelet-based quantile regression approach. *The North American Journal of Economics and Finance*, 45, 116–137.
- Yarovaya, L., Brzezczynski, J., Goodell, J. W., Lucey, B., & Lau, C. K. M. (2022). Rethinking financial contagion: Information transmission mechanism during the COVID-19 pandemic. *Social Science Electronic Publishing*, 79, Article 101589.
- Yousfi, M., Ben, Z. Y., Ben, C. N., Ben, L. B., & Bouzgarrou, H. (2021). Effects of the covid-19 pandemic on the us stock market and uncertainty: a comparative assessment between the first and second waves. *Technological Forecasting and Social Change*, [ISSN: 0040-1625] 167.
- Zhang, L., & Duan, B. (2013). Extensions of the notion of overall comonotonicity to partial comonotonicity. *Insurance: Mathematics & Economics*, 52(3), 457–464.

- Zhang, D. Y., Lei, L., Ji, Q., & Kutan, A. M. (2019). Economic policy uncertainty in the US and China and their impact on the global markets. *Economic Modelling*, 79, 47–56.
- Zhang, B., & Li, X. (2014). Has there been any change in the co-movement between the Chinese and US stock markets? *International Review of Economics & Finance*, 29, 525–536.
- Zheng, Y. T., Yang, J. P., & Huang, J. Z. (2011). Approximation of bivariate copulas by patched bivariate Fréchet copulas. *Insurance: Mathematics & Economics*, 48(2), 246–256.
- Zhu, B., Lin, R., & Chevallier, J. (2021). Intersectoral systemic risk spillovers between energy and agriculture under the financial and COVID-19 crises. *Economic Modelling*, 105, 1–21.
- Zorgati, I., & Lakhali, F. (2020). Spatial contagion in the subprime crisis context: adjusted correlation versus local correlation approaches. *Economic Modelling*, [ISSN: 0264-9993] 92, 162–169.